NORTH ATLANTIC TREATY ORGANIZATION

SCIENCE AND TECHNOLOGY ORGANIZATION

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STO TECHNICAL REPORT **TR-SET-227**

Cognitive Radar

(Radar cognitif)

Final Report of Task Group SET-227.

Published October 2020

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The NATO Science and Technology Organization

Science & Technology (S&T) in the NATO context is defined as the selective and rigorous generation and application of state-of-the-art, validated knowledge for defence and security purposes. S&T activities embrace scientific research, technology development, transition, application and field-testing, experimentation and a range of related scientific activities that include systems engineering, operational research and analysis, synthesis, integration and validation of knowledge derived through the scientific method.

In NATO, S&T is addressed using different business models, namely a collaborative business model where NATO provides a forum where NATO Nations and partner Nations elect to use their national resources to define, conduct and promote cooperative research and information exchange, and secondly an in-house delivery business model where S&T activities are conducted in a NATO dedicated executive body, having its own personnel, capabilities and infrastructure.

The mission of the NATO Science & Technology Organization (STO) is to help position the Nations' and NATO's S&T investments as a strategic enabler of the knowledge and technology advantage for the defence and security posture of NATO Nations and partner Nations, by conducting and promoting S&T activities that augment and leverage the capabilities and programmes of the Alliance, of the NATO Nations and the partner Nations, in support of NATO's objectives, and contributing to NATO's ability to enable and influence security and defence related capability development and threat mitigation in NATO Nations and partner Nations, in accordance with NATO policies.

The total spectrum of this collaborative effort is addressed by six Technical Panels who manage a wide range of scientific research activities, a Group specialising in modelling and simulation, plus a Committee dedicated to supporting the information management needs of the organization.

- AVT Applied Vehicle Technology Panel
- HFM Human Factors and Medicine Panel
- IST Information Systems Technology Panel
- NMSG NATO Modelling and Simulation Group
- SAS System Analysis and Studies Panel
- SCI Systems Concepts and Integration Panel
- SET Sensors and Electronics Technology Panel

These Panels and Group are the power-house of the collaborative model and are made up of national representatives as well as recognised world-class scientists, engineers and information specialists. In addition to providing critical technical oversight, they also provide a communication link to military users and other NATO bodies.

The scientific and technological work is carried out by Technical Teams, created under one or more of these eight bodies, for specific research activities which have a defined duration. These research activities can take a variety of forms, including Task Groups, Workshops, Symposia, Specialists' Meetings, Lecture Series and Technical Courses.

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List of Acronyms

ADC	Analog-to-Digital Converter
AESA	Active Electronically Scanned Array
AF	Attenuating Factor
AI	Artificial Intelligence
AR	Traditional Active Radar
ASK	Amplitude Shift Keying
ASpeN	Analytical Spectrum Notching
AWG	Arbitrary Waveform Generator
B&B	Branch and Bound
BTD	Binaural Timbre Difference
CBRS	Citizens Band Radio Service
CoFAR	Cognitive Fully Adaptive Radar
CPI	Coherent Processing Interval
CR	Cognitive Radar
CRLB	Cramér-Rao Lower Bound
CS	Compressed Sensing
DDS	Direct Digital Synthesis
DEM	Digital Elevation Model
DFRC	Dual Function Radar-Communications
DN	Doppler Null
DNB	Doppler Null Bandwidth
DoA	Direction of Arrival
DoF	Degree of Freedom
DVB-T	Digital Video Broadcasting – Terrestrial
ECCM	Electronic Counter Counter Measures
ED	Energy Detector
EDDB	Environmental Dynamic Database
EKF	Extended Kalman Filter
ELINT	Electronic Intelligence
ESA	Electronically Scanned Array
EW	Electronic Warfare
FAR	Fully Adaptive Radar
FD	Feature Detector
FFT	Fast Fourier Transform
FM	Frequency Modulation
FMCW	Frequency Modulated Continuous Wave
FOPEN	Foliage Penetration
FSS	Fast Spectrum Sensing
GMTI	Ground Moving Target Indication
GPS	Global Positioning System
HMI	Human Machine Interface
HPA	High-Power Amplifier

HRR	High-Resolution Radar
HRRP	High Range Resolution Profile
HRTF	Head-Related Transfer Function
IF	Intermediate Frequency
IFFT	Inverse Fast Fourier Transform
ILD	Inter-Aural Level Difference
IoT	Internet of Things
ISAR	Inverse Synthetic Aperture Radar
ISM	Industrial, Scientific and Medical
ITD	Inter-Aural Time Difference
KA	Knowledge-Aided
LFM	Linear Frequency Modulation
LTE	Long Term Evolution
MAB	Multi Arm Bandit
MAP-PF	Maximum a Posteriori – Penalty Function
MCPC	Multi Carrier Pulse Compression
MCTS	Monte Carlo Tree Search
MDP	Markov-Decision-Processes
MF	Matched Filter
MI	Mutual Information
MI	Mutual Information
MIMO	Multiple Input Multiple Output
MOO	Multi Object Optimization
MSE	Mean Square Error
MTI	Moving Target Indication
MUSIC	Multiple Signal Classification
NIH	National Institute of Health
NTIA	National Telecommunications and Information Administration
OFDM	Orthogonal Frequency Division Multiplexing
PAC	Perception-Action Cycle
PAPR	Peak-to-Average Power Ratio
PCC	Peak Cross Correlation
PCFM	Polyphase-Coded Frequency Modulation
PCL	Passive Coherent Location
PET	Passive Emitter Tracking
PNT	Position, Navigation and Timing
POMDP	Partially Observable Markov Decision Process
PRF	Pulse Repetition Frequency
PRI	Pulse Repetition Interval
PRO	Pseudo-Random Optimized
PSD	Power Spectral Density
PSK	Phase Shift Keying
PSL	Peak Sidelobe Level
QoS	Quality of Service
RD	Range Doppler

REM	Radio Environmental Map
RF	Radio Frequency
RFI	Radio Frequency Interference
RKHS	Reproducing Kernel Hilbert Space
RRM	Radar Resource Management
RUWO	Reiterative Uniform Weight Optimization
SAR	Synthetic Aperture Radar
SC	Spectrum Cartography
SINR	Signal to Interference plus Noise Ratio
SIR	Signal-to-Interference Ratio
SLA	Sense-Learn-Adapt
SNR	Signal to Noise Ratio
SNR	Signal to Noise Ratio
STAP	Space-Time Adaptive Processing
SWOT	Strengths, Weaknesses, Opportunities and Threats
TDOA	Time Difference Of Arrival
TV	Television
TX	Transmitter
UHF	Ultra High Frequency
VHF	Very High Frequency
WiMAX	Wireless Inter-operability Microwave Access

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Cognitive Radar

(STO-TR-SET-227)

Executive Summary

For NATO's military and peacekeeping operations radar is used in virtually all applications, including air defence, weapon locating, surveillance, reconnaissance and target acquisition. Radar systems are able to function during day and night, have relative immunity to weather, and can even provide over the horizon coverage. They can provide high-resolution imagery, detect, localize and track targets at all ranges. The emerging theme of cognitive radar sensing has roots in mammalian cognition. It embraces both the "perception-action cycle" and the more explicit generation and exploitation of memories. Applying the ideas of cognition to radar has the potential to usher in a new era of sensing, not just improving the performance of existing radar systems but opening up whole new capability areas. Cognition is ubiquitous and can be applied to all radar systems. Potential benefits include sensitivity enhancements to improved tracking, sensing for autonomous guidance and navigation, and many more.

The objectives of this Task Group have been to develop and conduct experiments and theoretical investigations to illustrate the benefits and challenges of enabling cognition-based capabilities in radar systems. Several of the participating groups have conducted experiments on cognitive, and the co-operation afforded by the task group has allowed ideas, experiences and results to be shared. At the outset of this study there had been little or no experimental work to demonstrate cognitive behaviour in a practical way. The work has been able to demonstrate true cognitive behaviour in a radar sensor. However, the work has also highlighted the difficulty of experimental work on cognitive sensing, and there is much more to be done.

The work has reviewed the different concepts and definitions in the literature and highlighted that a true cognitive system should incorporate *learning*, so that faced with a dynamically-changing target scene it will do better a second time. Nevertheless, some workers argue that the term 'fully adaptive radar' is more appropriate, since 'cognitive radar' almost promises too much.

The experimental work of the task group will undoubtedly continue beyond the time limit of this Task Group, since strong links have been forged. It is recommended that a further NATO Task Group be initiated on the subject of Cognitive Radar Networks. The radars of the future are likely to be distributed, intelligent and spectrally-efficient, so the extension of cognitive techniques to distributed sensing is a natural way forward. However, the means of resource management of a distributed network of this kind (and, indeed, the Position, Navigation and Timing (PNT) – especially in a GPS-denied environment, and the means of exchanging information between the nodes of such a network) still need to be fully understood and developed. The experimental work that has been undertaken in this Task Group can be extended to distributed sensing networks.

Radar cognitif

(STO-TR-SET-227)

Synthèse

Les opérations militaires et de maintien de la paix de l'OTAN utilisent théoriquement des radars dans toutes leurs applications, ce qui inclut la défense aérienne, la localisation des armes, la surveillance, la reconnaissance et l'acquisition d'objectifs. Les systèmes radars sont capables de fonctionner de jour comme de nuit, sont relativement immunisés contre les conditions météorologiques et peuvent même assurer une couverture au-delà de l'horizon. Ils peuvent fournir une imagerie à haute résolution, détecter, localiser et suivre les objectifs à toutes les distances. Le thème émergent de la détection par radar cognitif s'enracine dans la cognition des mammifères. Il englobe à la fois le « cycle de perception-action » et la production et l'exploitation plus explicite de souvenirs. L'application des idées de cognition au radar pourrait inaugurer une nouvelle ère de la détection, non seulement en améliorant les performances des systèmes radars existants, mais en ouvrant de tout nouveaux domaines de capacité. La cognition est omniprésente et peut être appliquée à tous les systèmes radars. Les avantages potentiels sont notamment l'amélioration du suivi par le renforcement de la sensibilité et la détection pour le guidage et la navigation autonomes, parmi tant d'autres.

Les objectifs de ce groupe de travail étaient d'élaborer et de mener des expériences et des investigations théoriques pour illustrer les avantages et les défis de la mise en place de capacités fondées sur la cognition dans les systèmes radars. Plusieurs groupes participants ont réalisé des expériences sur la cognition ; la coopération offerte par le groupe de travail a permis le partage des idées, des expériences et des résultats. Au début de cette étude, il n'existait pas ou peu de travaux expérimentaux pour démontrer le comportement cognitif en pratique. Les travaux réalisés ont fait la démonstration du comportement cognitif réel d'un capteur radar. Cependant, ils ont également mis en lumière la difficulté du travail expérimental sur la détection cognitive et il reste beaucoup à faire.

Les travaux ont passé en revue les différents concepts et définitions de la littérature et souligné qu'un véritable système cognitif devait incorporer l'apprentissage, afin que, confronté à une scène d'intérêt qui change dynamiquement, il fasse mieux la deuxième fois. Toutefois, certains chercheurs avancent que l'expression « radar entièrement adaptatif » est plus appropriée, car l'expression « radar cognitif » est presque trop prometteuse.

Les expériences du groupe de travail se poursuivront sans aucun doute après la fin de ce groupe de travail, car des liens solides ont été forgés. Il est recommandé de créer un autre groupe de travail de l'OTAN au sujet des réseaux de radars cognitifs. Les radars du futur seront probablement répartis, intelligents et efficaces sur le plan du spectre, de sorte que l'élargissement des techniques cognitives à la détection répartie va de soi. Néanmoins, il faut encore comprendre en détail et développer les moyens de gestion des ressources d'un réseau réparti de ce type et, en réalité, le positionnement, la navigation et la référence temporelle (PNT) – notamment dans un environnement où le GPS est bloqué – ainsi que les moyens d'échange d'informations entre les nœuds d'un tel réseau. Les expériences entreprises dans ce groupe de travail peuvent être étendues aux réseaux de détection répartis.

Chapter 1 – CONTEXT AND DEFINITIONS

1.1 WHAT IS COGNITION?

In the literature, cognitive and adaptive concepts are used interchangeably because the definition of cognitive concept is not clearly made. Therefore, before evaluating the subject of cognitive radars, it is important to clarify the cognitive concept. There exist some prominent features for the radars to be considered cognitive:

1) Cognitive radars:
   a) Can learn and react differently in the same environment and clutter conditions;
   b) Can search the parameter set for better performance, and
   c) Can measure the effectiveness of radar processes with selected parameters,
2) Cognitive radars can determine how the targets/environment will behave in a future time period with the knowledge acquired from the targets/environment, and choose optimum parameter set accordingly.
3) Cognitive radars can update the state space models that are used for estimation.
4) The success criteria of cognitive radars are more abstract, and cognitive radars can make decisions based on top-level criteria such as mission success rather than instant performance improvements.

1.2 ADAPTIVE FEATURES OF MODERN RADAR SYSTEMS

Modern radar systems can adjust the waveform parameters such as frequency, pulse width, pulse compression code, PRI and number of pulses using digital signal generators. Moreover, the radar systems that have phased array antenna structures can adjust the transmit and receive antenna patterns. In order for these features to be considered adaptive, the environment must be evaluated, and the waveform parameters must be selected by the radar according to this evaluation. In modern radars, the waveform parameters of track beams are determined adaptively depending on the kinematics and characteristics of the tracked targets. In multi-function radars, radar transmit times and the priority between search or track beams are determined adaptively according to the environmental conditions and target characteristics.

In addition to the beam properties, adaptive properties are used extensively in signal processing and tracking algorithms. In modern radar systems, tracking algorithms are capable of selecting models according to target kinematics. CFAR algorithms at the signal processing level can determine threshold levels adaptively based on measured noise characteristics. Algorithms that prevent the radar from false trace initiation by using information from road maps can be described as adaptive. Radars with multi-channel signal processing feature can be implemented with Space Time Adaptive Processing. In this way, the characteristics of the clutter and interference signals are estimated, and adaptive filtering is performed in Space Time.

1.3 THE IMPORTANCE OF COGNITION IN RADARS

When considering the applicability and necessity of cognitive abilities in radars, one of the most important questions is the possibility that the radar can adapt to its environment with the radar function. For example, waveform parameter change in the middle of imaging process for a SAR radar is not feasible, but adaptive operations can be utilized during target tracking phase. For each radar and each defined radar function, this evaluation is required.

Cognitive algorithms have high applicability for tracking radars where target data can be collected continuously. It is observed that adaptive capabilities are used extensively during the tracking function of modern radars both in determining the waveform parameters and in data processing algorithms. The target range and velocity information enable the use of adaptive capabilities, such as the adjustment of the waveform parameters; such as PRI and pulse width, of the transmitted waveform as well as the selection of the pulse compression filters and the utilization of signal processing algorithms to reduce the range migration effects.

Cognitive abilities are important for all radars operating on the border and providing high added value for task performance. These radars have the best performance in situations where the environment can change very quickly, and the response times are too short.

The very short response time criterion is also applicable to multi-function radars and radars on combat platforms. The timeframe for the planning of the radar beams under conditions where a large number of targets are simultaneously monitored, and a wide search space is covered is far below the decision and response time of the people. For combat platforms, especially the aerial platforms, the location of the targets in the background of clutter, and the positions of the targets relative to each other change very quickly. It will not be possible for the radar operator to adjust the radar parameters in accordance with this rapid change. Under these conditions, cognitive abilities become important for all radars that are expected to operate in these conditions.

1.4 OBJECTIVES AND METHODOLOGY

For NATO’s military and peacekeeping operations radar is used in virtually all applications, including air defence, weapon locating, surveillance, Reconnaissance and Target Acquisition (RSTA), etc. Radar systems are able to function during day and night, have relative immunity to weather, and can even provide over the horizon coverage. They can provide high-resolution imagery, detect, localize and track targets at all ranges. The emerging theme of cognitive radar sensing has roots in mammalian cognition. It embraces both the “perception-action cycle” and the more explicit generation and exploitation of memories. Applying the ideas of cognition to radar has the potential to usher in a new era of sensing, not just improving the performance of existing radar systems but opening up whole new capability areas. Cognition is ubiquitous and can be applied to all radar systems. Potential benefits include sensitivity enhancements to improved tracking, sensing for autonomous guidance and navigation, and many more. As a continuation of similar effort, this activity would also leverage the technical relationships and technical accomplishments of the SET-179 and SET-182 RTGs on Waveform Diversity and Radar Spectrum, respectively.

The objectives were stated in the TAP to be:’ to develop and conduct experiments and theoretical investigations to illustrate the benefits and challenges of enabling cognition-based capabilities in radar systems. Specifically, bio-inspired and bio-mimetic approaches borrowed from nature will be leveraged along with memory-based learning and control paradigms. The overarching theme will be upon incorporating greater autonomous decision-making and feedback-controlled adaptivity into the sensor’.

The topics to be addressed were listed in the TAP as:

- Theoretical concepts/models for cognitive radar sensing;
- Intelligent and adaptive waveform design;
- Adaptive feedback for enhanced detection and tracking;
- Spectrum-agile and spatially-distributed cognitive sensing;
- Cognitive concepts for scene perception and target recognition;
- The role of knowledge and memory in cognitive radar sensing;

- Autonomous decision-making in advanced radar systems;
- Bio-inspired/bio-mimetic sensing; and
- Transmitter/waveform co-design and reconfigurable microwave systems.

The methodology adopted was to construct a matrix of these topics against the list of participants, with a leader identified for each topic, and with the intention that each topic should form a chapter in this report. As the work progressed, some refinement was made to the matrix to reduce the number of topics to six, but the same essential methodology was followed.

1.5 REPORT STRUCTURE

The structure of this report follows the methodology outlined above, so that each chapter of the body of the report covers one of the six topics. Finally, Chapter 9 draws conclusions and makes some recommendations.

References are listed in Chapter 10. Annex A lists the locations and dates of the meetings of the group. Annex B provides a list of the outputs of the group.

Chapter 2 – COGNITIVE PROCESSES

2.1 INTRODUCTION

There exist a number of definitions of cognitive processes with standpoints in different disciplines, ranging from cognitive psychology to neuroscience. Some neuroscientists have taken a low-level Hebbian view based on the functions of connected neurons [1], whereas cognitive psychologists have taken more of a systems view of the brain and its cognitive processes [2]. There has been some disagreement between the fields of cognitive neuroscience and cognitive psychology on issues, but the cognitive processes used in both disciplines have been remarkably similar. The following sections will look into definitions of cognitive processes and examine the impact of cognitive science.

2.2 DEFINITIONS OF COGNITIVE PROCESSES

Although the definition of cognitive processes can vary, standard texts on cognitive psychology [2], [3] all describe very similar cognitive processes, which are listed in Table 2-1. Although some of these processes are to an extent present in existing radar systems, developing a radar system that possesses all of these cognitive processes is a highly challenging task, which may not even be desirable.

Table 2-1: Cognitive Processes Common to Most Definitions.

Perceptual	Memory	Language	Thinking
Perception generation	Long-term memory	Concepts and categorisation	Problem solving
Attention	Working memory	Language processing	Reasoning
Recognition	Learning	Language production	Decision making and judgement
		Language comprehension	Anticipation

2.2.1 Learning

Learning is the process of acquiring new knowledge on the environment, which is used to enhance perception generation, as well as to make well informed decisions and execute well informed actions. The huge significance of the learning process for humans is evident from the long learning period between birth and cognitive maturity.

The relevance of learning for cognitive radar can be seen, for example, in matched illumination, where it is necessary to learn a model of the radar channel in order to control the degrees of freedom for the transmit waveform and the receiver filter. Generally, all cognitive radar methods utilise some models, either for perception generation or for action selection. However, many of the techniques, such as the QoS optimisation methods, utilise fixed performance models that are not learnt based on the observed data obtained while the radar is operational. Also, the time duration over which acquired knowledge is exploited is presently very short. Exploiting knowledge that has been acquired by learning over extended time periods, potentially the entire lifetime of the radar system, is a defining feature for a cognitive radar system. Fortunately, the field of machine learning has seen great advances in the last decade, which can certainly be transitioned into the radar domain.

2.2.2 Problem Solving

The process of problem solving is critical to cognition and it is clear that humans and animals continuously face problems that must be solved. An insightful definition of a problem is given by Duncker and Braisby [2], [4]:

> *a problem exists when a living organism has a goal but does not know how this goal is to be reached.*

From this definition, it is clear that the goal is crucial to the process of problem solving, and effective problem solving must lead to goal-directed behavior.

Conventionally, at design time, a radar system has a specific performance specification for a limited number of situations, which leads to a fixed configuration during operation. Consequently, the radar performance and effectiveness vary depending on the actual current situation and the specific mission requirements respectively. Mission requirements can be for example, protection of the radar platform and interception of hostile platforms. In contrast, a problem solving cognitive radar has the goal of satisfying the mission requirements by reconfiguring to alter the radar behavior based on everything that is known about the current situation. Therefore, it must generate waveforms and extract information that is linked to higher level mission goals and objectives in order to generate robust, stable performance in unexpected (or previously unspecified) situations. Traditional approaches formulate objective functions based on lower level performance criteria, such as the signal-to-interference ratio, track estimation error or information production. It is then implicitly assumed that optimising these lower level criteria aggregate to a successful mission. However, a successful mission may not be achieved as the true goal is not explicitly considered.

2.2.3 Concepts and Categories

A concept is an internal idea that applies to a category of things, enabling sets of objects to be sorted into categories. Categorising according to a concept is a key human cognitive process that enables humans to respond to objects depending on category instead of the unique object itself. Semantic memory stores known relationships between concepts, for example it is known that ships belong on water. The process of human categorisation and hence concept definition is very complex, with a variety of theories [3] that are not yet able to completely explain the process.

The cognitive process of categorisation based on concepts may sound abstract, however, it bears a striking resemblance to higher level information fusions systems and situation assessment methods. Situation assessment characterises the relations and patterns between objects that are perceived in the current situation. Then, the relations that are stored in semantic memory are used to reason about unobservable properties of the situation. The cognitive process of categorisation and reasoning is often described in the literature on higher level information fusion [5], but rarely discussed in the context of a cognitive radar. This could be because situation assessment is not typically seen as a radar capability.

2.2.4 Language

Language processing, language comprehension and language production are also identified as cognitive process in Table 2-1. The language processes draw upon many of the cognitive process already described, such as memory, concepts and reasoning. For a cognitive radar system, it is necessary for the system to communicate effectively with the operator through the Human Machine Interface (HMI). Not only must the operator be able to effectively communicate objectives and requirements, the radar system must provide the necessary information to justify the decisions that the radar system takes, otherwise the operator will not trust the radar. Therefore, cognitive radar also creates new challenges for developing effective HMIs.

In addition to the operator, it is desirable for the radar system to communicate with other sensor systems or platforms. Networks of sensor systems offer many benefits in terms of robustness against failures as well as improved performance resulting from complementary sensing characteristics or target perspectives. Developing networked sensor systems is currently a large and evolving area of research. As communication is a crucial task for a cognitive radar system, the development of language processes (language processing, language comprehension and language production) is an open challenge.

2.2.5 Reasoning

Reasoning is the process of inferring a conclusion based on premises, by following logical laws. Reasoning is present in Bayesian target tracking, as the target state is inferred from noisy measurements, potentially also using context or negative information. However, reasoning can be extended to the higher situation and mission levels, where categorisation plays a crucial role. For example, when someone drives a previously unfamiliar car, although nothing is known about the car, it is possible to reason that the car has brakes due to the person's concept of a car. Likewise, a radar can reason about the current situation or mission, based on previously experienced situations or missions. Reasoning is currently rarely mentioned in the context of cognitive radar but is a key component of existing situational assessment methods, which can be applied to radar problems.

2.2.6 Decision Making and Judgement

Current radar management methods perform a basic level of decision making, such as selecting the measurement time or waveform. However, radar management is relatively underdeveloped in comparison to adaptive processing at the receiver. Therefore, a challenge for cognitive radar must be to advance the decision-making processes applied in radar management. Interestingly, the study of human decision making indicates that humans are prone to making irrational or non-expectation maximising decisions, which result from cognitive biases. Two from many possible examples of cognitive biases are:

- Bandwagon Effect – The number of believers of a belief or idea influences the adoption of the belief or idea by others, and
- Neglecting Probability Bias – Tendency to disregard probability when making decisions, leading to a higher valuation of low probability events and a lower valuation of high probability events.

These cognitive biases indicate that humans utilise a variety of learnt heuristics, as it is more important to rapidly reach a decision than to perform an exact but very computational and time intensive assessment. This is also a critical consideration for cognitive radar: although improved decision making algorithms are required, they must be capable of rapid reaction. Cognitive biases serve as a warning that even the most advanced cognitive systems are error prone.

2.3 COGNITIVE SCIENCE AND ITS CONNECTION TO COGNITIVE PSYCHOLOGY

2.3.1 History of AI

Modeling higher human cognitive capabilities in a computer has traditionally been the research domain of Artificial Intelligence (AI), as *the science and engineering of making intelligent machines* [6]. On the other hand, there was a lot of impact from experimental results in psychology or cognitive science. Both streams mutually influenced each other as will be illustrated next.

2.3.2 Influence of Artificial Intelligence

Historically, AI research oscillated between two poles which were described by Minsky [7] as "*Logical Versus Analogical or Symbolic Versus Connectionist or Neat Versus Scruffy*". This tension between a formal and mathematically exact approach versus a rather holistic, interdisciplinary approach proved fruitful and pushed the development of the novel research discipline.

The eager claim to implement human intelligence by computer programs is illustrative of the early epoch of AI research (1952 – 1969), which Russel and Norvig [8] term "*Early enthusiasm, great expectations*". Many groundbreaking concepts, such as the knowledge-based approach that separates a generic processing or inference architecture from domain-specific knowledge models were introduced, e.g., by the "*Advice Taker*" [9]. The "*General Problem Solver*" [10] simulates human problem solving strategies by a search algorithm, which was later extended to the general "*Cognitive Systems Paradigm*" [11].

The ambitions of the early years and the early implementations of search algorithms and syntactic transformation rules could, however, not be scaled to larger problem instances. An epoch that Russel and Norvig [8] term "*a dose of reality*" (1966 – 1973): "*The fact that a program can find a solution in principle does not mean that the program contains any of the mechanisms needed to find it in practice*". In the following period (1969 – 1979), knowledge-based systems became increasingly popular. These systems operate on a very narrow, concisely defined problem structure, e.g., the medical diagnosis system MYCIN [12].

The 1980s bear a stronger formalization as pointed out by Russel and Norvig [8]: "*AI adopts the scientific method*" (1987 – today). For selected (sub)-problems of AI, e.g., automated planning, representative test-cases are generated and statistically evaluated. This brings objectivity and makes the performance of different algorithms more comparable. Despite this methodological progress, Russel and Norvig [8] regard the comprehensive, agent-oriented concept as a major trend: *"Perhaps encouraged by the progress in solving the subproblems of AI, researchers have also started to look at the 'whole agent' problem again. The work of Allen Newell, John Laird, and Paul Rosenbloom on SOAR (Newell, 1990; Laird et al., 1987) is the best-known example of a complete agent architecture. […] One consequence of trying to build complete agents is the realization that the previously isolated subfields of AI might need to be reorganized somewhat when their results are to be tied together*".

The "*human-level AI*" movement goes even further in its ambition, claiming a return of AI to its original goal of addressing human intelligence in all its aspects instead of concentrating in particular applications, e.g., chess-playing or autonomous driving.

As illustrated in Figure 2-1, there are four options, when implementing a cognitive system, that have all been historically followed and influenced each other.

The top row of Figure 2-1 deals with pure reasoning processes (thinking), whereas the lower row investigates the observable behavior (acting). The left column suggests human-like behavior as a success metric whereas the right column strives for rational behavior, that is *"A system is rational if it does the 'right thing', given what it knows."*

Modeling of rational behavior follows the long philosophical tradition of logicians (Aristotle, 384 – 322 BC) and formal inference. A disadvantage of this approach lies in formalizing the required real-world knowledge and the complexity of the inference process.

Besides pure reasoning, the advent of robotics emphasizes physical interaction and embeddedness in a work-environment. Already in 1950, Alan Turing invented his "Turing-Test", that declares a computer program intelligent if, after a five-minute written interaction, a human expert is unable in 30% of the cases to decide whether he communicated with a man or a machine.

	Like humans vs.	*rationally*
Thinking	Systems that think *like humans* (Newell & Simon, GPS, Kognitionswissenschaft)	Systems that think *rationally* (Formale Logik)
vs.		
Acting	Systems that act *like humans* (Turing Test, NLP, Computer Vision, Robotics)	Systems that act *rationally* (Intelligent / Rational Agents)

Figure 2-1: Structuring of Intelligent Systems According to Russel and Norvig [8].

2.3.3 Influence of Cognitive Psychology

Cognitive science investigates the human cognition process. This strategy is necessarily an experimental approach, involving e.g., MRT-imaging techniques of neuroscience or psychologist investigating human problem solving strategies in computer programs: "*a cognitive theory should be like a computer program*" [13].

For the psychological concept of *intelligence*, several definitions exist:

- "Judgment, otherwise called "good sense," "practical sense," "initiative," the faculty of adapting one's self to circumstances" [14];
- "A general capacity of an individual consciously to adjust his thinking to new requirements... a general mental adaptability to new problems and conditions of life" [15];
- "The aggregate or global capacity of the individual to act purposefully, to think rationally, and to deal effectively with his environment" [16];
- "Goal-directed adaptive behavior" [17]; and
- "Intelligence measures an agent's ability to achieve goals in a wide range of environments" [18].

The term *cognition* comes from the Latin word "cognoscere", which means to conceptualize or to recognize. It is often stated that cognition encompasses an information processing act. While in the early 20th century, behavioristic psychology was dominant, with the "cognitive revolution" around the year 1956, the emphasis shifted towards internal, mental processes. Higher human cognitive capabilities encompass e.g., situation awareness, attention, problem solving, planning, remembering, learning and language understanding. In the following twenty years, several cognitive capabilities were analyzed and understood by psychologists using symbol processing computer programs. This "*Computer-Metaphor*" is based on the *physical symbol system hypothesis*, which states that "*A physical symbol system has the necessary and sufficient means for general intelligent action*." [19]. AI software based on symbol-manipulation, such as the "*General Problem Solver"* is nowadays often referred to as "Good Old Fashioned Artificial Intelligence" [20]. Modern software-tools in cognitive psychology hence also include sub-symbolic approaches, e.g., based on activation patterns or neural nets.

2.4 SITUATIONAL AWARENESS AND CONNECTION TO PERCEPTION-ACTION CYCLE

Situation Awareness (SA) is a psychological concept, that is closely linked to others like perception, attention, and workload. Several definitions exist, including:

- *"Continuous extraction of environmental information, integration of this knowledge to form a coherent mental picture, and the use of that picture in directing further perception and anticipating future events"* [21],
- *"Just a label for a variety of cognitive processing activities that are critical to dynamic, event-driven and multitask fields of practice"* [22], and
- *"Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future"* [23].

Mica Endsley's definition and the model shown in Figure 2-2 are particularly widespread. She describes three levels of SA, whereas level 1 ("*perception of elements in current situation*") encompasses all directly perceived objects (e.g., cars, aircrafts, pedestrians) in a scene and their state (e.g., position, dynamics, mode of operation). Level 2 SA ("*comprehension of current situation*") describes the association between perceived objects towards an abstract description of the situation. For this, an interpretation and assessment of the facts due to a-priori knowledge and experience is required. Level 3 ("*projection of future status*") extrapolates L1 and L2 elements perceived into the future. This represents an even further degree of abstraction and allows statements about future events.

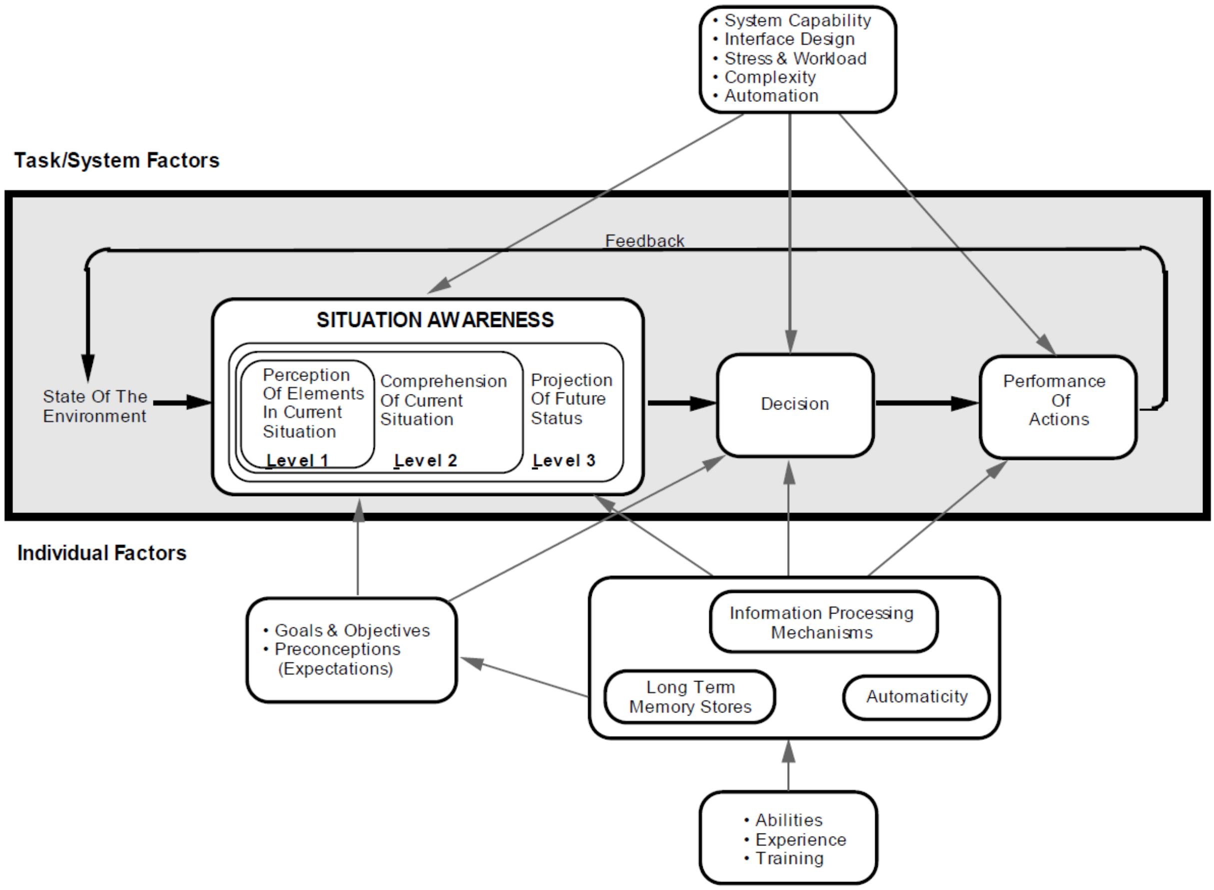


Figure 2-2: Endsley's Model of Situational Awareness.

The information processing scheme according to Wickens [24], shown in Figure 2-3, is a standard model in many cognitive architectures. The approach distinguishes between the pure reception of a stimuli by the receiving organs and the information processing by higher cortical structures in the brain. The reception of the stimuli is represented by the *short-term sensory store*, which can hold a large amount of data for short time (e.g., 0.1 – 0.5 seconds) to provide the incoming signals to the subsequent perception and pattern recognition processes.

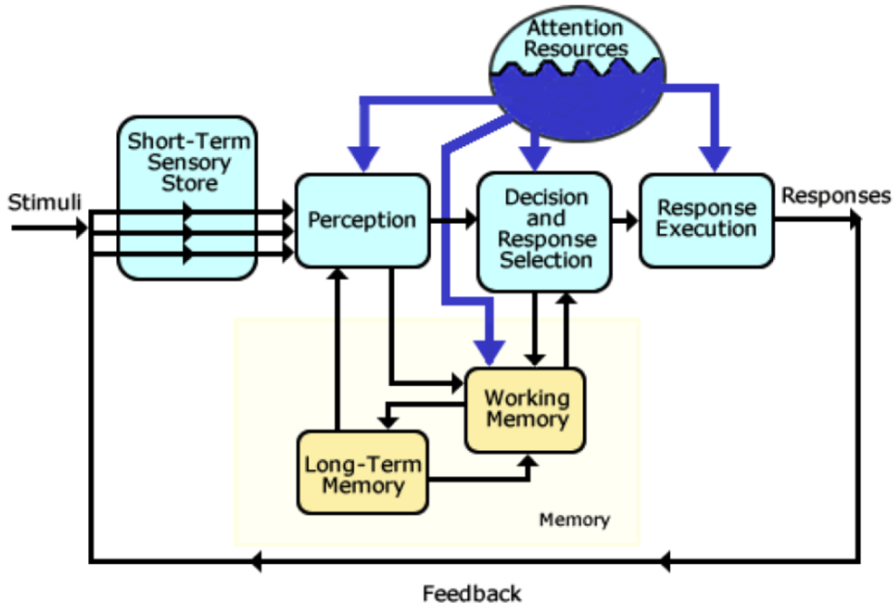


Figure 2-3: Wickens' Model of Information Processing [24].

The interpretation of the signal into an internal, semantic representation (called *mental models*) happens in the "*perception*" block. The "*decision and response selection*" and "*response execution*" blocks represent subsequent human decision-making and plan execution stages. The *working memory* can temporarily hold information for about 20 – 45 seconds. According to Miller [25], its capacity is restricted to 7 ± 2 chunks of information (e.g., remembering the digits in a telephone number). *The long-term memory*, in contrast, retains large chunks of information for long time periods (e.g., a lifetime). In the Wickens model, a limited amount of Attention Resources is available to be distributed among the different information processing blocks.

Chapter 3 – ARCHITECTURES AND COMPONENTS

3.1 INTRODUCTION

This chapter introduces the cognitive radar architecture and its main functionalities. The main scientific findings in the cognitive radar area are firstly reported. The chapter is then focussed on the design of a cognitive radar architecture based on multiple layers. Then, examples of radar applications exploiting cognitive architectures are presented together with a set of meaningful results. Finally, a Strengths/Weaknesses/Opportunities/Threats (SWOT) analysis is presented in order to highlight the main advantages and potential weaknesses of the cognitive paradigms.

3.2 COGNITIVE RADAR: HIGH LEVEL ARCHITECTURE

The concept of cognition to empowered engineering systems has been introduced and formalized for the first time by Haykin in 2006 [26]. According to Haykin's statement, Cognitive Radar architectures are characterized by one or more feedback loops from the radar receiver to the transmitter, controlling the Radar's operational parameters to continuously optimize some performance metric [26]. The National Institute of Health (NIH) defines cognition as "conscious mental activity that informs a person about his or her environment. Cognitive actions include perceiving, thinking, reasoning, judging, problem solving, and remembering" [27]. There is have still no exact definition in the community, on what general building blocks a cognitive radar architecture must possess. However, there is common a notion that cognitive radar should resemble the cognitive skills of humans or certain animals, such as bats or dolphins. It is well known (see e.g., Simons, 1973 [28] and Thomas et al., 2004 [29]) that bats and dolphins are able to "see" very small prey (as compared to their own size) and can track them by adjusting both the duration and the repetition frequency of the emitted pulse bursts based upon the range and the velocity of the targets. Some dolphin species, such as the Bottlenoses, are able to detect, classify, and localize targets the size of a sardine, in cluttered background, over ranges from 0 m to about 150 m, in any sea condition, and all maritime environments, from the open ocean to rivers and estuaries [30], [31]. Of course, it is not trivial to implement in a real radar system all the functionalities of a well-trained bio-sonar, which has been evolving over millions of years, although some effort along these lines has been successfully pursued. In this direction, several architectures have been proposed in the literature for various purpose, the basic architectures are here recalled.

3.2.1 Guerci's Perspective and Architectures

Guerci envisions a Cognitive Radar (CR) capable of "sensing, learning, and adapting to complex situations with performance approaching or exceeding that achievable by a subject matter expert, especially for real time operations which demand automation" [32], [33]. He proposed the following mapping of biological cognitive properties to cognitive radar:

- Perceiving →Sensing;
- Thinking, reasoning, judging, problem solving → Expert Systems, Rule-Based Reasoning, Adaptive Algorithms and Computation; and
- Remembering→ Memory, Environmental Database.

The fully adaptive radar architecture proposed by Guerci in his book [32] and other publications in 2010, thus envisioned an integration of Knowledge-Aided (KA) algorithms with an Adaptive Transceiver. Drawing upon an Environmental Dynamic Database (EDDB), which would contain endogenous and exogenous information sources, the radar system would thus both adapt on receive, vis-à-vis the adaptive signal processing algorithms used to analyze the received data, as well as adapt on transmit, by selecting optimal waveforms (Figure 3-1).

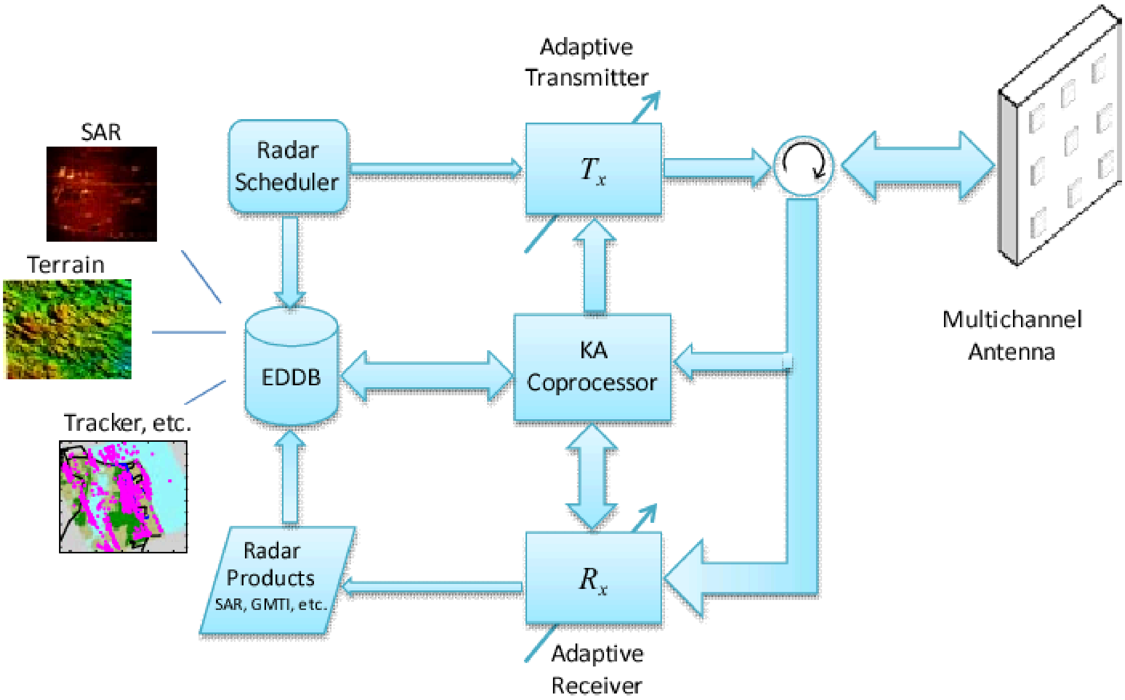


Figure 3-1: Cognitive Radar Architecture Proposed by Guerci [27].

While the terms "fully adaptive" and "cognitive" were in the early years seen as synonymous, beginning in 2015 the definitions began to diverge, so that the term "cognitive" also embodied a distinct requirement for learning to be incorporated in the system. Accordingly, in 2014 Guerci began to use the term "Cognitive Fully Adaptive Radar" (CoFAR) to describe a revised version of the 2010 cognitive radar architecture [33]. In this new architecture, a "Sense-Learn-Adapt" (SLA) cycle, pictured in Figure 3-2, was proposed to represent the elements of cognition:

- Sense – Transmit and receive functions jointly optimized to enhance performance; utilized in new ways to enhance channel estimation;
- Learn – KA expert systems utilizing supervised learning; and
- Adapt – Adaptive parametric approaches; waveform and spatial diversity.

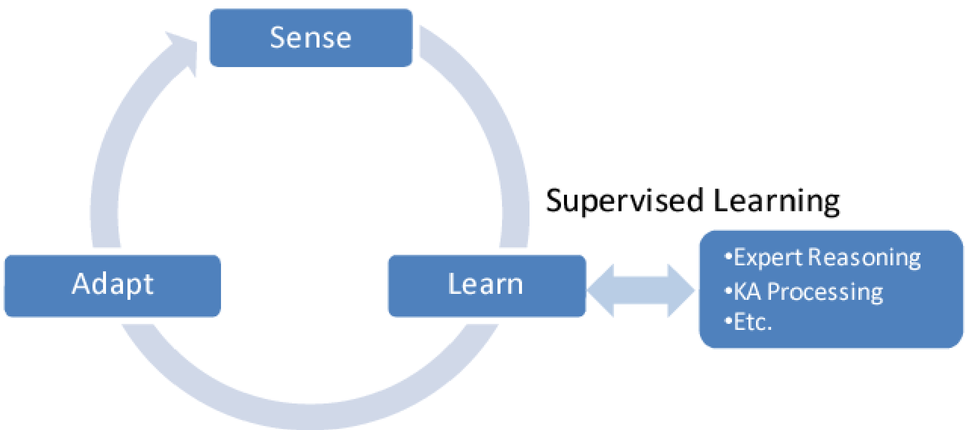


Figure 3-2: Sense-Learn-Adapt Cycle [27].

These concepts led to the proposed CoFAR architecture shown in Figure 3-3, which is fundamentally similar to the original 2010 architecture but employing "CoFAR" blocks enabling "sense-learn-adapt" functions to be distributed throughout the system.

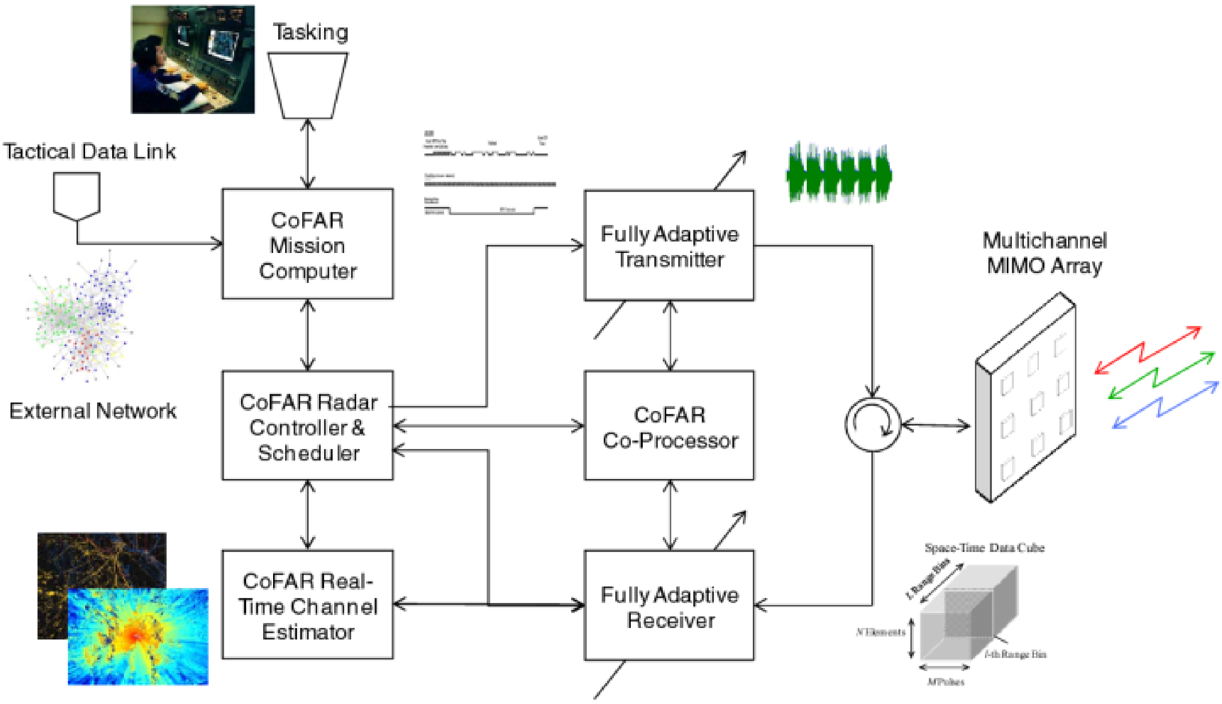


Figure 3-3: CoFAR Architecture Proposed by Guerci [33].

3.2.2 Haykin's Perspective and Architecture

Haykin introduced cognitive radar (Figure 3-4) as a radar system with three basic ingredients:

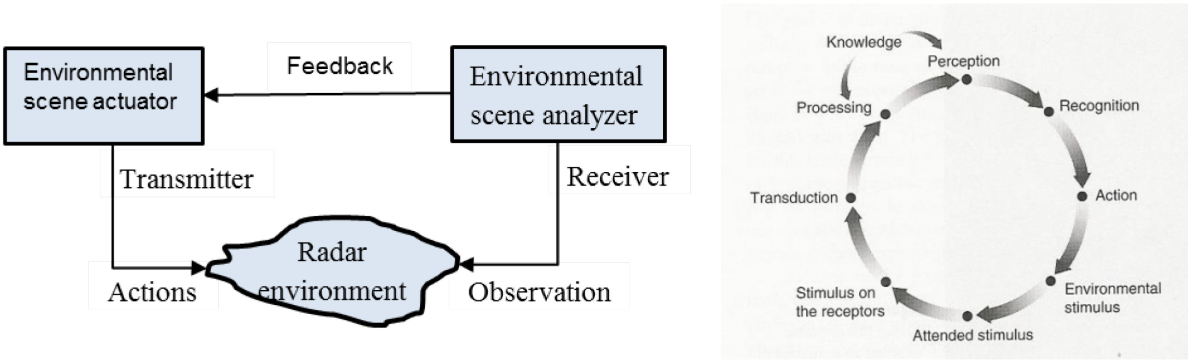
1) Intelligent signal processing, which builds on learning through interactions of the radar with the surrounding environment;
2) Feedback from the receiver to the transmitter, which is a facilitator of intelligence; and
3) Preservation of the information content of radar returns by the radar scene analyzer.

Later in his book he elaborated the high level diagram of cognitive radar with perception-action cycle, memory, attention and intelligence [34].

The Perception-Action Cycle (PAC) is now widely accepted as the key idea of cognitive radar.

The PAC (Figure 3-4(b)) constitutes a dynamic closed feedback loop, in which the transmitter supplies intelligent illumination of the environment, while the "receiver continuously learns about the environment through experience gained from interactions with the environment and, in a corresponding way, continually updates the receiver with relevant information on the environment".

In addition to the concept architecture, Haykin indicated that for the radar to be cognitive, adaptivity has to be extended to the transmitter from the receiver adaptivity in traditional radar [26]. To account for this, a CR has to embody four ingredients: the PAC, memory, attention, and intelligence. The PAC and memory, occupying their distinctive places within the radar system architecture, are depicted in Figure 3-5 [35], [36].



(a) **(b)**

Figure 3-4: Haykin's Diagram of Cognitive Radar: (a) Concept Architecture; (b) Perception-Action Cycle.

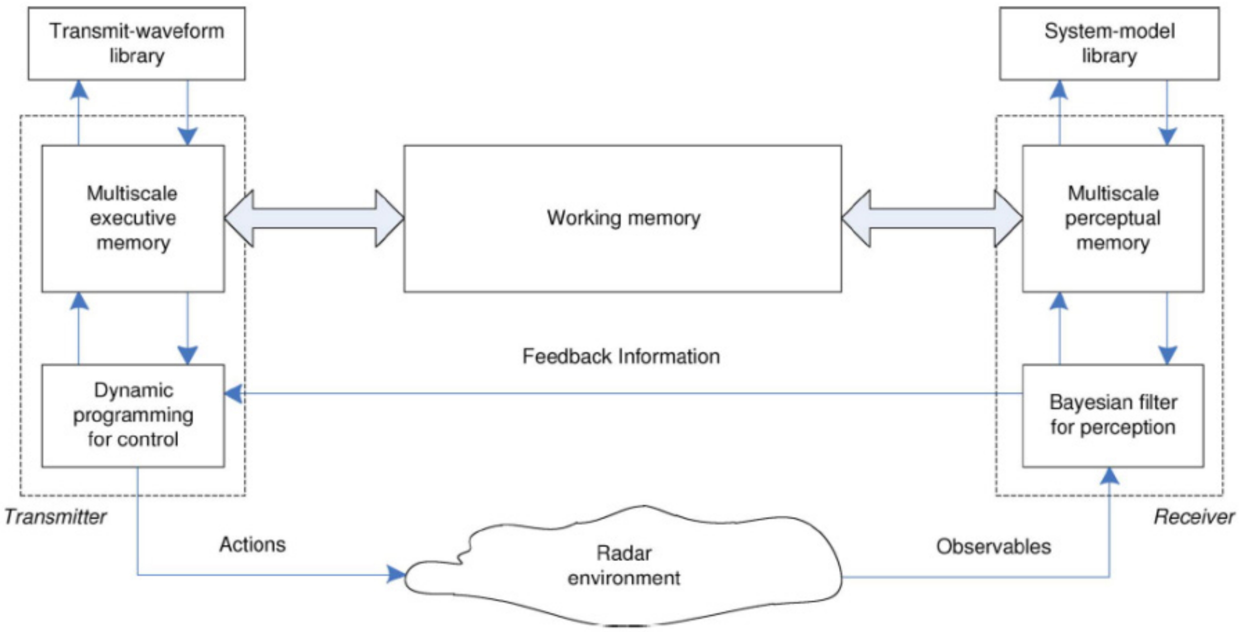


Figure 3-5: Diagram of Cognitive Radar with Memory.

The radar cognition is driven by the perception-action cycle and memory. Through waveform adaptation, which is performed in the perception-action cycle, cognitive radar gains control over certain aspects of the sensing process. Therefore, the perception-action cycle ties together estimation (through sensing) and control. Hence, cognition equips a radar with controlled-sensing ability to counteract the effect of environment. In the extended architecture (Figure 3-5), Haykin described three kinds of **memory**: perceptual memory, executive memory and working memory.

- Perceptual Memory: The part of memory that resides in the receiver is called perceptual memory. It would be desirable for the perceptual memory to have a multiscale structure.
- Executive Memory: The part of the memory that resides in the transmitter is called the executive memory, whose structural composition follows a similar format to that of the perceptual memory, with the following basic difference. Whereas the perceptual memory sees the radar environment

through the measurement vector directly, the executive memory sees the radar environment indirectly through the feedback information about the environment supplied to the transmitter by the receiver. Note also that the executive memory is reciprocally coupled to another library called the transmit-waveform library.

- Working Memory: The working memory is a dedicated memory with limited capacity that provides an interface between perception and action by linking the perceptual and executive memories together. Unlike the perceptual and executive memories that are long-term memories, working memory has a short-term nature, and it is therefore used for temporary information storage.

Subsequently, Haykin presents a Bayesian framework for the example of target tracking (Figure 3-6), which utilizes a continuous-discrete cubature Kalman filter, along with simulation results for the design. In this framework the aforementioned neural-network-based three-part memory design is not utilized, with the state-space formulation of the Kalman filter instead serving to emulate the perception-action-cycle. The cycle begins with the transmitter illuminating the environment. The radar returns produced by the environment are fed into two functional blocks: radar scene analyzer which gives information on the environment and Bayesian target-tracker which gives traditional target state estimation, implementing the following steps:

- One-step predictor, whose output is described by the conditional probability;
- Filter, whose output is described by the conditional probability; and
- Smoother, whose output is described by the expanded conditional probability.

It is important to point out that the function of the radar scene analyzer, which is of critical importance to the decisions made by the receiver on possible targets of interest, builds on two sources of information-bearing signals:

- Radar returns, which are produced by the environment in response to the radar's own transmitted signal; and
- Other relevant information on the environment (e.g., temperature, humidity, pressure, sea-state), which is gathered on the fly by sensors other than the radar itself.

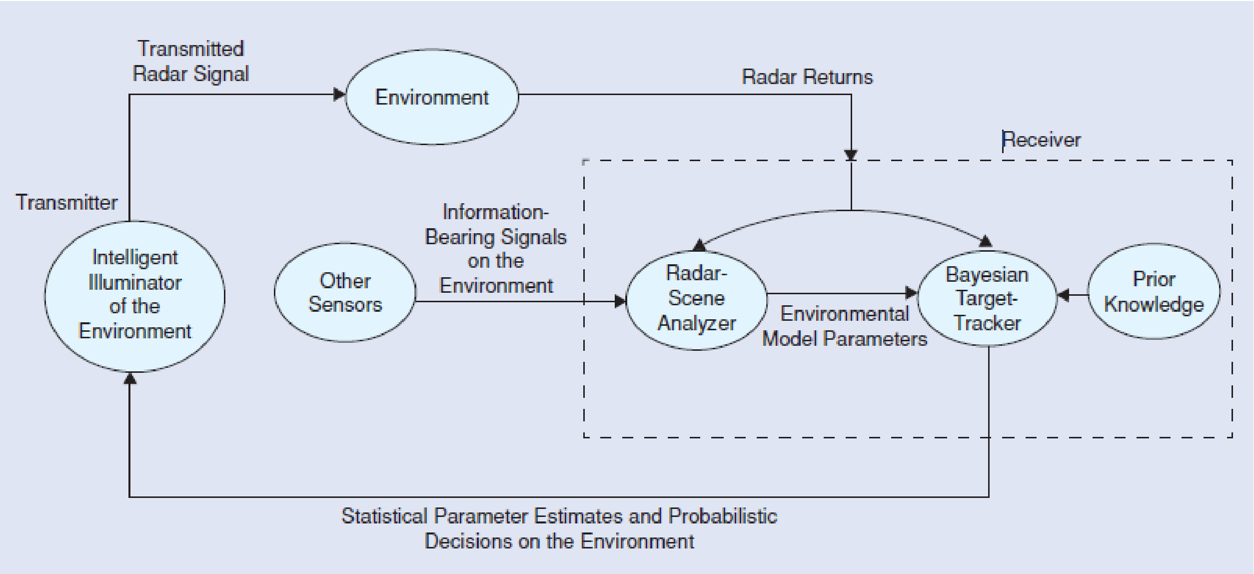


Figure 3-6: Block Diagram of Cognitive Radar as a Dynamic Closed-Loop Feedback System.

From Haykin's definition, a cognitive radar has four abstracted elements. These elements are actually applicable to a general cognitive system, formulating the so-called "perception-action" cycle:

- To sense and analyze the environment (perception);
- To learn important features about the target and the background at the receiver (learning);
- To decide feedback information to the transmitter (decision); and
- To act out the transmitted waveform (action).

Memory plays a critical role in human cognition and in cognitive radar systems too. Memory is not only just the recorded data, but also the intelligent way of accessing and reprocessing the data when needed. Other CRs key ingredients are "Attention" and "Intelligence".

Attention is defined as "(a) memory driven algorithmic mechanism that indirectly exploits inputs from (the) perception-action cycle; it is made up of perceptual attention in the receiver and executive attention in the transmitter." For the tracking application, an "explore-exploit strategy" for search from cycle-to-cycle in the neighborhood of a center point is given as a means for implementing executive attention and enable temporal stability on the time rate of change in the transmit waveform.

Intelligence is defined as an "attention-driven algorithmic mechanism that is distributed in an abundant use of feedback loops throughout the radar; it exploits inputs from attention directly, and indirectly from memory and perception-action cycle. The function of intelligence is to enable the controller in the transmitter to pick a transmit-waveform vector, so as to exercise control over the receiver in a robust manner in the face of environmental uncertainties and disturbances".

Although Haykin's work emphasizes waveform design and selection, so as to adapt the transmitted signal in response to information learned from the environment and in consideration of current performance, in the most general sense the implementation of action is not limited to just adapting the transmit waveform, but involves control of adaptive hardware in general, such as:

- Antenna beam pattern;
- Polarization;
- Frequency;
- Adaptive transceiver components, including filters and amplifiers; and
- Piezo-electric materials and meta-materials.

A generalization of Haykin's ideas to include multiple sensors, with explicit depiction of radar resource management tasks, such as scheduling and control, is reflected in the generalized cognitive radar framework proposed by Martone in 2014 (Figure 3-7) [37].

In this work, Martone specifies the fundamental components of all cognitive systems as:

- Informed decision making via the decision-theoretic approach;
- Passive environmental sensors and radar sensors;
- Learning algorithms to improve performance and adapt to unknown environmental scenarios;
- A knowledge database that contains environmental, clutter, target and other a priori information;
- A waveform-solution space for known targets of interest; and
- Receiver-to-transmitter feedback to mitigate clutter/interference and maximize target information.

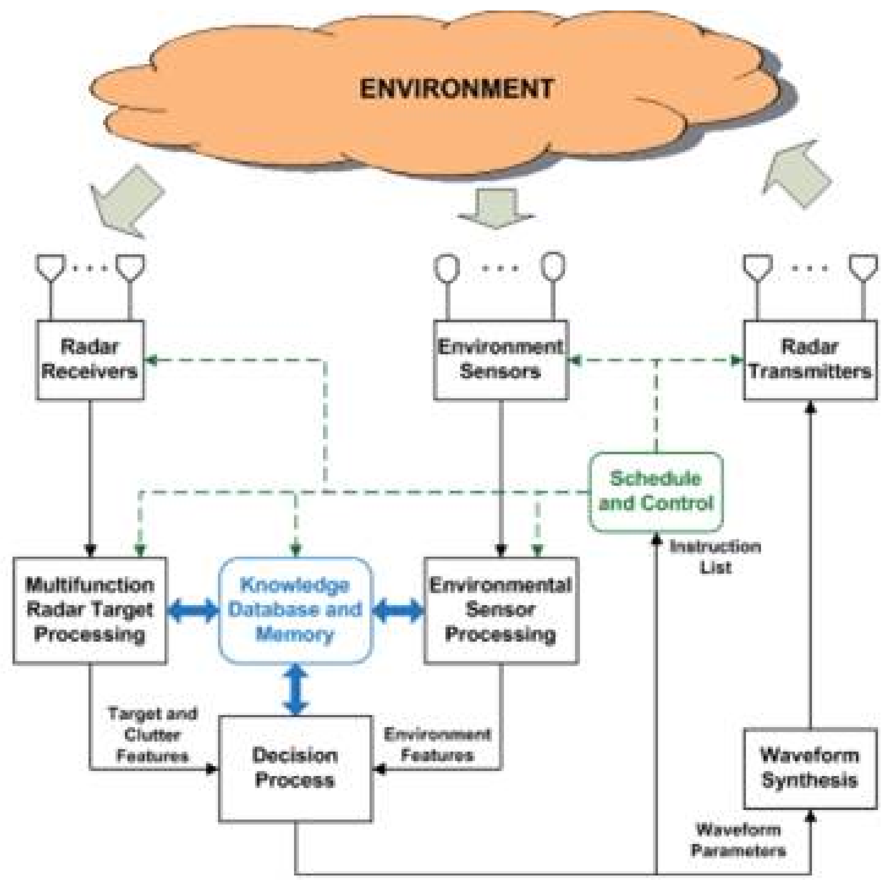


Figure 3-7: Martone's Proposed Cognitive Radar Framework.

3.3 DESIGN OF COGNITIVE RADAR ARCHITECTURES

The main concepts proposed in the previous section, are faced in the design of the cognitive radar architecture based on multiple layers:

1) Cognitive Radar Architecture Based on Information Abstraction Levels; and
2) Design of a three-layer cognitive radar architecture.

3.3.1 Cognitive Radar Architecture Based on Information Abstraction Levels

In order to realise cognitive radar a suitable system architecture is required, which comprises the essential perception-action feedback and memory. A typical requirement is that the architecture consists of multiple hierarchical levels, because it is necessary to make decisions on different time scales. Additionally, it is desirable that a cognitive radar architecture extends standard radar architectures, such that standard radar techniques are clearly identifiable. This section describes a cognitive radar architecture from Charlish and Hoffmann [38], which is based on information abstraction levels. The architecture was adopted by the NATO SET-223 group on adaptive radar resource management and hence this description is a slightly altered version of the description available in the group's report [39]. A cognitive radar system architecture can be constructed based on a hierarchy of information abstraction levels. Abstraction levels for sensor data and information processing have been widely studied, most notably by the JDL model [40] and its revised versions [41], [42]. Based on these studies, information abstraction levels relevant for a radar system can be identified as the signal, measurement, object, situation, and mission levels. This information abstraction hierarchy acts as a bridge between radar signals and the operator's mission objectives or requirements.

Key activities performed at each level are:

- **Assessment / Perception Generation.** Extract information from observed sensor data and process the data to generate perceptions (e.g., of objects, situations or missions).
- **Learning and Reasoning.** Learning to construct and refine models that explain the observed sensor data as well the influence that actions can have on the environment.
- **Management /Action.** Performing decision making and control of the radar data collection process.
- **Communication.** Sharing of acquired knowledge.

These processes can be performed at each of the previously identified abstraction levels. Figure 3-8 illustrates an adapted version of the cognitive radar architecture by Kester [43] and Smits et al. [44]. Examples of common radar signal and measurement data processing techniques as well as examples of radar management techniques are illustrated at the appropriate abstraction level in the assessment and management branches respectively.

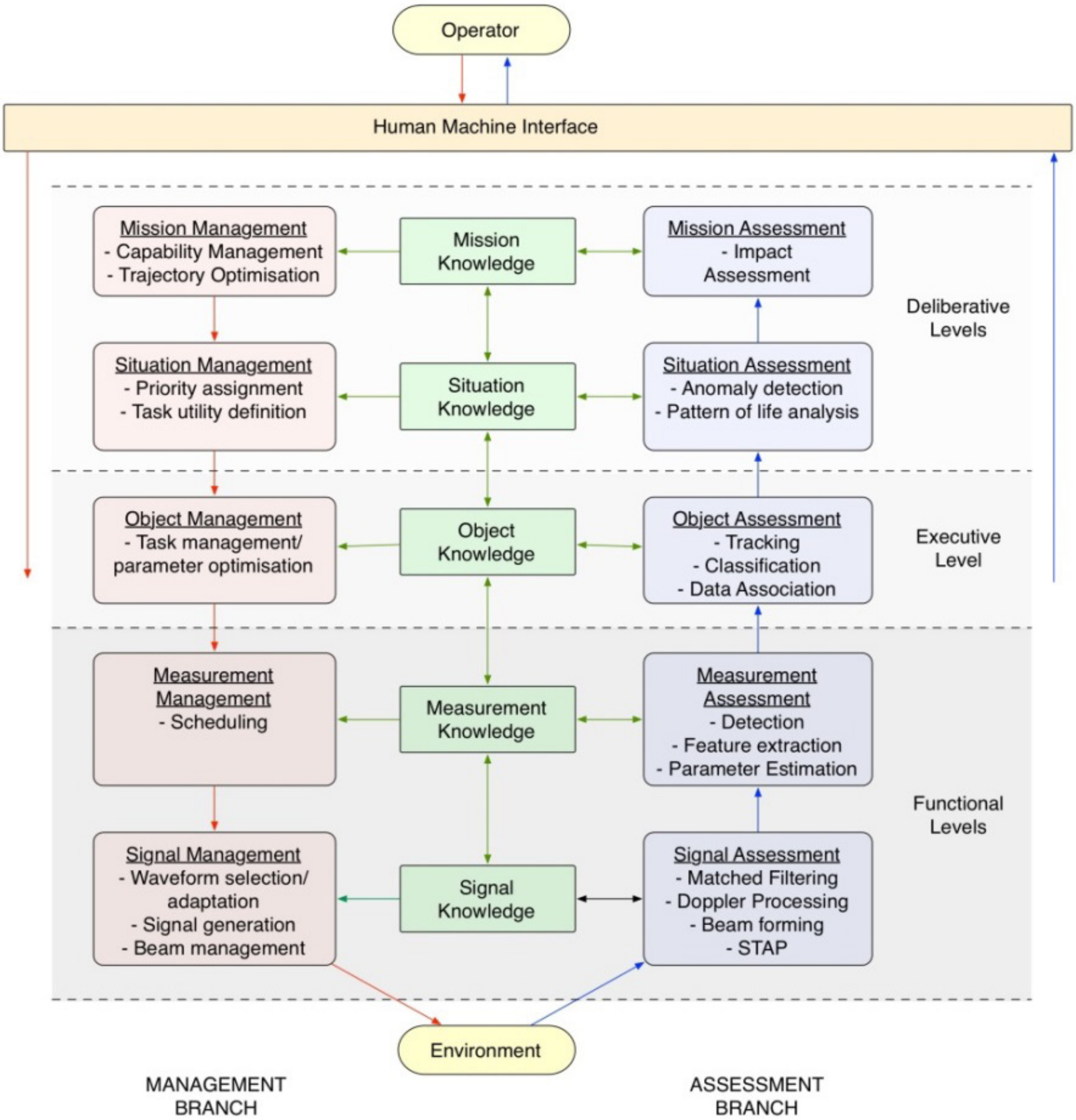


Figure 3-8: Radar System Architecture, Structured in Information Abstraction Levels.

The abstraction levels can be grouped as functional, executive, or deliberative levels. The functional levels execute a specific capability and are focussed on short time horizons, with a rapid feedback and hence reaction time. The executive level deals with the state of tasks and how tasks are executed, utilizing the capabilities of the functional levels. The deliberative levels assess and manage the current situation and mission and generate the tasks that are necessary to perform. The deliberative levels react slowly and deliberate over longer time horizons. The deliberative levels are traditionally associated with a command and control system and not normally thought of as a radar capability. A key characteristic of the multiple hierarchical levels is that each level has a different feedback and reaction time. The signal level can react potentially in sub milliseconds, the measurement level in milliseconds, the object level in seconds, the situation level in tens of seconds and the mission level over minutes or hours.

In the cognitive radar system architecture illustrated in Figure 3-8, the assessment branch is responsible for processing data to a higher information abstraction level. At the signal level, standard techniques such as matched filtering, Doppler processing or Space-Time Adaptive Processing (STAP) can be applied to filter received radar signals to suppress interference. At the measurement level, detections can be generated by applying an appropriate threshold on the signal intensity and multiple detections can be combined to generate radar measurements. These measurements, consisting of unambiguous position and velocity point measurements for instance, can then be passed to the object level. At the object level, radar measurements can be used to perform tracking or classification to estimate object data such as kinematic parameters or the object class. These components comprise the traditional radar signal and data processing chain.

At the deliberative levels, relations between different objects' data can be used at the situation level to estimate properties of the current situation, such as detecting anomalies. Flags of anomalous or threatening behaviour are examples of data that can be passed to the mission assessment level. Finally, the current situation can be assessed with respect to the mission objectives at the mission level, to achieve an impact assessment. The ability to adapt the assessment processing to the environment enhances the extraction of relevant information, which strongly influences the fidelity of the signal, burst, measurement, object, situation and mission assessment that is constructed at each level.

The data assessment branch relies on prior or acquired knowledge that is relevant to each abstraction level. The combination of knowledge acquisition and data assessment constitutes adaptive processing. For example, STAP techniques at the signal level are required to learn the clutter or interference covariance matrix so that the interference can be suppressed and the signal to interference ratio enhanced. At the measurement level, knowledge of the current clutter and target statistics enables the correct detection threshold to be set for the current environment. At the object level the target motion models can be learnt for robust tracking of manoeuvring targets or clutter maps can be learnt for robust track extraction in cluttered environments. At the situation level, knowledge of the situation pattern of life can be learnt to aid anomaly detection. The extent to which knowledge is learnt clearly influences the performance of the data assessment processes.

Given the acquired knowledge and the multi-level perception generated by the data assessment processes, the management branch manages the data assessment processes as well as defining the requirements for the level below. At the mission level, radar capabilities can be planned over the mission duration, such as adjusting the sensing requirements for different mission phases. Based on these sensing requirements and the current situation assessment, the situation manager can assign priorities, objective or utility functions to specific tasks or objects. The task priorities or utility functions can be used by the object manager for task management, to generate optimized task control parameters that control aspects such as the waveform selection or task revisit interval time. At the measurement level, radar dwells and bursts can be scheduled for radar tasks, adhering to the task control parameters from the object level. Finally, at the signal management level, the waveform can be adapted and generated given knowledge of the radar channel as well as the radar burst schedule. The ability of the management branch to generate mission, scenario, and environment dependent signals clearly influences the quality or relevance of the information contained in the radar signals that are returned.

3.3.2 A Three-Layer Cognitive Radar Architecture

Figure 3-9 depicts a three-layer cognitive radar architecture [45] that is inspired by the Rasmussen model [46] of human cognitive performance and exhibits the four fundamental cognitive abilities postulated by Haykin – including provisions for learning. The traditional perception-action-cycle concept is applied on different layers and attempts to also address high cognitive abilities. To account this, the architecture is explained. Then, each layer is illustrated with some examples from the broader field of non-cooperative target classification. On the skill-based layer, we present matched illumination results for optimal waveform generation. Rule-based behaviour is explained using an illumination policy for target classification. Finally, knowledge-based behaviour is described by task-based execution of a ground target reconnaissance mission.

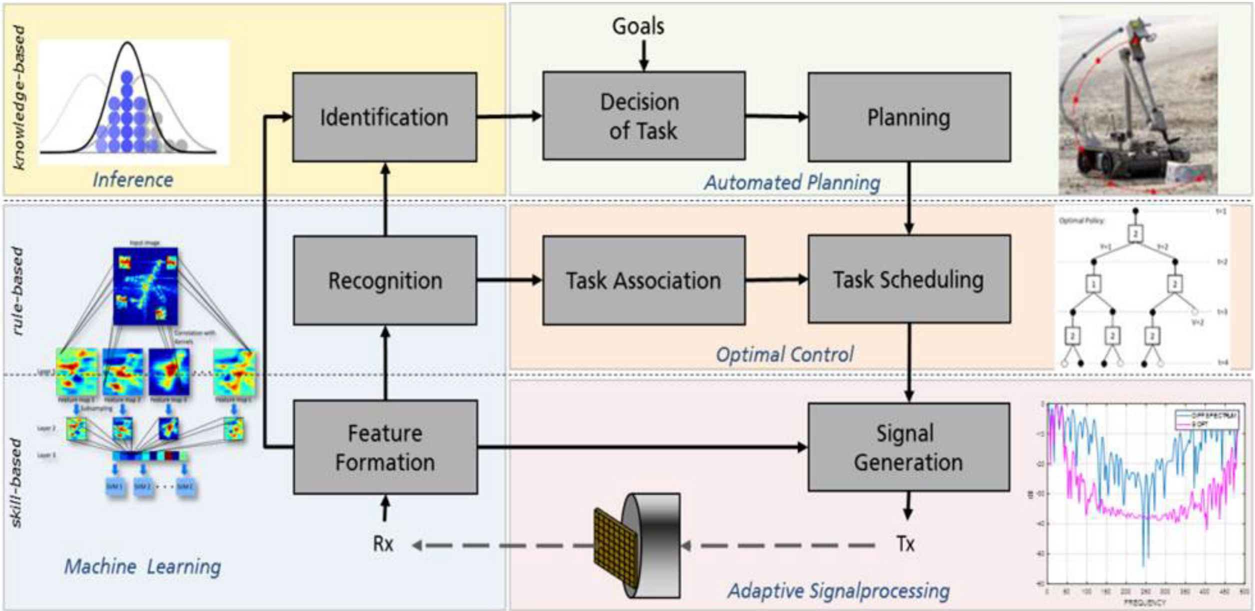


Figure 3-9: Three-Layer Cognitive Radar Architecture.

As stated above, the concept shown in Figure 3-9 is derived from the Rasmussen model of human cognitive performance [46], that has been successfully applied in cognitive psychology, human factors and robotics. Rasmussen characterized human behaviour when operating complex machinery on three layers of increasing abstraction. The skill-based-behaviour (lowest layer) describes subconscious, continuous control tasks (e.g., keeping the lane when driving a car). In the radar analogy, we map the subsymbolic, low-level signal generation and processing tasks to this layer. The rule-based layer is characterized by conscious control and symbolic representation. It allows a human to efficiently react to known cues in the environment by the execution of pre-stored procedures, e.g., reacting to a red traffic light. The transition between the subsymbolic and symbolic representation of the environment, known as semantic gap, is not an easy task, but has recently been successfully bridged by deep learning methods [47]. We summarize on the rule-based layer reactive and immediate behaviour, that is however not directly operating on the raw-signal data. Optimal control decision making and resource management methods are major driver in this layer. The highest level of abstraction is denoted as knowledge-based behaviour. It allows a human to further infer and abstract from the situation. There are no pre-stored rules, deliberation happens based on explicit knowledge, e.g., bypassing a traffic jam by using a map. Decision making and planning are typically long-term, and in a goal-oriented manner, e.g., each long-term action of the cognitive radar on this layer can be traced to high level goal. For a human, and presumably also a cognitive radar system, the three layers are interwoven and not as clearly separable. In the following, radar examples for action in each of the three layers are presented:

1) **Skill-Based Layer.** As a cognitive radar example on the skill-based-behaviour, an example for the coexistence of radar and other RF-emitters is reported [48]. As shown in Figure 3-10, a wideband radar signal HRR imaging between 5 – 7 GHz was created using a stepped frequency approach. The range profiles in the simulation shown on the right illustrate five-point scatterers at 5 m, 7 m, 16 m, 20 m, 21.5 m. A stepped frequency waveform with 400 subcarriers with uniform frequency steps are shown. In Figure 3-10b, to Figure 3-10d, traditional IFFT processing of the received signal is shown in black, a new novel compressed sensing approach using OMP is shown in red. It is apparent, that the number of subcarriers can be reduced to a quarter, while the point scatterers are still visible from the noise. Using traditional IFFT processing, the noise flor raises. A cognitive radar system could monitor and predict such spectral holes to dynamically adjust the TX frequency steps to avoid interference. In the literature, there are many other options of matching the transmit signal to the target impulse response or the transmission channel [32].

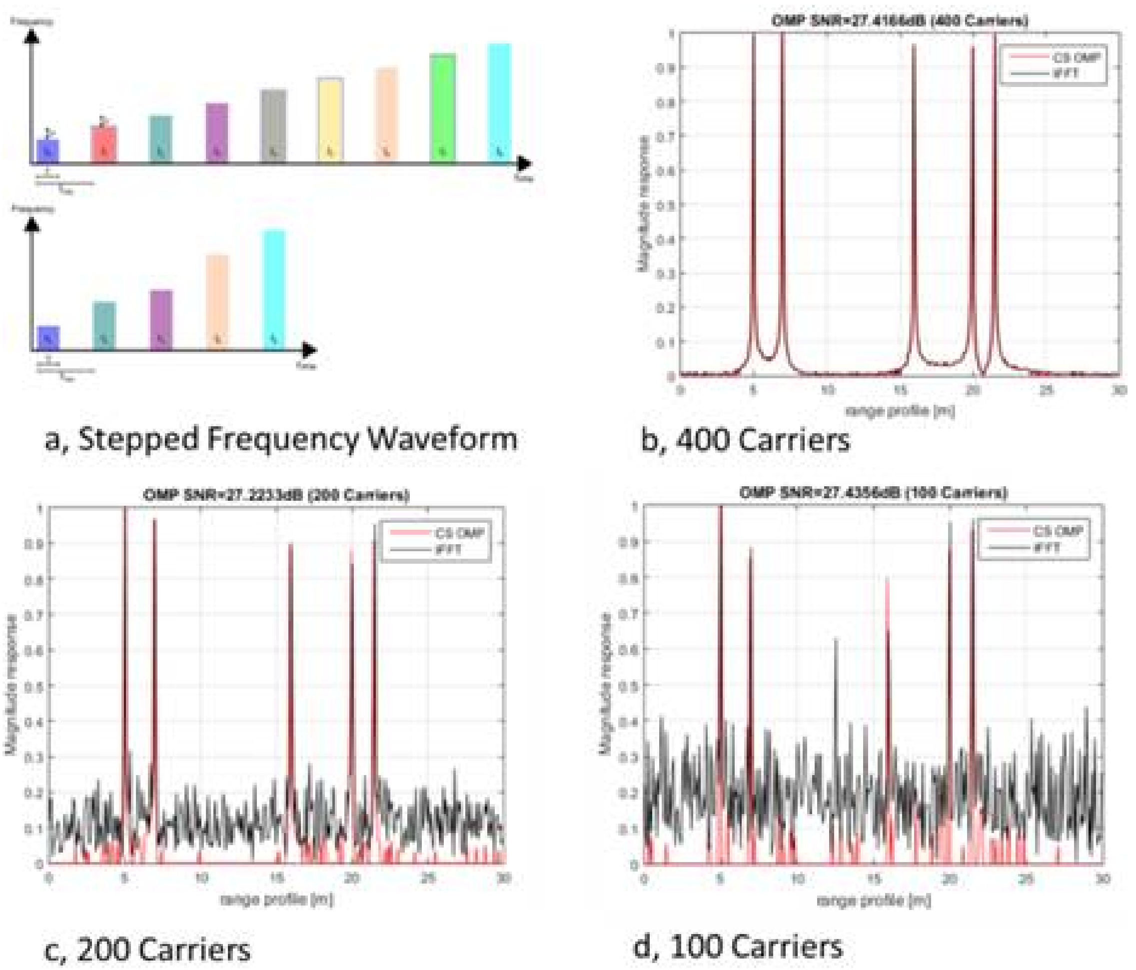
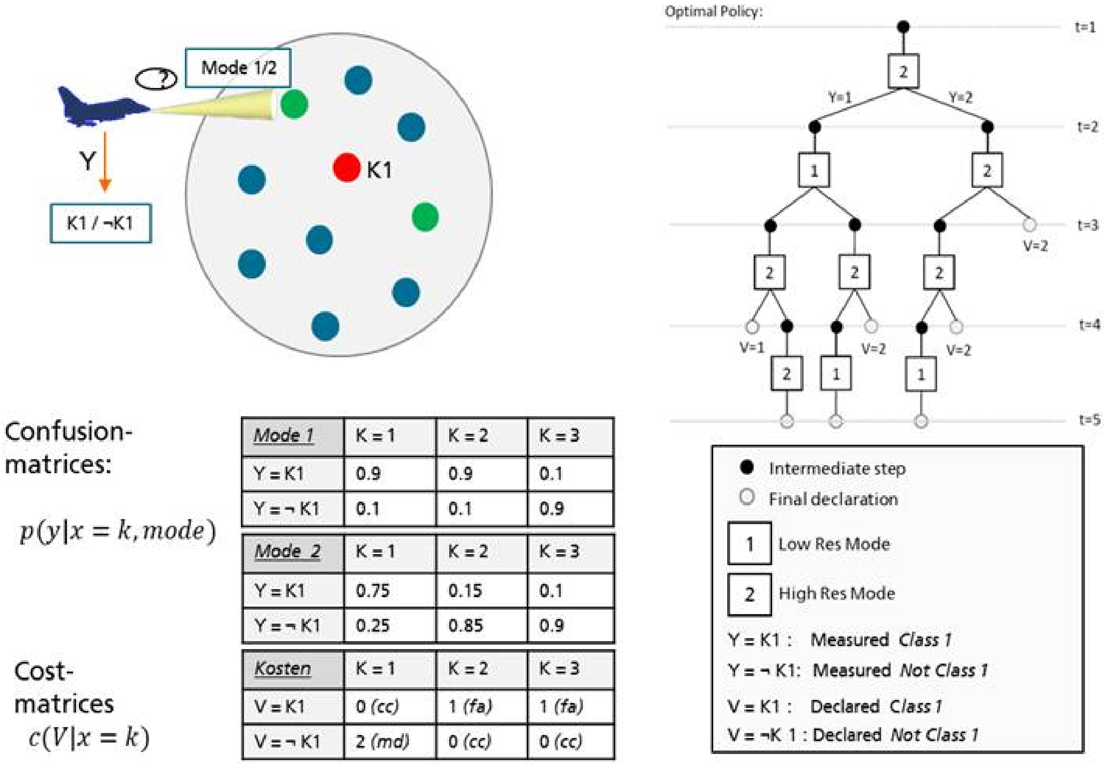


Figure 3-10: RF Coexistence Using Compressed Sensing the Frequency Domain.

2) **Rule-Based Layer.** In the rule-based layer we will illustrate decision making using Markov-Decision-Processes (MDP). The example is an application of the work from Castañón [49] for the classification of air-targets. As shown in Figure 3-11, three different types of target are present (blue, green and red). The objective is to discriminate the high-value target K1 with a high probability against the other two classes (not K1). The confusion matrix shows the probability for correctly classifying target = K1 (given the true class), for a low resolution mode #1, and a higher

resolution mode #2. It is assumed here that higher bandwidth leads to a better separation between K = 1 and K = 2. Also, a cost matrix is given, which defines the cost for a false alarm and missed detection. With this information, a Markov Decision Problem can be stated and solved for minimization of the expected cost. The result is called an optimal decision policy and shown in the upper right picture. Based on the result of the first interrogation with the high resolution waveform, the cognitive radar system will branch and request further illuminations or state a final target declaration. MDPs are a quite flexible mathematical tool to derive a predefined decision policy for cognitive radar applications.



Mode 1	K = 1	K = 2	K = 3
Y = K1	0.9	0.9	0.1
Y = ¬ K1	0.1	0.1	0.9

Mode 2	K = 1	K = 2	K = 3
Y = K1	0.75	0.15	0.1
Y = ¬ K1	0.25	0.85	0.9

Kosten	K = 1	K = 2	K = 3
V = K1	0 *(cc)*	1 *(fa)*	1 *(fa)*
V = ¬ K1	2 *(md)*	0 *(cc)*	0 *(cc)*

Figure 3-11: MDP for Optimal Illumination Sequences for Target Classification.

3) **Knowledge-Based Layer.** The knowledge-based layer addresses long-term situation awareness and mission planning problems [50]. The deliberation algorithms applied here typically do an online-search in the task space from the current state to some state that satisfies the goals. It is a symbol transformation process, so the result of the inference or planning procedure can be made explicit to the operator. Algorithms suite for this class of problems are constraint satisfaction, mixed-integer linear-programming or automated planning tools. Figure 3-12 shows an example for RF-Mission planning using PDDL planning. The figure on the right shows different tasks for RF-systems and the platform with parallel temporal execution.

The three presented layers operate on different levels of abstraction, time scales and knowledge representation. Example radar applications for each of the layers have been reported. A key challenge is to combine and coherently integrate the various behaviours in a consistent and comprehensive fashion. Individual perception-action loops have been validated in simulation and with small-scale laboratory experiments. The perspective of the proposed architecture relies on the full potential of this cognitive radar architecture which could be exploited in upcoming, flexible, software-defined Active Electronically-Scanned Array (AESA) radars in combination with next generation platform mission management systems and human operator interfaces.

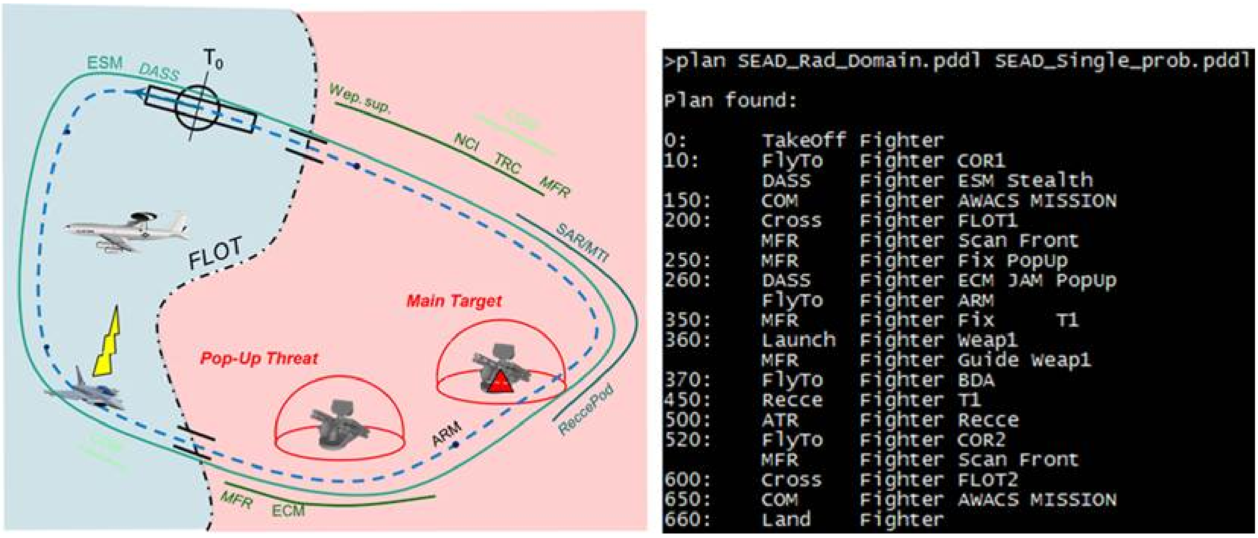


Figure 3-12: Knowledge-Based Planning.

3.4 COGNITIVE ARCHITECTURES FOR RADAR APPLICATIONS

The implementation of a cognitive radar architecture changes on the base of the radar application of interest. This is due to the flexibility, versatility and scalability of such systems. This aspect is analyzed in the framework of multi-function radar in resource-constrained systems and spectrum-constrained availability. Specifically, an example of cognitive architectures for imaging radar with detection capability and for spectrum sensing applications will be presented in the following.

3.4.1 Imaging Radar Cognitive Architecture

To be cognitive, a radar system should be able to "intelligently" adapt its own behaviour in a self-organized manner and in accordance with the environmental changes through a process called learning from experience [26]. This adaptation is accomplished through three main functions: intelligent signal processing, receiver-transmitter feedback, and preservation of information (see Section 3.1). Figure 3-13 represents a cognitive radar high level architecture applied to the imaging radar with detection capability. The architecture demonstrates the implementation of these three functions through the following components:

1) **The Radar Transmitter and Receiver**. The transmitter acts on the transmitted waveform over time according to the environmental changes to optimize performance through an "intelligent" signal processing on the receiver. The intelligence on the receiver is built on learning through a continuously interactions of the radar with the environment and enables the signal processing to adapt in a dynamic way itself to the measured performance in order to enhance them. Cognitive also means intelligence adaptive waveform. In other words, it also acts on transmitted waveform.

2) **The Cognitive Block.** This block exploits the information given by the signal processing block in order to learn on the most suitable action to be performed by the transmitter block in order to meet the needs of the radar mission (e.g., Clutter cancellation, interference mitigation, detection, imaging) according to a desired performance. This process is based on an iterative improvement of the performance measured a number of ad hoc indexes. This measure of the level of the radar mission success provides the necessary feedback to ensure that the system is able to learn from its past actions.

The cognitive block generally includes (Figure 3-14):

- A system success measure block enabling the link from the receiver to the transmitter so as to inform it about the received signal processing results. This functionality is made feasible through the controlling functions which represent an intrinsic measure of the system performance because their dependency of performance indexes (output of performance calculation block). The controlling functions change over the performance indexes and handle the actuating function to perform the adjustment of the system reconfigurable parameters (e.g., waveform parameters).
- A memory block embodying the consciousness of the system. It provides the means for learning from past experiences. Memory is dynamic because its content continually changes over time in accordance with the environment changes. Specifically, if the radar environment changes suddenly or if it is completely unknown the radar has to probe the surrounding to enrich the memory by updating the rules used to adapt the actuating functions accordingly.
- A feedback-based decision making block identifying the better way to change the system parameters (e.g., waveform parameters) and the signal processing techniques by investigating both the memory and the success blocks. This process is feasible through the actuating function whose role is to alert the system when something goes wrong during the reception.

For further details on the implementation of the presented architecture, please refer to the "Applications" chapter (Section 6).

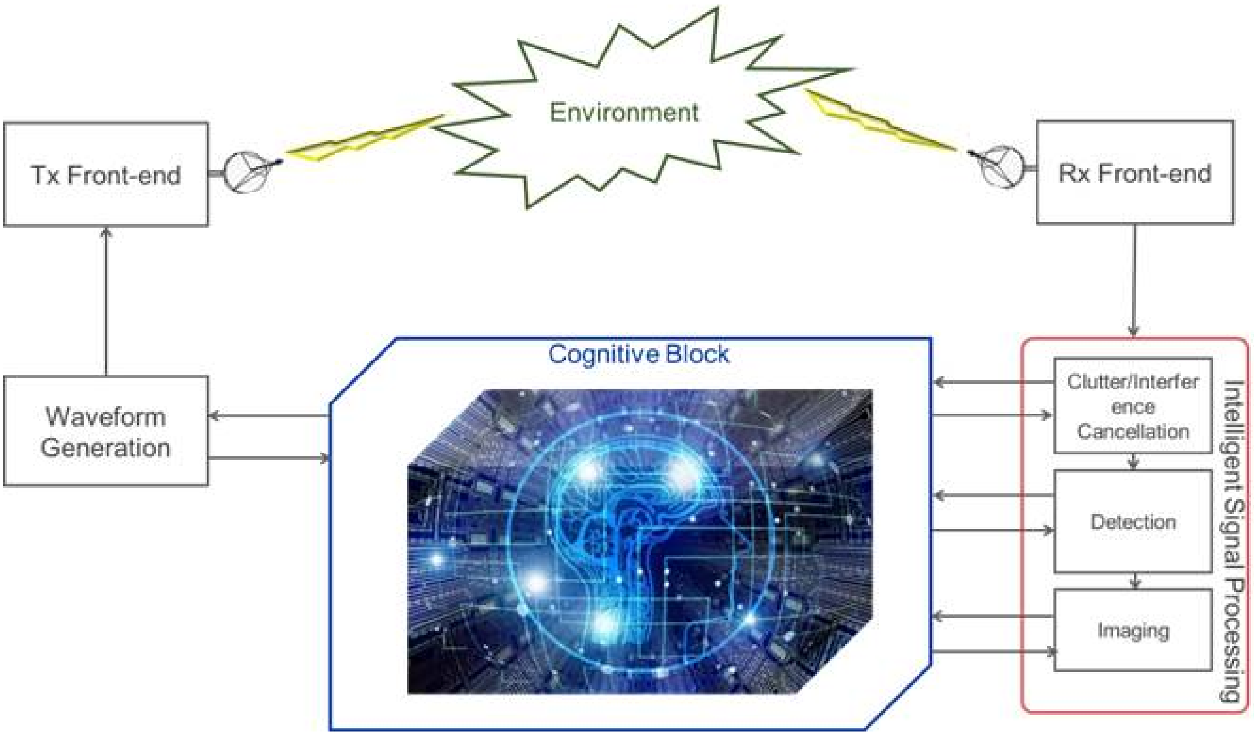


Figure 3-13: Cognitive Radar High Level Architecture Applied to Radar Imaging.

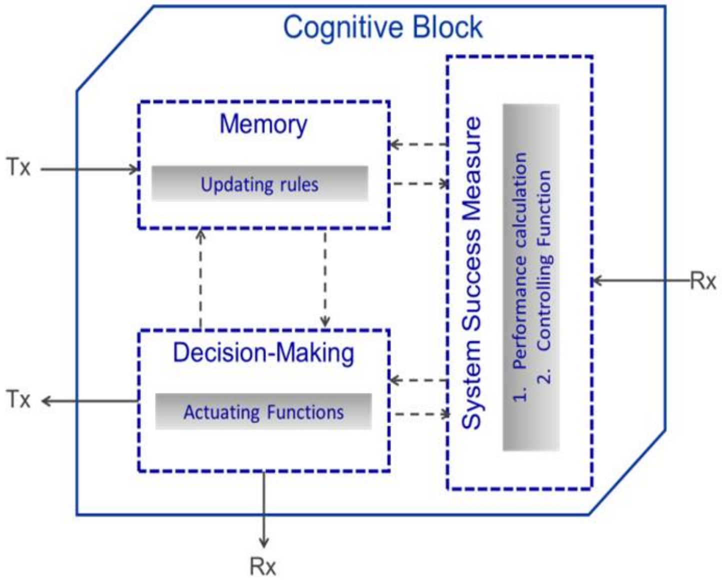


Figure 3-14: Example of the Cognitive Block Ingredients.

3.4.2 Spectrum Sensing Architecture for Cognitive Radar

The problem of the RF spectrum sharing by the growing number of system and services is here dealt with from the point of view of the cognitive radar paradigm. The cognitive radar is conceived as a potential way to mitigate the conflict among the scarcity of spectrum, the inefficient usage of it and the maintenance of radar capabilities. To face with these issues, the radar should be able to estimate the behaviour of other emitters to adapt its transmission to the spectrum ongoing usage by exploiting the maximum availability bandwidth and minimizing the mutual interferences with primary services (e.g., communication services). To account this, the cognitive radar must adopt a strategy that is conceptually summarized in the cognitive cycle shown in Figure 3-15.

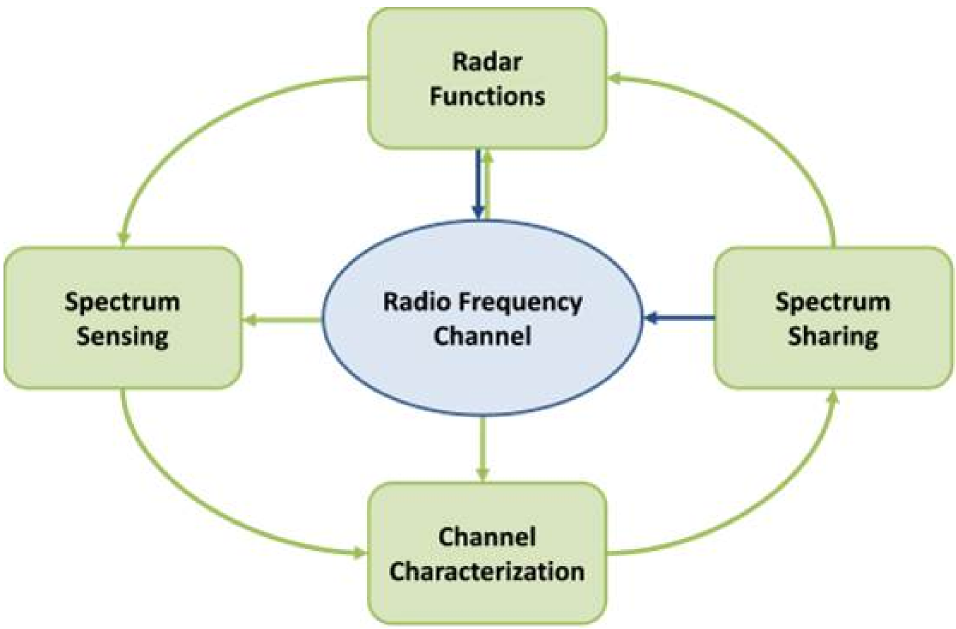


Figure 3-15: Cognitive Radar Cycle.

The main functionalities behind this concept are the spectrum sensing, the channel characterization and the spectrum sharing. Specifically, the Spectrum Sensing function has the goal to obtain necessary observations about the radio frequency channel, such as the presence of other users and the appearance of spectrum opportunities where it is possible to transmit without interfering. This observation is obtained by exploiting the signal at the radar receiver or, with a separate receiver chain, by observing directly the radio frequency channel.

Proceeding in the counter-clockwise direction, the decisions on the free/busy channels feed the Channel Characterization function. The role of this function is to characterize statistically the spectrum usage of the primary user, to find the most appropriate model for the primary user dynamics, and to estimate the channel parameters that describe the model.

The Channel Characterization function feeds the Spectrum Sharing function, which has the goal to limit interference from the radar to other services and vice versa. The Spectrum Sensing function processes the information arising from the Channel Characterization function to control the Radar Functions. These functions are the typical functions of a radar system, with the exception that in each time slot, which coincides with the Pulse Repetition Interval (PRI) or with the Coherent Processing Interval (CPI), the transmit and receive parameters (e.g., the transmission power and the operating frequency) are dynamically adapted in order to achieve efficient spectrum utilization and avoid interference. The Cognitive Cycle summarized in Figure 3-15 represents the perception-action cycle as defined by Haykin [26]. The perception-action cycle is the fundamental layer of a cognitive system; in our context, the perceptors are the Spectrum Sensing and Channel Characterization functions, while the actuator is the Spectrum Sharing function. In response to feedback information about the environment from the perceptor, the actuator controls the perceptor via the environment, and the cycle goes on. In other words, the perceptor guides the actuator by virtue of what it learned about the environment, and the actuator controls the perceptor by acting in the environment. The benefit resulting from the perception-action cycle is that of maximizing the information gained from the environment.

Figure 3-16 shows a possible system architecture of a cognitive radar system. As shown, the cognitive layer is an additional layer that directly controls the transmitter and the receiver of a radar system. In the more complex systems, the Spectrum Sensing and the Channel Characterization functions directly observe the radio frequency channel with separate receiver chains. On the other hand, in the simpler and cheaper systems these functions process the signal at the radar receiver. In both cases, the radar transmitter is directly controlled by the cognitive layer that elaborates the feedback information arising from the receiver. The cognitive functions are described in the following subsections.

Spectrum Sensing is the first critical step toward dynamic spectrum management. Through this function, a cognitive radar can obtain necessary observations about the radio frequency channel, such as the presence of primary user and the appearance of spectrum opportunities where it is possible to transmit without interfering with the primary users of the channel.

Typically, Spectrum Sensing is performed in time, frequency, and space domains. When the cognitive radar is a phased array using beamforming technology, multiple users can utilize the frequency channel at the same time in the same geographical location. Thus, if a primary user does not transmit in all directions, extra spectrum opportunities can be created for secondary users in the directions where the primary user is not operating, and Spectrum Sensing needs also to take the angles of arrivals into account [51], [52], [53].

Spectrum Sensing can be performed via two different architectures: single-radio and dual-radio [54]. In the single-radio architecture, only a specific time slot of the signal at the radar receiver is allocated for Spectrum Sensing. Because of this limited sensing time, only a certain accuracy can be guaranteed for Spectrum Sensing results. The obvious advantages of single-radio architecture are simplicity and lower cost.

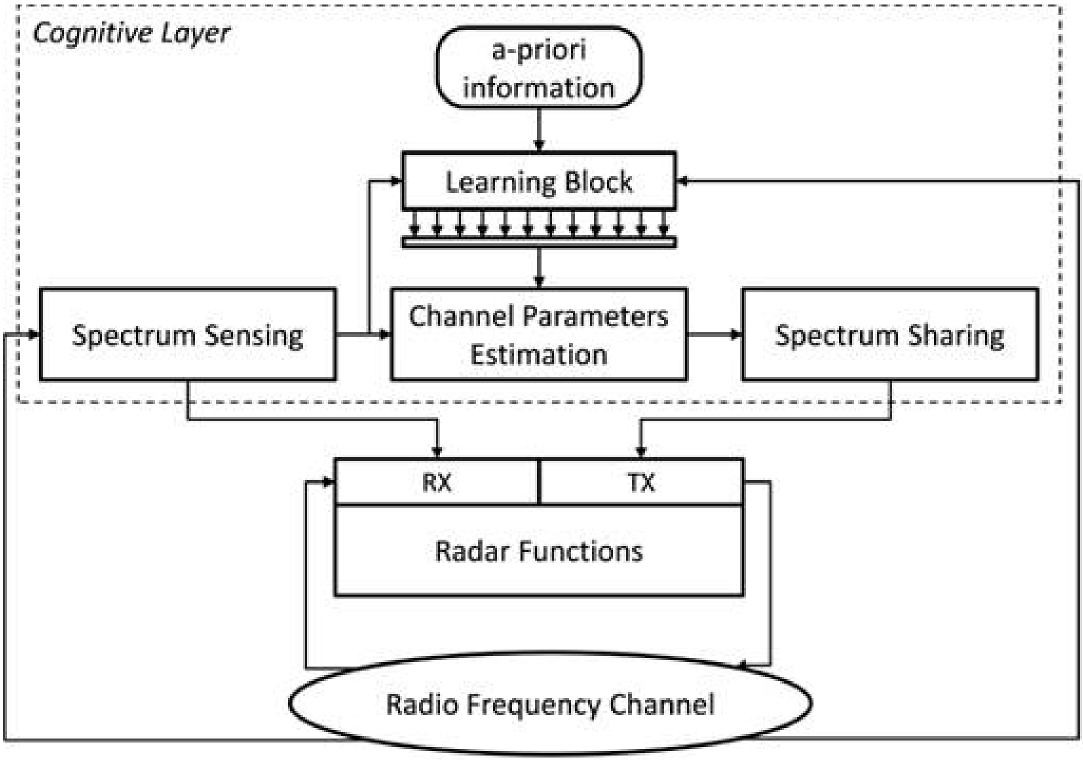


Figure 3-16: System Architecture of a Cognitive Radar.

In dual-radio sensing architecture, one radio chain is dedicated to the radar operations while the other chain is dedicated to Spectrum Sensing. Note that a single antenna would be sufficient for both chains.

However, in a multi-function radar framework, where the required time used to estimate the spectrum occupancy is very short and the monitored frequency band is wide, the main drawback of the dual-radio architecture is the increased power consumption and hardware cost, as the related systems requires high sampling rate and high resolution Analog-to-Digital Converters (ADCs) with large dynamic range, plus the use of high speed signal processors.

However, for this particular scenario, some recent works (see e.g., Gromek et al. [55]) proposed the use of Compressed Sensing (CS) for Spectrum Sensing to solve important problems related to hardware complexity, because of the need to design a responsive Spectrum Sensing system, able to react quickly to the changes within the radio channel.

The open literature on Spectrum Sensing focuses on primary transmitter detection based on the local measurements made by the secondary users, since detecting the primary users that are receiving data is in general very difficult. According to the a priori information they require and the resulting complexity and accuracy, Spectrum Sensing techniques can be clustered into the following main categories [30]: Energy Detector (ED), Feature Detector (FD), and matched filter (MF) detector techniques.

The ED is the most common Spectrum Sensing detector because of its low computational cost and implementation complexity. In addition, it does not need any a priori knowledge on the signal emitted by the primary users. Detection is performed by comparing the output of the energy detector with a threshold, which depends on the noise floor. Some of the drawbacks of the energy detector are the inability to differentiate interference from primary users and noise, inefficiency for detecting spread spectrum signals, and poor performance in low signal-to-noise ratio situations [53].

The threshold of the energy detector is selected as a trade-off between the probability of detection and the probability of false alarm. It is important to note that typically in a radar detector, the probability of false alarm is set to a desired value and the probability of detection is maximized according to the Newman-Pearson criterion. For radar functions, it is convenient to keep constant the probability of false alarm to a low value because a false alarm is more problematic than a missed detection. In fact, for each detection many radar procedures, such as target tracking and target identification, are activated. Hence, if there are many false alarms, a great portion of the system memory and computational capabilities are occupied for the tracking of inexistent targets. For the problem of Spectrum Sensing, being the radar the secondary user of the channel, the more problematic event is the missed detection, i.e., when the channel is declared as free while, in reality, the primary user is transmitting. For this reason, it is more convenient to set the probability of detection to a desired value and minimize the probability of false alarm. However, this requires knowledge of noise and detected signal power levels. The noise power can be estimated, but the signal power is difficult to estimate as it changes depending on ongoing transmission characteristics and the distance between the cognitive radar and primary user.

In practice, also for the Spectrum Sensing detector the threshold is usually chosen using the Newman-Pearson criterion. In this case, the threshold depends on the noise variance. Consequently, a small estimation error of the noise power causes a significant performance loss.

Several works addressed the following problems:

1) Dynamical estimation of the noise level by separating the noise and signal subspaces using MUltiple Signal Classification (MUSIC) algorithm [31];
2) Design of iterative algorithms to find the decision threshold to satisfy a given probability of false alarm [31]; and
3) Design of forward methods based on energy measurements for unknown noise power scenarios in Metcalf et al. [56].

Another type of Spectrum Sensing detector is the FD. There are specific features associated with the signal transmitted by a primary user. For instance, the statistics of many communication signals show some inherent periodicities such as the modulation rate or the carrier frequency. Such features are usually viewed as cyclostationary features, based on which a detector can distinguish cyclostationary signals from stationary noise. The cyclostationary feature detector was first introduced by Simons [28]. Since the transmitted signals in most communication systems are modulated signals coupled with prefix cycles, headers and pilots, while the additive noise is generally wide sense stationary with no correlation, cyclostationary feature detectors can be utilized to differentiate noise from primary user’s signals. Compared with energy detectors that cannot detect weak signal in noise and are prone to high false alarm rate due to noise uncertainty, cyclostationary detectors are good alternatives because they can differentiate noise from primary user’s signal and have better detection robustness in a low-SNR regime. However, the computational complexity and the significant amount of observation time required for adequate detection performance prevent a wide use of this approach.

The last kind of detector is the MF detector. Matched filtering is known as the optimum method for detecting primary users when the transmitted signal is known. The main advantage of matched filtering is the short time to achieve a given probability of false alarm or a given probability of missed detection [29] as compared to the other methods discussed in this section. However, matched filtering requires a perfect knowledge of some primary users signaling features, such as bandwidth, operating frequency, modulation type, pulse shaping, and frame format. Moreover, since cognitive radio needs receivers for all signal types, the implementation complexity of sensing unit is impractically large. If the MF design relies on wrong information, the detection performance will be largely degraded.

Table 3-1 summarizes the main Spectrum Sensing techniques described in this section, focusing on their main advantages and disadvantages.

Table 3-1: Summary of Spectrum Sensing Techniques.

Type	Test Statistics	Advantages	Disadvantages
Energy Detector	Energy of the received signal	• Easy to implement • Doesn't require prior knowledge about primary signals	• High false alarm rate due to noise uncertainty. • Very unreliable in low-SNR regimes. • Cannot differentiate a primary user from other signal sources.
Feature Detector	Cyclic spectrum density function of the received signal	• More robust against noise and better detection in low-SNR than energy detector. • Can distinguish among different types of transmissions and primary systems.	• Specific features must be associated with primary signals. • Higher complexity than energy detector.
Matched Filtering	Projection of the received signal in the direction of the known primary signal	• More robust against noise and better detection in low-SNR than feature detector. • Require fewer signal samples to achieve good detection.	• Require prior information about certain waveform patterns of primary signals. • High complexity, mostly unpractical.

To further increase the spectrum awareness of a cognitive system (radio or radar), it has been proposed to use a Radio Environmental Map (REM). The idea behind the REM is to store and process a variety of data to extract all the available information on transmitter locations, propagation conditions, and spectrum usage in space and time. Exploiting the REM, the radar could become aware of the surrounding electromagnetic environment, and then intelligently use the transmit bandwidth and probing waveforms.

3.5 CONCLUSIONS

The cognitive radar paradigm has been treated from an architectural point of view. Advances have been achieved towards the design of cognitive radar systems, as proved by the many conference and journal papers published over the last decade. Nevertheless, implementation of its principle both at the hardware and software level represents a gap to be filled. For instance, in active radars, cognition requires waveforms and circuits to be reconfigurable and optimizable in real time. Initial progress has been made in each of these two fields [57], [58], but a fully optimized solution that includes all the important aspects of radar circuitry has not yet been presented [59] even though some attempts to consider the radar as a holistic system (hardware-in-the-loop) have been presented, for instance, Stinco et al., 2016 [60]. This point of view is highlighted by the proposed SWOT analysis in Table 3-2.

Table 3-2: SWOT Analysis.

STRENGTHS	WEAKNESSES
✓ Identification of the spectrum availability (environment sensing). ✓ Statistically characterization of the behaviour of the electro-magnetic environment. ✓ Adjustment of the transmitted waveform on the fly according to the spectrum availability and the surrounding environment. ✓ Choice of the most apt signal processing technique at receiver according to the spectrum availability and mission priority (e.g., compressive sensing or adaptive filter techniques). ✓ Dynamic resource management.	• The implementation of the whole cognitive process requires a high computational cost. • The electro-magnetic environment characterization is currently based mostly upon statistical rules. • A large and heterogeneous dataset are needed to meet a consistent memory.
OPPORTUNITIES	**THREATS**
✓ Flexibility, scalability and intelligence. ✓ Ability to statistically estimate the environmental changes exploiting the process of learning from experience. ✓ Ability to guarantee a good trade-off between performance and environment constraints (spectrum availability, interference, clutter).	• Technology may not be ready to guarantee the desired level of intelligence/adaptability for specific applications. • The TRL of this system is at the moment very low.

Chapter 4 – TECHNIQUES AND APPROACHES

4.1 PERCEPTION-ACTION CYCLE AND FEEDBACK

To provide a common starting point for implementing diverse cognitive radar tasks, the Fully Adaptive Radar (FAR) framework is a general model for the Perception-Action Cycle (PAC) [61], [62]. Figure 4-1 illustrates the general FAR framework organized into distinct perceptual and executive processors. It also shows the sensor hardware as a separate block that interacts directly with the environment. This structure is organized differently but has the same functionality as previous implementations of the FAR framework [62], [63], [64]. The current dual-processor construction was chosen because it better aligns with Fuster's neuropsychological cognitive structure [65], the JDL fusion levels [66], and the various cognitive radar architectures [38], [44], [67], [68], [69].

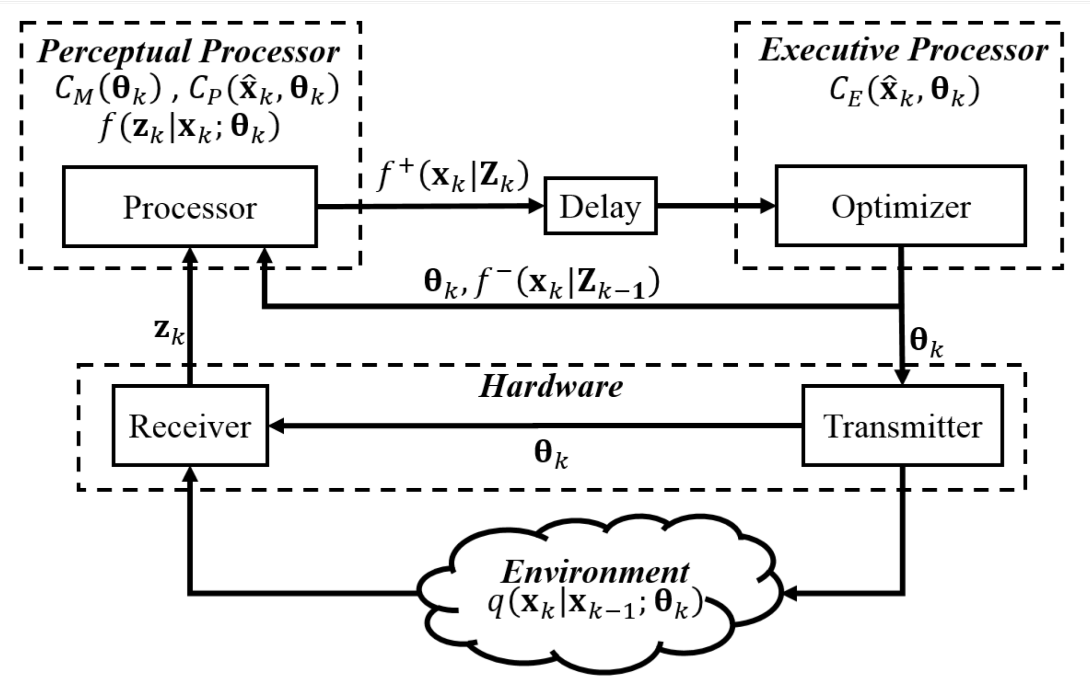


Figure 4-1: General Block Diagram of the FAR Framework for Cognition [61].

The framework in Figure 4-1 emulates the PAC through communication between the two processors. The aim of the radar is to adapt its perception parameters, $\boldsymbol{\theta}$, to estimate the value of the target state $\mathbf{x}_k$ while meeting a series of objectives. At time *k,* the perceptual processor receives information about the environment in the form of measurement $\mathbf{z}_k$ and uses the information to form a perception of the environment. Here, the perception is the posterior density $f^+(\mathbf{x}_k|\mathbf{Z}_k)$, where $\mathbf{Z}_k = \{\mathbf{z}_1, \dots, \mathbf{z}_k\}$ is the measurement history up to time *k*. The executive processor is responsible for the action portion of the PAC, selection of the next value of $\boldsymbol{\theta}$ in response to the latest perceptions. The new $\boldsymbol{\theta}$ is then passed back to the perceptual processor, completing one iteration of the PAC. The hardware layer also receives $\boldsymbol{\theta}_k$ and forms measurement $\mathbf{z}_k$ based on the perception parameters, but the PAC arises from the interaction between the two processors, not the hardware. Some PACs may not interface directly with hardware at all.

The perceptual processor is characterized by its measurement likelihood function, $f(\mathbf{z}_k|\mathbf{x}_k; \boldsymbol{\theta}_k)$, its measurement cost function, $C_M(\boldsymbol{\theta}_k)$, and its performance cost function $C_P(\hat{\mathbf{x}}_k, \boldsymbol{\theta}_k)$. The measurement likelihood defines how the measurements $\mathbf{z}_k$ are related to the target state $\mathbf{x}_k$, and is instrumental in determining how the measurements are converted into perceptions of the scene. The measurements may or may not be conventional radar measurements, such as range-Doppler surfaces, depending on the nature of the PAC. The measurements may be more abstracted if the perceptual processor does not interface directly with receiver hardware. The measurement cost function reflects the relative cost of obtaining a measurement with parameters $\boldsymbol{\theta}_k$. The performance cost function quantifies how well the system is performing its tasks based on the estimate of $\mathbf{x}_k$, denoted $\hat{\mathbf{x}}_k$, and $\boldsymbol{\theta}_k$. The perceptual processor determines the next estimate $\hat{\mathbf{x}}_k$ by minimizing the performance cost function given the current measurement $\mathbf{z}_k$ obtained with parameters $\boldsymbol{\theta}_k$.

The executive processor is characterized by its executive optimization cost function, $C_E(\hat{\boldsymbol{x}}_k, \boldsymbol{\theta}_k)$, and the formulation of the executive optimization method itself. The executive processor determines the perception parameters $\boldsymbol{\theta}_k$ by minimizing the executive optimization cost function, which is a combination of the measurement and performance cost functions, with respect to $\boldsymbol{\theta}_k$.

The measurement, performance, and executive cost functions are scalar functions that are designed to balance multiple objectives for system performance and multiple preferences for system operation. Designing cost functions is somewhat subjective, however in Mitchell et al., 2018 [70], some strategies are developed for defining cost functions for FAR following approaches common in the multi-objective optimization literature. The measurement objective function might include preferred parameter settings and constraints on parameters. The performance objective function might include multiple performance objectives, such as position and velocity tracking error standard deviations. The individual objective functions are then transformed, weighted, and combined to yield the scalar cost functions. The particular formulations of the perceptual and executive optimization problems and their solution methodologies then depends on the nature of the cost and objective functions; the optimization choice may accommodate possible nonlinear or non-differentiable functions or the use of particular solvers.

4.2 METRICS FOR OPTIMIZATION

A critical element of cognitive radar is an optimization problem in which the next set of radar parameters is chosen to achieve a set of system goals. Articulating the system goals in a mathematical form suitable for optimization is thus critical to the operation of a cognitive radar system. As the number of radar system tasks and the number of parameters available for adaptation grow, this becomes increasingly difficult. In Mitchell et al., 2018 [70], a generalized approach to cognitive radar optimization design is developed by treating cognitive radar as a Multiple-Objective Optimization (MOO) problem. This optimization design methodology results in objective-based cognitive radar cost functions which are not specific to any single radar application.

Most of the early cognitive radars found in literature are implemented using bespoke structures designed specifically to yield a desired adaptive behavior. To provide a common starting point for implementing diverse cognitive radar tasks, the Fully Adaptive Radar (FAR) framework is a general model for the perception-action cycle, as outlined by Bell et al. [62]. The adaptive behavior produced by the FAR framework depends on the specifics of its constituent cost functions. Examples of these cost functions have been derived for waveform parameter optimization [64], [71], sensor resource management [62], [63], [72] and multiple target tracking [73]. Despite the generalized architecture, the cost functions and optimizations themselves still varied greatly between applications, and the existing FAR framework literature offers little guidance in designing functions suitable for problems outside the target tracking domain. Furthermore, most of the available examples focus on optimizing processor performance without regard to the relative cost of different radar sensor settings.

While they have not been applied using the FAR framework, cost functions have been explored in the context of radar resource management in general. Of particular note is the Quality of Service (QoS) framework for resource management. Originally formulated for managing computer networks and multimedia systems, this approach looks to plan and allocate system resources given a set of disparate QoS measures and relevant resource constraints [74], [75]. QoS has since been applied to the problem of radar resource management, with demonstrations successfully managing multiple tracks [76], balancing search and tracking radar tasks [38] and coordinating resource management within a radar network [77]. However, the QoS resource allocation problem is NP-hard, and requires the use of specialized algorithms such as Q-RAM to solve [38], [76].

Some have sought to manage system resources based higher level mission objectives instead of task level objectives. Rather than focus on minimizing the uncertainty in the target tracks, Katsilieris propose sensors which choose actions with the aim of reducing uncertainty regarding the targets' threat levels [78]. In de Groot et al., 2018 [79], the authors link the adaptable parameters directly to the probability of mission-success, as defined by the end-user. Each action is then judged by its impact on the overall mission, rather than specific quality measures.

In many cases, information theoretic measures have also been optimized in place of task-based cost functions [80], [81], [82], [83], [84]. These measures allow the value of disparate tasks to be compared directly based upon the expected information gained by performing each task. However, the final values of information theoretic measures are difficult for the end-user to understand and attribute to specific operational goals [85]. Additionally, Kreucher finds that task-based methods do outperform information theoretic based approaches at their tasks of interest [86].

In Mitchell, et al. 2018 [70], a generalized cognitive radar cost function design methodology inspired by the field of multi-objective optimization is developed. The related field of Multi-Criteria Decision Analysis (MCDA) has been successfully applied to radar target tracking in the past [88], but the MCDA metric was used as a performance metric by which to compare other resource management algorithms. In Mitchell, et al. 2018 [70], the focus is on real-time optimization based on the MOO inspired costs themselves. The cost functions are applied to enable waveform adaptation while tracking a single target. Cost functions based on different high-level radar objectives are implemented to demonstrate how the general cost functions may be instantiated to suit specific applications. Both simulated and real-time experimental results are provided. The simulations confirm the direct impact of changing the cost functions while observing identical target scenes, and the experimental results highlight that the proposed cognitive optimization may be implemented in real-time systems.

4.3 WAVEFORM OPTIMIZATION

Waveform optimization is one of the key features of a cognitive radar equipped with fully adaptive transmitters and receivers. I waveform optimization one may be able to choose waveforms from a library or codebook of pre-defined waveforms. Alternatively, the waveform is a continuous argument in the optimization that can take arbitrary value that maximizes or minimizes the employed objective function while satisfying all the imposed constraints.

Waveforms may be optimized for a specific radar task or multiple tasks simultaneously. Situational awareness is important side information for the optimization task. For example, target tracking task can take advantage of the fact that different targets scatter electromagnetic energy in a different way. The radar can match its transmitted waveform to the target response, including channel gain, target range profile and RCS, of the object it is tracking. This way the radar receives maximum energy reflected off the target. Waveform design is typically modeled as an optimization problem with an objective function that needs to be maximized or minimized under some constraints. Waveform optimization may consider using all available degrees of freedom in transmitters or receivers in the process of finding the best solution. Exploiting diversity (e.g., spatial diversity in multiantenna and multistatic radar sets, beampatterns, frequency, time, code, polarization) is in the core of waveform optimization since the degrees of freedom in optimization are typically associated with different sources of diversity. An example of multistatic radar system where multiple waveforms are used simultaneously is illustrated in Figure 4-2.

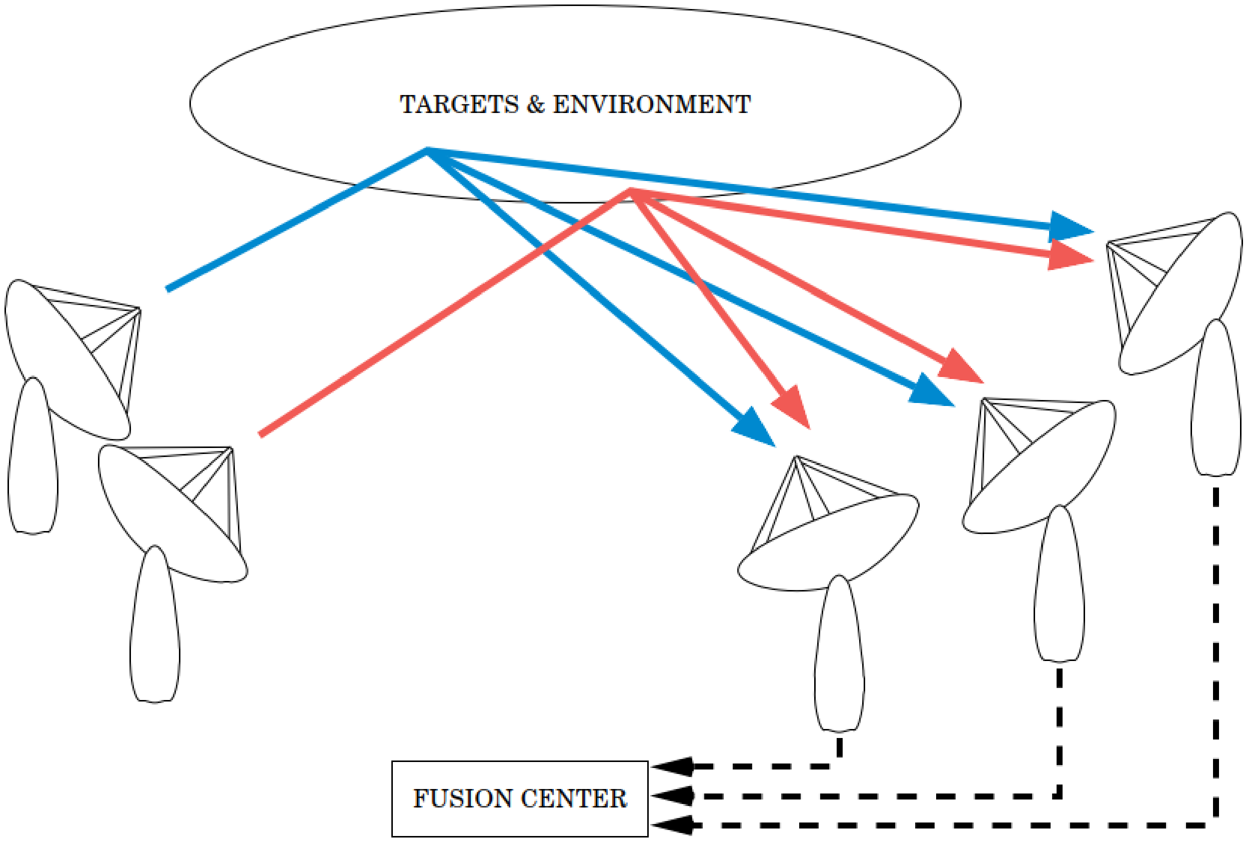


Figure 4-2: Multistatic Radar Operating in a Cooperative Mode. Transmitters and receivers can be spatially distributed to illuminate and observe the target from many different directions and provide spatial diversity.

The employed objective function may stem from information theoretical criteria such as Mutual Information (MI) or Kullback-Leibler divergence. These criteria are not necessarily directly connected to performance in a particular radar task. Statistical performance criterion as an objective can be directly associated with a radars task, for example Cramer-Rao Lower Bound for target parameter estimation, Neyman-Pearson or Bayes criterion for target detection or minimum Mean Square Error (MSE) for target tracking. As an intuitive example, one could design a waveform for target detection purposes using the Neyman-Pearson strategy while taking advantage of feedback from the receiver in terms of channel gains and levels of intentional and unintentional interference (SINR value). Moreover, the constraints could ensure that the ambiguity function is sufficiently close to the ideal thumbtack ambiguity shape, the waveforms have close to constant modulus property for efficient use of amplifiers, and the total or per antenna power constraints are satisfied. The employed radar codes, pre-coders at transmitters and de-coders at receivers, power levels, antenna beampatterns, antenna selection, frequency subbands and polarization could be selected or adaptively adjusted in order to find an optimal solution for the employed objective function. Furthermore, the radar receiver could be optimized to cancel jammers, have low Peak Sidelobe Levels (PSL) and low Peak Cross Correlation (PCC) over all Doppler frequencies and delays, or to maximize Signal to Interference and Noise Ratio (SINR) at the receivers. Improving SINR has a direct positive impact on the performance on most radar tasks. An example of such receiver optimization is the mismatched filter design by Aittomäki and Koivunen [88].

Waveform optimization may take place in different radar tasks, target scenarios and propagation environments. In the case of target tracking, the radar may constantly adjust its operational parameters, like transmitted waveform, Pulse Repetition Frequency (PRF), or pulse duration for example, in order to achieve a desired level of performance. In the case of plain surveillance, the radar can use a different update rate for a target at the edge of the detection range, moving away from the radar, compared to a fast adversary target approaching the radar in close proximity. The PRF is one parameter adjusted in the latter example. In the case of a weapon system radar, the target would be tracked at a tighter loop.

The form of cognition that just adjust physical radio transmitter parameters can be considered a low-level cognition. Cognition can take place at all the levels of the radar system from physical radio to mission planning and control. This is similar to cognition in communications in all OSI layers. Another form of radar adaptation and cognition is related to the decision-making task in a dynamic, constantly evolving operational environment. This requires a far greater complexity and sophistication than the above described form of cognition of mainly adjusting radio operating parameters. It aims at augmenting intelligent human behavior or even achieving a fully automated operation instead of a narrowly focused, well-defined radio parameter adaptation. Such form of cognition can be considered a high-level cognition.

Waveform optimization for target tracking task has been addressed in many publications. Many of the waveform optimization methods require awareness on clutter frequency response, target velocity, and general additive noise. Waveform optimization may focus on several areas of uncertainty, for example moving targets, as well as intentional and unintentional interference. The challenges posed by moving targets are highlighted in Rufang et al., 2015 [89], where the optimal waveform design algorithm maximizing the SNR is tested for range-Doppler resolution performance. It is demonstrated that the resulting waveform has a poor ambiguity function. In particular, the resulting waveform has a lower Doppler resolution than comparable Linear Frequency Modulated (LFM) or Barker code waveforms, as well as a highly ambiguous delay performance. It is concluded by Rufang et al., [89] that ambiguity function should be considered when designing cognitive radar waveforms. In Nieh et al, 2014 [90], the focus is to design the optimal waveform for detection and identification of moving targets. A closed-loop scheme to determine such optimal waveform for the case of an extended moving target is presented by Nieh et al, [90]. The scheme employs range-Doppler maps obtained from the measurements in the optimization of the future transmitted waveforms. The optimization is based on the Probability Weighted Eigenwaveform (PWE) technique. The approach in Nieh et al, 2014 [90] is further developed in Nieh et al., 2015 [91] for the detection of multiple extended moving targets. In both papers, a Range-Doppler Map (RDM) is employed in order to identify the target type.

Another waveform optimization example is dealing with a scenario where a jammer becomes active. The radar should sense the jammer and estimate its parameters including angle of arrival, employed waveform and bandwidth. Consequently, it could employ various adaptation methods or countermeasures to mitigate it or use its power and other radar system resources in such way that the jamming becomes ineffective.

4.4 INFORMATION THEORETIC METHODS IN WAVEFORM DESIGN

Information theory has been used in radar waveform design since the pioneering works of Woodward [92] and Bell [93]. Modern cognitive radar systems with fully adaptive transmitters and receivers obviously have more degrees of freedom that can be used as optimization variable and consequently a higher dimensional design space. Several different information theoretic criteria have been used for radar waveform design and optimization. Typically maximizing Mutual Information (MI) or minimizing or maximizing some information theoretic divergence criterion is used as an objective function. Such divergence criteria include relative entropy, also known as Kullback-Leibler (KL) divergence, J-divergence [94], [95], [96], and Bhattacharyya distance. For example, divergence between the two densities under hypotheses H_0 and H_1 may be maximized in detector design [96], [97]. According to Stein's lemma, for a fixed probability of false alarm or a fixed probability of detection, the maximization of the corresponding KL divergence $D(f_0||f_1)$ or $D(f_1||f_0)$ where f_0 and f_1 denote the densities under hypotheses H_0 and H_1 respectively) leads to an asymptotic maximization of the probability of detection or minimization of the probability of false alarm respectively [96]. The Bhattacharyya distance simultaneously provides an upper bound on the probability of false alarm and a lower bound on the detection probability [98]. It is claimed by Laz [99] that the Bhattacharyya distance is a better optimization criterion than the J-divergence for detection performance. It has been proven by Zheng et al. [100] that maximizing the J-divergence (which is in fact the sum of the two KL divergences – $D(f_0||f_1)$ and $D(f_1||f_0)$) is equivalent to maximizing the SINR. Dynamic power allocation among transmitters in a distributed MIMO radar system is found using different information theoretic divergence criteria by Aittomäki et al. [101]. The allocation is optimized in order to ensure a desired detection performance level in every part of a specified surveillance volume.

Target characterization task is addressed for cognitive radars using information theoretic criterion [102] in the optimization, in particular Mutual Information (MI). MI maximization is employed as an objective to find an optimal waveform that allows extracting information from multiple targets, both in the presence and absence of clutter. The optimization methods in Romero et al., 2011 [102], Wang et al., 2016 [103], and Romero et al. 2009 [104] make use of prior knowledge on second order statistics of the channel, which contains the clutter, target and noise. This prior knowledge is the situational awareness that the cognitive radar needs before the transmitter or receiver optimization can be employed. The solutions to the optimization problem are optimal power spectral densities of the transmitted waveform based on the power spectral densities of the targets and clutter. In many cases, the optimization leads to water filling solutions where power and other resources are allocated to degrees of freedom such as frequencies, channels or antennas where the signal experiences very little attenuation or interference. For example, for the water filling solutions by Wang et al. [103], a trade-off between the power spectral densities of the targets and clutter is observed.

A MI based waveform design strategy has been proposed for a cognitive radar network. The MI minimization between the subsequent radar returns is applied in order to ensure a maximization of information that is extracted from the target. This facilitates learning the environment and choosing an appropriate operational mode. A positioning algorithm could then use this information to generate more accurate location estimates. Numerical results show improved detection performance, as well as better delay-Doppler resolution. It can be observed using ambiguity function plots. Mutual Information based waveform design for target detection task in a spectrum sharing and radar-communications coexistence scenario has also been proposed [105]. It is described in more detail in the context of spectrum sharing in cognitive radars.

Mutual Information based criteria have been applied to MIMO radar waveform design by Chen et al. [106], and Yang et al. [107]. Waveform optimization for MIMO radar in colored noise based on maximizing MI is proposed by Tang et al. [108]. The obtained solutions are power allocations given by a water filling solution. It is demonstrated that power should be allocated in the direction where the target is present, and the energy of the noise is the smallest. It means that the optimal waveform can preserve the energy of the target signal and suppress the noise simultaneously. Awareness on the radar channel and target is needed before employing the optimization methods in Tang et al., 2010 [108].

An information theoretic approach to design radar waveforms suitable for simultaneously estimating and tracking parameters of multiple extended targets is proposed by Leshem et al., [109]. Several different design criteria are introduced. For example, a weighted linear sum of the MIs between target radar signatures and the corresponding received beams is employed. A design criterion that weights various targets according to their priorities is also considered. A generalized criterion for designing multiple waveforms under a joint power constraint when beamforming is used both at the transmitter and the receiver is considered as well.

4.5 RADAR RESOURCE MANAGEMENT

The operation of an Electronically-Scanned Array (ESA) is highly flexible in that a range of control parameters can be reconfigured nearly instantaneously. Consequently, an ESA is capable of executing numerous tasks supporting multiple functions, multiplexed in time and angle. However, this flexibility creates a challenging operation and resources management problem, in that a new radar dwell complete with beam direction and transmit waveform must be chosen within the time taken to execute the previous radar dwell. As controlling the operation of an ESA is beyond the capability of a human operator, it is desirable to automate the cognitive processes of a human operator in the system. The extent to which cognition can be implemented in management techniques is emerging as key performance factors for the next generation of multifunction radar systems.

4.5.1 Management Components

The core radar management components are priority assignment, task management and scheduling:

- **Priority Assignment –** The priority assignment module assigns a priority value to each radar task, which represents the task's entitlement to antenna usage relative to other tasks. Priorities can be defined by the operator based on the operational context and needs, or automatically for certain tasks, such as weapon guidance.
- **Task Management –** The task manager is responsible for selecting control parameters for each radar task-based on its priority and other task-specific requirements. Examples of control parameters include the next time to execute a radar dwell and the corresponding transmit waveform to use. The task manager issues job requests to the scheduler, based on the selected control parameters for the task and its priority.
- **Scheduler –** The scheduler is responsible for creating a timeline of jobs from the multiple job requests. Time conflicts between the job requests can be resolved using the task priority.

These core components are described in the following sections.

4.5.2 Priority Assignment

Tasks in the radar can have differing priority, to reflect the fact that different tasks have differing importance or differing sensitivity to scheduling delays. When the radar scheduler is under-loaded priority has little influence, however, when the radar scheduler is overloaded, the priority determines which jobs are not executed by the radar. Existing approaches to priority assignment are based on rule sets or alternatively using fuzzy logic. The simplest approach to priority assignment is to decide priority based on the function to which the task/job belongs. This reflects the fact that some functions, such as track maintenance, are more mission critical than other functions, such as calibration. Alternatively, priority can be assigned on situation dependent rules sets or fuzzy logic, to enable a higher fidelity priority assignment.

4.5.3 Rule-Based Task Management

Traditionally, control parameters for radar tasks have been fixed at design time. Presently, radar systems with an ESA antenna use a limited set of rules to enable adaption to the encountered scenario. Typical rules for operation depend on the radar function:

Search. In search management it is possible to configure the search area, the spacing between search beams, the search lattice type, the revisit interval and dwell time in a beam position as well as the modulated signal used (e.g., frequency, pulse repetition frequency, pulse modulation, etc.). Generally, the beam spacing and search lattice are selected to cover the required search volume evenly. Studies have shown that a beam spacing around 0.85 3dB beamwidths gives a very flat optimum in terms of the cumulative detection probability in overlapping beams. Potentially the search revisit interval can be varied for each beam position during runtime, however, typical rules choose a revisit interval time determined by either a required search reaction time or based on the revisit time that result from a required dwell time (and SNR) and number of beam positions. The dwell length is selected to give a required detection range, while avoiding range and Doppler cell migration. Sets of PRFs are selected in order to provide enough cumulative detection probability in multiple bursts to cover the desired search space without ambiguities within the required search space.

Alert Confirm. Simple rules can also design to control the alert confirm process, whereby the radar executes a rapid `look-back' confirmation dwell to determine whether a search detection was due to the presence of a target or a random false alarm. The rapid nature of the look tries to exploit a correlated radar cross section fluctuation between the search and confirm looks.

Tracking. In additional to tracking targets using measurements from search, an ESA can also schedule dedicated radar dwells that are optimized to the target, a process that is known as active tracking. If the target is actively tracked, the track manager must also decide the revisit interval time as well as the transmit waveform to use. Track management can be performed with simple rules, for example the targets chosen to be actively tracked are based on priority, the revisit interval can be based on priority and the number of pulses based on off-boresight scan angle. A significant advance on these simple approaches came in the form of adaptive tracking, whereby the revisit interval is adapted based on the target manoeuvres and the number of pulses is adapted based on the estimated radar cross section and distance. Through the benchmark problems, these methods were shown to minimize the resource required for tracking while also preventing track loss. This work is clearly an implementation of a perception-action cycle.

4.5.4 Scheduling

The scheduler is responsible for creating a transmittable timeline of jobs from multiple potentially conflicting job requests. Each job request consists of the job priority, job duration τ_c and the job timing constraints. The job timing constraints are the earliest time t_e, the desired time t_d and the latest time t_l that the job can be scheduled. The objective of the scheduler is to maximize the radar time utilization, while satisfying the job request constraints. Because the scheduler operates on a lower architectural level with a faster reaction time, it is typically based on queues or basic rules. Since it simply solves the juggling of timing constraints, the application of cognition is probably rather limited.

Queue Schedulers. Queue-based schedulers operate by selecting the next best job from a queue or set of queues. The next best job is decided upon an ordered list of the jobs that are eligible to be executed. Such a list can be ordered based on timing constraints, such as earliest deadline first, desired time first or earliest time first. Additionally, a queue-based scheduler will respect the priority of jobs, such that high priority jobs experience less scheduling delay.

Frame-Based Schedulers. Frame-based schedulers generate a timeline by arranging jobs in a time allocation slot of fixed duration. Whilst the previous allocation frame is being executed, the next allocation frame is being calculated. For a given measure of optimality an exhaustive search could be used, but often heuristics are used to guide the placing of jobs within the allocation frame. Generally, as frame-based schedulers optimize the placing of the job in the allocation frame, they can generate good quality schedules that are better than queue-based schedulers. However, since they are computationally much more complex, queue schedulers are generally preferred.

4.5.5 Attention and Effective Radar Resource Management

Radar Resources Management (RRM) addresses the two key problems of deciding how to allocate finite radar resource between numerous radar tasks, as well as deciding how to optimize the selection of control parameters for each individual radar task. Conventional radar resources management approaches optimize individual radar task control parameter selection using rules and heuristics, which are tuned by the system designer (as described previously). This optimization is done with an implicit assumption that a set of successful tasks leads to a successful mission. In contrast, effective resources management aims to manage the radar resource with respect to the mission objectives. This represents a shift of a cognitive process from the operator to the radar system, as the attention of the radar is focused on mission objectives. This section describes how quality of service techniques can be applied to achieve effective resources management.

4.6 ANTICIPATION AND STOCHASTIC CONTROL

A Partially Observable Markov Decision Process (POMDP) is a framework for sequential decision making on the selection of actions that trigger stochastic transitions in a system state that is only partially observable through noisy measurements. In radar applications the state is the sensed environment and the actions controlled by the POMDP can be measurement times for radar tasks and the corresponding waveforms. As the system state is not fully observable, the controller constructs a belief state, which is a probability distribution on the state space. This belief state can be thought of as a perception of the memory of all previous measurements. Actions, to schedule measurements and waveforms, are taken based on the belief state, but also based on the expected evolution of the system state over a time horizon in the future. By taking actions that consider the future system evolution, the radar is able to act with anticipation.

4.6.1 Partially Observable Markov Decision Processes

A POMDP consists of the following components:

State Space – The state space describes the range of possible states of the system. For radar tracking the state can be the true positions of the target and the radar platform.

Action Space – The action space describes the range of possible actions that can be taken. The action can be the scheduling of a measurement at a certain time with a corresponding waveform.

State Transition Probability – The state transition probability function gives the probability of transitioning to a specific state at the next time step from a specific state at the current time step, when a specific action is taken.

Observation Space – The observation space describes the range of possible measurements that can be observed.

Observation Likelihood Function – The observation or measurement likelihood function describes the probability of observing a measurement given that the system is in a certain state.

Reward Function – The reward function gives the reward received when an action is taken when the system is in a certain state. This reward must reflect the radar's sensing objective.

Once the above components have been defined, the objective of the POMDP is to use the optimal policy π_t^* that gives the action that maximizes the Q-Value Q_H:

$$\pi_t^*(b_t) = \arg\max_a Q_H(b_t, a) \tag{4-1}$$

where b_t is the belief state at the current time t, a is a candidate action and the Q-value:

$$Q_H(b_t, a) = R(b_t, a) + E[\, V_{H-1}^*(b_{t+1}) | b_t, a] \tag{4-2}$$

where $R(b_t, a)$ is reward at the current time step and $E[\, V_{H-1}^*(b_{t+1}) | b_t, a]$ is the expected reward over future time steps.

The solution to the POMDP attempts to maximize a mix of the current reward with the possible predicted rewards. Therefore, actions are taken based on all the knowledge on the system that is available at the current time while also planning in the future for rewards that may only be achievable many time steps in the future. Unfortunately, this Q-value is almost impossible to calculate exactly, which necessitates the use of approximate methods.

4.6.2 Cognitive Processes

The POMDP formulation incorporates the following cognitive processes:

Memory and Perception **–** The concept of memory and perception is central to the POMDP, as the belief state represents the interpretation of the partially observable system state. This perception is clearly based on memory, as is conditioned on the entire action-measurement history.

Decision Making **–** Decision making to select actions is the core task of a POMDP. The best action is sought based on the memory of previous actions and measurements, and the perception of the partially observable system state.

Anticipation **–** By evaluating the expected rewards over a future time horizon, a POMDP selects actions based on how the system state is anticipated to evolve in the future. The following two cases demonstrate the differentiation between adaptation and anticipation:

- Case 1 – Time horizon H = 1: The POMDP objective simplifies to the reward that is achievable from the current time step, and therefore based only on the belief state at the current time. Action selection based only on the current belief state can be thought of as adaptive.
- Case 2 – Time horizon H>>1: The POMDP objective is comprised of a trajectory of future actions and states, therefore the POMDP reasons about the rewards it anticipates to receive in the future. This anticipation of future rewards can be considered a cognitive process.

The effect of the time horizon in a POMDP is widely discussed in the sensor management literature as myopic (considering only the present) or non-myopic (considering also the future) management.

4.6.3 Anticipative Target Tracking Example

In this example, the objective is for the controller to select the time interval between radar measurements for a target track, such that a desired estimation error is achieved and track loss is prevented with the minimum resource usage. An ESA antenna is assumed, such that measurements are made by steering the beam to the estimated target position. As a scenario may dictate that measurements provide different amounts of information, the anticipated future development of the situation must be taken into account. This is done with a rollout-based approach.

The scenario consists of an airborne radar platform and a target with nearly constant velocity motion at 200 m/s, as illustrated in Figure 4-3. In the scenario, the target is unobservable during a certain period of time. This non-observability could be due to a number of reasons, such as a blockage to the line of sight, a jammer, or the unavailability of a multifunction radar when a different non-interruptible function is executed. It is assumed that the borders of the unobservable region are known.

Figure 4-4 plots the number of measurements per second that are executed by adaptive tracking and the POMDP for a 2 km occlusion. It can be seen that both methods use a high number of measurements at the start of the simulation to initialise the track. It can also be seen that the POMDP anticipates the occlusion by scheduling an increased number of measurements just before the target enters the occluded region. Consequently, the POMDP is able to maintain the tracks during the occlusion and continue tracking once the target is again observable. In contrast, adaptive tracking does not anticipate the occlusion and therefore tracks are lost during the occlusion, which must then undergo a resource expensive track reacquisition when the target is again observable.

In Figure 4-5, the probability of a track loss is shown, evaluated over 100 Monte Carlo runs. It can be seen that the probability of a track loss is significantly reduced by the rollout-based method, because it anticipates the occlusion and therefore schedules a number of additional measurements shortly before the target is occluded.

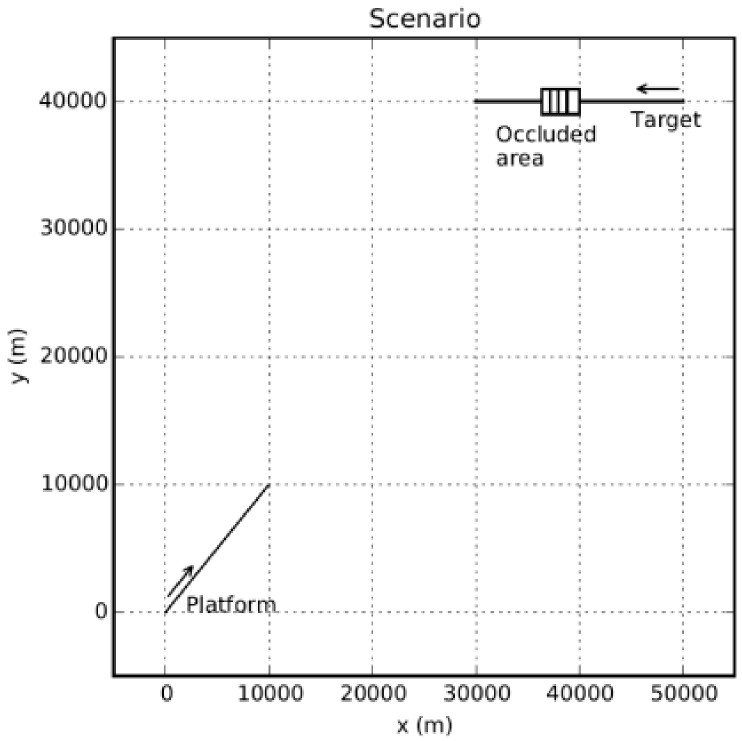


Figure 4-3: Example Scenario.

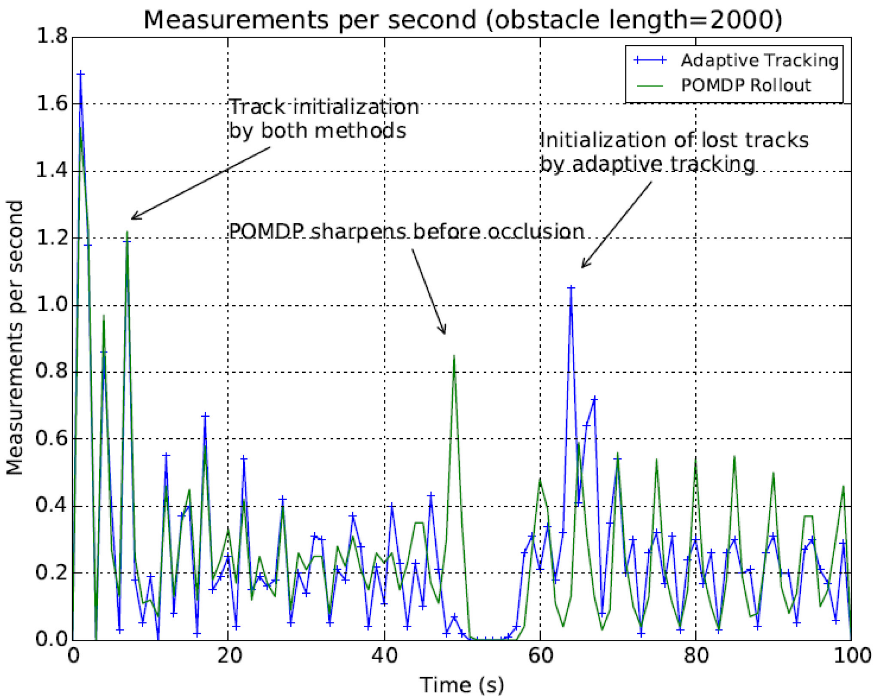


Figure 4-4: Number of Measurements per Second Executed by Adaptive Tracking and the POMDP for a 2 km Occlusion.

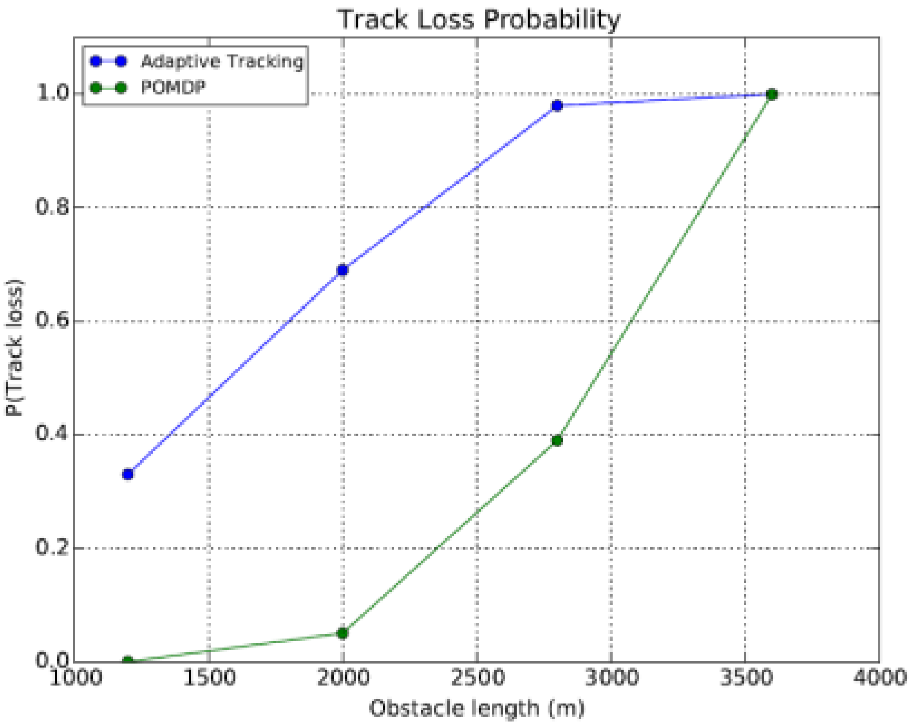


Figure 4-5: Probability of Loss of Track.

4.7 BIOLOGICALLY-INSPIRED WIDEBAND TARGET LOCALISATION

4.7.1 Introduction

The natural world contains a great many echolocating species, animals that expertly use acoustic calls to enhance perception of their environment. Radar systems are based on the principles of echolocation and use electromagnetic radiation to build up a perception of the environment in a similar way to their biological counterparts. Yet many radar systems bear only a passing resemblance to the echolocators of the natural world. Previous radar work has considered biomimetic and cognitive approaches related to echoic flow [110], [111], high range resolution profiles [111], dynamic parameter control [31], and adaptive waveform design [112], [27] (for more biologically-inspired radar techniques and approaches see Balleri et al., 2017 [113]).

This work develops previous work by the same authors [114], [115] and employs similar techniques to work carried out in the sonar domain [116].

Acoustic Echolocation. A large number of natural echolocators, including humans, bats, and dolphins share several features across their echolocation calls, despite the very different environments in which they operate.

Many echolocating species use wide acoustic bandwidths for echolocation; human expert echolocators use clicks with frequency content ranging across 2 – 13 kHz [117], bats have shown calls using the 15 – 120 kHz range [118], [119], and dolphins have shown calls from 29 – 42 kHz [120]. It is worth noting that these signals have a large fractional bandwidth (bandwidth divided by center frequency) of 1.47, 1.56, and 0.36 respectively. When considering wideband signals in the radar domain a similar fractional bandwidth may be achieved with a 2 – 6 GHz band (fractional bandwidth of 1). Further, a radar signal at 3 GHz has approximately the same wavelength as a 3 kHz audio signal, and so we may expect some correspondence with echolocation in the scales of objects and environments that may be observed using a radar with comparable wavelengths.

There is evidence to suggest that several echolocators use very wide beamwidths to completely illuminate the space in front of them. This is true for human echolocators who have beamwidths of 120°[117] and is true for certain species of bats which show dynamic control of their echolocation beamwidths in the range of 40 – 120° [121]. To achieve a wide area of illumination in a radar system, an antenna with a suitably large beamwidth should be used.

Perhaps the most straightforward commonality between echolocators, is the use of a binaural hearing configuration. The use of two ears to perceive sound enables the use of comparative localisation cues described in the following section.

The final, and least tangible feature of all echolocator activity is the cognitive processing used to interpret the reflected signals in the brain. It is known that there are certain signal properties (such as frequency and time delay) that are extracted from the reflected signals in the lower brain, and that these properties are preserved and passed to higher levels of cognitive processing [122], [123].

Psychoacoustic Cues. In the field of psychoacoustics there are several well-described cues that are used by people when localising the source of a sound [124], [125], [126], [127], [128], [129], [130], [131]; the Inter-Aural Level Difference (ILD), the Inter-Aural Time Difference (ITD), and the Binaural Timbre Difference (BTD). These cues are the subject of much psychoacoustic research and so only a brief overview is given here. All of these cues rely on the binaural nature of hearing, the ILD represents the power difference of a signal between the two ears [124], [130], [131]. The ILD finds its closest radar analogue in amplitude-comparison monopulse, where the radar compares the magnitude of the received signal at two antennas in order to locate a target.

The ITD represents the Time Difference Of Arrival (TDOA) of a signal at the two ears. As a first order estimate this may be considered to be the time difference caused by the geometrical path difference between the sound source and the two ears [124], [125], [131], [132]. The closest radar analogue to the ITD is TDOA.

The third cue, the BTD can be thought of as how the timbre of a sound varies between the two ears. Timbre is the quality of a sound and is composed of a complex layering of different tones and overtones, all with different magnitudes. Changes in timbre occur based on the direction of arrival of an acoustic signal because the mass of the head and the shape of the pinna (the outer ear) introduce direction-dependent filtering of acoustic signals. This filtering process can be described by the Head-Related Transfer Function (HRTF), an example from the CIPIC HRTF database [133] is shown in Figure 4-6.

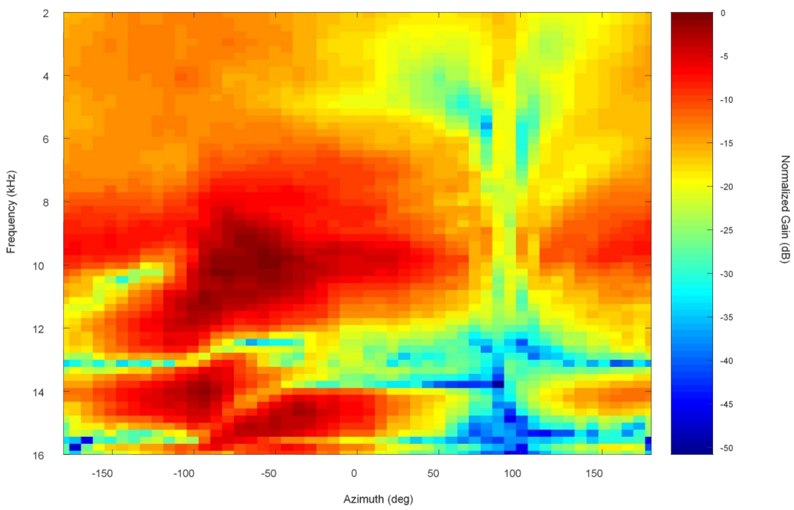


Figure 4-6: Head-Related Transfer Function (HRTF) for a Human Left Ear. Subject 003 from the CIPIC HRTF Database [133].

This HRTF shows how the power of each frequency component of an audio signal is attenuated which leads to an altered timbre of the sound [124], [126], [127], [129]. For instance, at an azimuth angle of 90° the attenuation of a sound is at its highest due to the entire mass of the head being between this sound source and the left ear. There is no well-established radar analogue to the BTD and the HRTF, but it has been demonstrated that a horn antenna demonstrates frequency-dependent filtering of a radar signal, and that this may be exploited for target localisation [114]

4.7.2 Theory

Table 4-1 defines the mathematical symbols referred to in this section. The subscript *i* is used throughout and can take a value of either 1 or 2 to denote the relevant receiving antenna.

Table 4-1: Reference for Mathematical Symbols.

Symbol	Definition	Unit
θt	Target angle from transmitter to boresight	radians
θ0	Receiver angle from transmitter boresight	radians
f	Frequency	Hertz
PRi	Signal power received at the i^{th} receiving antenna	Watts
PTx	Power fed to the transmitting antenna	Watts
GTx	Gain of the transmitting antenna	
GRi	Gain of the receiving antenna	
c	Speed of light in a vacuum	m s^{-1}
σ	Radar Cross Section (RCS) of the target	m^2
L	Losses	

Figure 4-7 shows, schematically, the relative locations of the target, transmitter, *Tx*, with phase center located at the origin and pair of receivers, R_1 and R_2 located such that all three antennas are collinear. The receiving antennas are separated by a baseline, d.

By taking inspiration from the ILD and the BTD, we can formulate a power-based angular localisation technique [114]. The radar equation for the power at the output of the receiving antenna is formulated as in Equation (4-3), with the relevant parameters described in Table 4-1.

$$P_{Ri} = \frac{P_{Tx} G_{Tx}(\theta_{\mathrm{t}}, \boldsymbol{f}) G_{Ri}(\theta_{\mathrm{t}} \pm \theta_0, \boldsymbol{f}) c^2 \sigma(\theta_{\mathrm{t}}, \boldsymbol{f})}{(4\pi)^3 \left(r_{tx} + r_i\right)^4 f^2 L(\theta_{\mathrm{t}})} \tag{4-3}$$

For a single measurement, there are several parameters that vary with frequency (including the target RCS and the attenuation in space), but providing that the antenna baseline d is sufficiently small $d << r_{tx}$, then the difference in these terms between the two receiving antennas is sufficiently small and is negligible.

Considering the ratio of received signal powers between R_1 and R_2 yields Equation (4-4) and the interesting result that the signal ratio is independent of target range or reflectivity.

$$\frac{|s_1|^2}{|s_2|^2} = \frac{\boldsymbol{P}_{R1}\left(\theta_{\mathrm{t}} + \theta_0, \boldsymbol{f}\right)}{\boldsymbol{P}_{R2}\left(\theta_{\mathrm{t}} - \theta_0, \boldsymbol{f}\right)} = \frac{\boldsymbol{G}_{\boldsymbol{R1}}\left(\theta_{\mathrm{t}} + \theta_0, \boldsymbol{f}\right)}{\boldsymbol{G}_{\boldsymbol{R2}}\left(\theta_{\mathrm{t}} - \theta_0, \boldsymbol{f}\right)} = \boldsymbol{A}\left(\theta_{\mathrm{t}}, \boldsymbol{f}\right) \tag{4-4}$$

This result means that by having prior information about the ratio of receiver gains across all angles of interest and all frequencies in the band it is possible to build up a map function which describes the expected result of a measurement in the presence of a target. This map function depends only on the angle to the target, and a known system characteristic (the antenna beam patterns) and is given in Equation (4-5), where $\boldsymbol{\theta}$ represents a set of all possible angles to a target.

$$\frac{\boldsymbol{G}_{\boldsymbol{R1}}\left(\boldsymbol{\theta} + \theta_0, \boldsymbol{f}\right)}{\boldsymbol{G}_{\boldsymbol{R2}}\left(\boldsymbol{\theta} - \theta_0, \boldsymbol{f}\right)} = \boldsymbol{M}\left(\boldsymbol{\theta}, \boldsymbol{f}\right) \tag{4-5}$$

In this approach the signal ratio is the cue and the map function represents the prior information held by the system. What is required is some way of relating the measured signal ratio to the prior information held by the system. To do this, the Pearson correlation coefficient is calculated between the signal ratio and the frequency profile across each angle in the map function. The Pearson correlation coefficients represent the degree of similarity between the measured signal ratio and the expected profile at each candidate angle. By extracting the peak from this likelihood profile, the best estimate of the angle to the target is found.

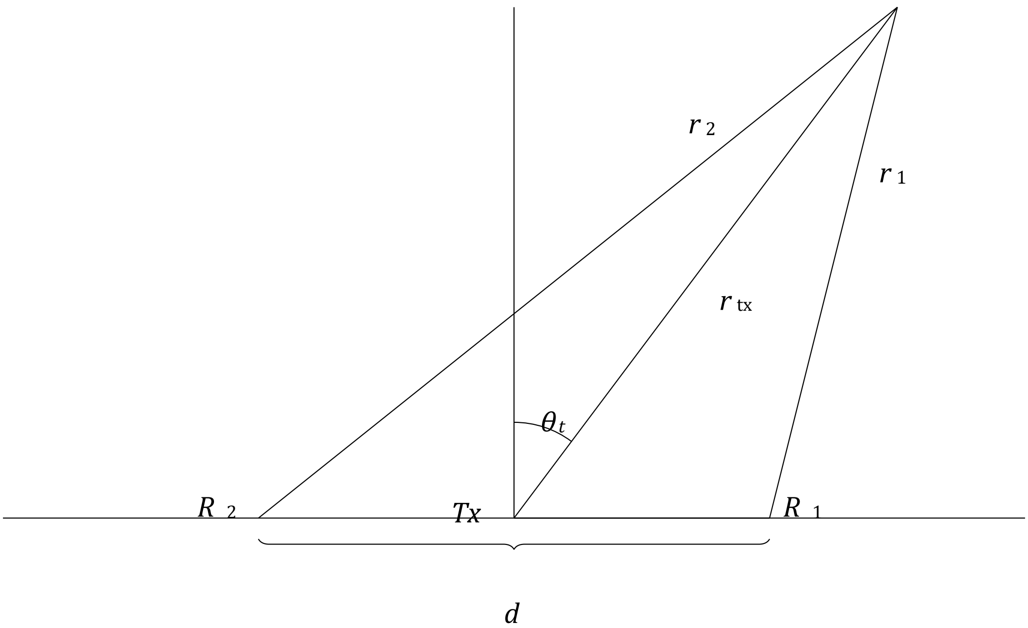


Figure 4-7: System Geometry for Two Receivers and a Single Transmitter in a Binaural Configuration.

4.7.3 Experiment

Method: Horn antennas from Q-par Angus (WBH1-18) which satisfied the requirements of a wide beamwidth and a wide operational bandwidth were used; Figure 4-8 shows how the antenna beamwidth varies across the 2 – 6 GHz frequency band, presenting a broad beam with beamwidths of approximately 120° at 2 GHz and 60° at 6 GHz. In order to mimic the binaural hearing configuration of echolocators two spatially-separated identical receiving antennas were used, as presented in Section 4.7.2. To complete the biological analogy, a third identical antenna was used exclusively for the transmit signal, mimicking the central placement of the mouth, the originator of echolocator clicks.

The antennas were mounted as in Figure 4-9 and were placed with a target in an anechoic chamber. The antennas were mounted on a rotation table such that measurements could be made over the desired range of angles to the target. The target, a single mirrored sphere of 36 cm diameter, was placed on a plinth to raise it into the same plane as the antennas, at a distance of 3 m.

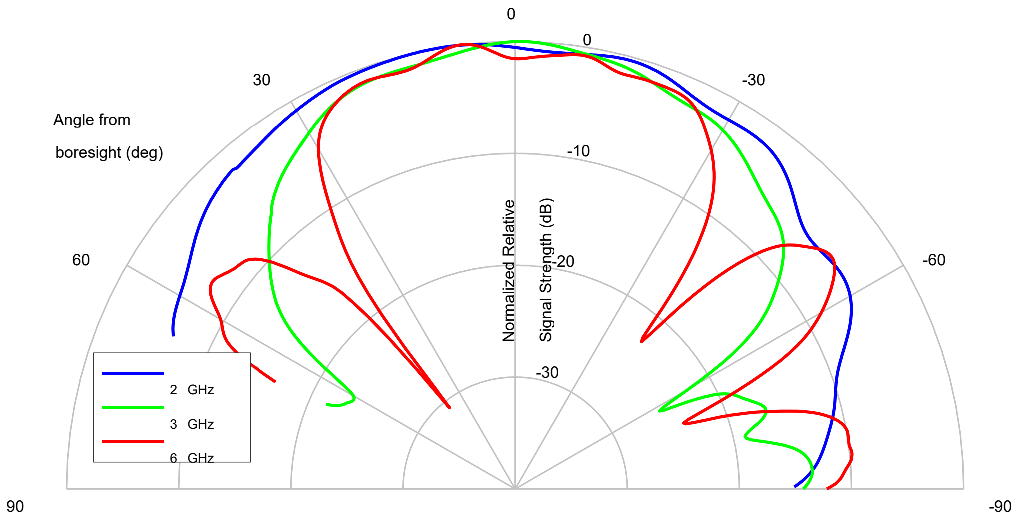


Figure 4-8: Antenna Beampattern Measured Across a 2 – 6 GHz Band, Showing 3 dB Beamwidths of Approximately 120° at 2 GHz and 60° at 6 GHz.

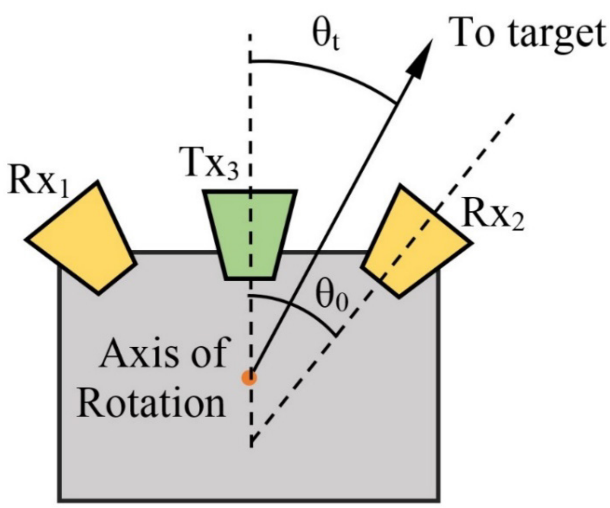


Figure 4-9: The Biologically-Inspired Radar Configuration.

A Vector Network Analyser (4-port Rohde & Schwarz ZVA-67) was used to generate the required band of frequencies and was placed on the rotation table below the antennas as shown in Figure 4-10. The rotation table used was a Parker 200RT which was suitable to make measurements at 0.5° intervals across a range of – 90° to + 90° to the target.

The measurements made consisted of s_1 and s_2 measured across a frequency band of 2 – 6 GHz with a frequency step of 10 MHz. In order to minimize the clutter response of the chamber, an initial background measurement of the environment (across - 90° to + 90° and across the 2 – 6 GHz band) was made in the absence of the target and subtracted from all subsequent measurements made in the presence of a target.

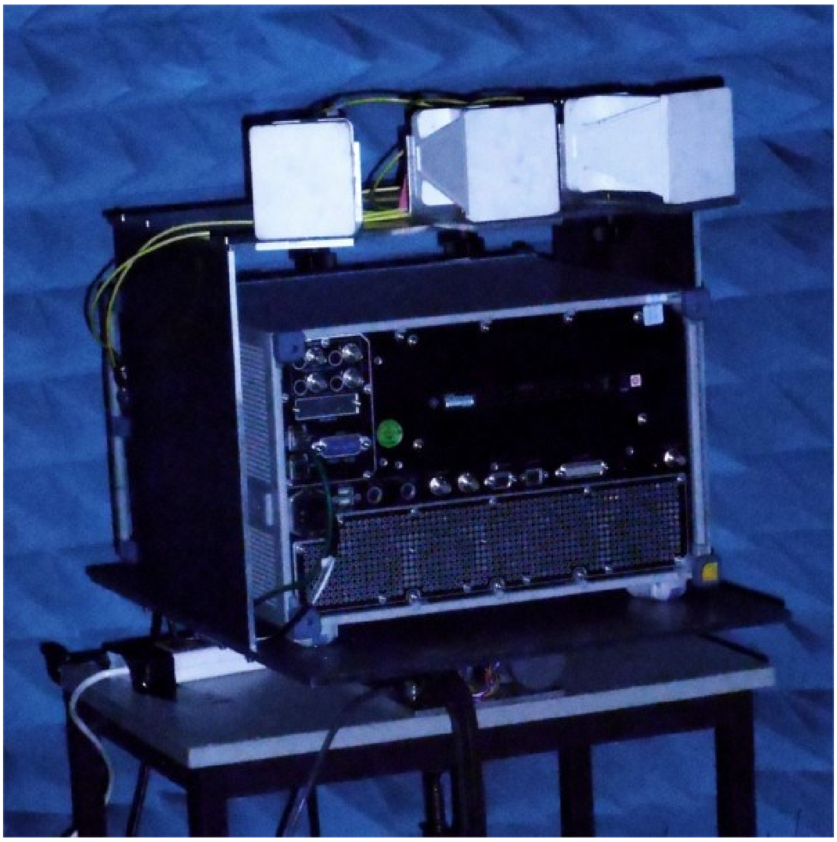
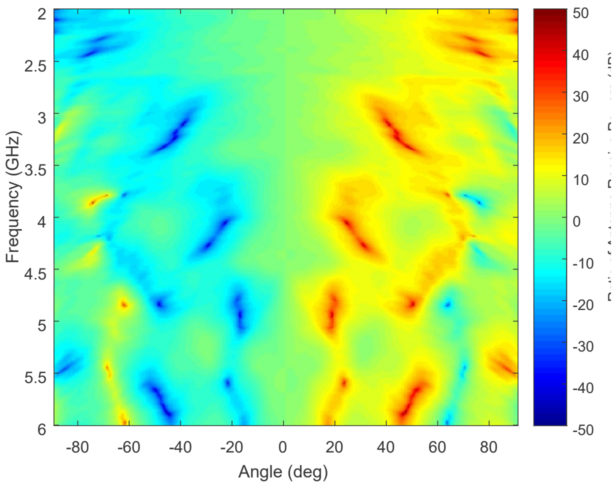


Figure 4-10: The Experimental Setup Using the Vector Network Analyser (ZVA-67) and Three Wideband Horn Antennas.

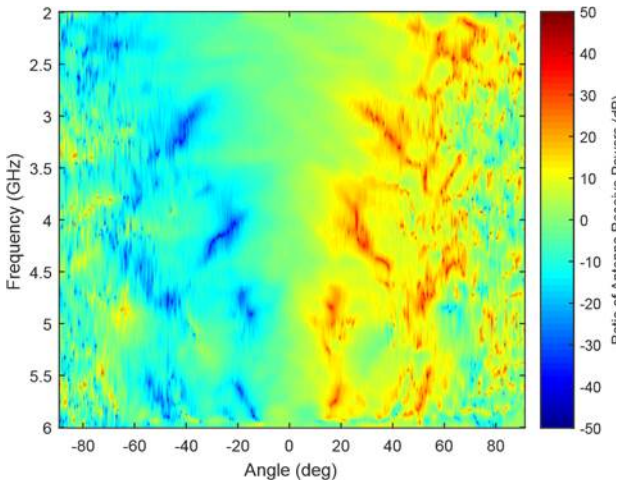
Results The magnitudes $|s_1|$ and $|s_2|$ are calculated before dividing the signals which results in the measured signal ratio (evaluated over several measurements at different angles) shown in Figure 4-11(a). By the same method, the power map function is evaluated and is shown in Figure 4-11(b). Here, the map functions indicate a coding of space as a function of frequency by the antennas and show the expected result of measurements in the presence of a target at any possible angle. It can be seen that there is good agreement between the spectral structures present in the signal ratio and those present in the map function. The most significant disagreement occurs further from the boresight direction where noise corrupts the signal and the Signal-to-Noise Ratio (SNR) decreases.

The correlation was then computed using the Pearson correlation coefficient and shown in Figure 4-11(c), and the peaks were extracted and used to estimate the angular location of the target for each measurement. The error between the estimated angle and the correct angle to the target was then plotted and can be seen in Figure 4-11(d).

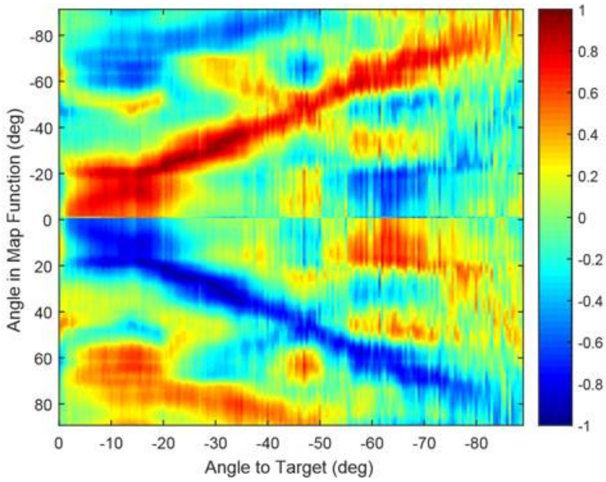
This method is capable of localising the target in azimuth with an error of 2.48° over the range $0° \leq \theta \leq 70°$, and the phase-based approach locates the target in azimuth with an error of 1.80° over the range $0° \leq \theta \leq 70°$.



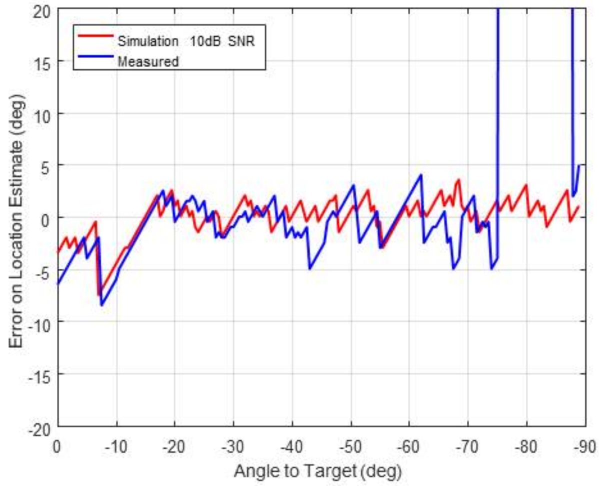
(a) Signal Ratio Measured in the Presence of Target.



(b) Power Map Function.



(c) Result of the Pearson Correlation Between Each Frequency Profile in the Map Function and the Signal Ratio, Using the Power-Based Approach.



(d) Result for Target Localisation in Azimuth Using the Power-Based HRTF Technique. Simulation results for 10dB SNR are shown in red, and measurement results (with variable SNR) are in blue.

Figure 4-11: Results for the Power-Based Approach.

4.7.4 Conclusions

The results presented in the previous section show that the biologically-inspired radar cues allow for good angular localisation performance over a wide angle of operation. A 'rule of thumb' for monopulse techniques is that target angular location accuracy can be performed to approximately 10% of the antenna beamwidth. For example, the narrowest beam present in the used band (at 6 GHz) has a beamwidth of approximately 60°, and so the rule of thumb would indicate that the angular location accuracy should be only 6°subject to an SNR of approximately 15 dB. Both techniques outperform this figure and have a wider range of operation. This descriptive result demonstrates that these biologically-inspired techniques can extend the performance and range of existing radar methodologies.

We have shown that it is possible to take inspiration from the biological worlds of echolocation and sound localisation in order to present a wideband radar technique that is capable of high accuracy angular localisation over a wide range of angles. By using a wide bandwidth, we have also explored ways to exploit the natural coding introduced by antennas over a wide band and have shown that it is possible to use this to enable angular target localisation.

4.8 MACHINE LEARNING APPROACHES FOR RADAR RESOURCE MANAGEMENT

4.8.1 Introduction

Modern phased array multiple function radar is widely used for both civil and military applications. In this type of radar, each function has multiple tasks to be scheduled. Radar Resource Management (RRM) is the central unit to coordinate all the tasks for scheduling [134]. The problem has been known as an NP-hard problem, thus the complexity could be rather high in order to find the optimal solution. Conventional scheduling methods, such as the Earliest Start Time (EST) or the earliest deadline consume very little time, but the performance is not desirable. In order to develop better solutions, machine learning approaches, including supervised learning and reinforcement learning, are investigated. In this section, we present what we have done in machine learning for RRM. Also presented is the simulation result to demonstrate the efficiency and effectiveness of machine learning approaches.

4.8.2 RRM Problem Formulation

We consider N tasks, to be scheduled in a defined time window with a length L. Assume that the radar system is designed for handling N tasks, then the averaged t_{dwell} of these tasks should be L/N to make the total t_{dwell} of all the tasks equal to L. To generalize the problem in this report, a normalized time window is used, i.e., $L = 1$, and hence the ideal averaged $t_{dwell} = 1/N$. Note that in a real situation, the number of the input tasks (N_{actual}) may not be the same as N as it was designed, for instance, in practice the scheduler could be under-loaded if $N_{actual} < N$, or over loaded if $N_{actual} > N$.

Five parameters of each task are input to the radar scheduler, including the aforementioned t_{start}, t_{dwell}, and p. Two other parameters are the earliest start time ($t_{earliest}$) and the latest start time (t_{latest}) that a given task is allowed to be executed. All the tasks are firstly passed to the radar for scheduling, then the decision (a schedule, or a sequence of all the tasks) is made based on all the received tasks. Finally, part or all of the tasks are executed, according to the determined schedule.

A total cost (J) of a scheduled task sequence is defined as the summation of all the individual task cost $C(n)$ in a mean squared error format. The equations are expressed as follows:

$$J = \sum_{n=1}^{N_{actual}} C(n), \tag{4-6}$$

$$\begin{aligned} \tau &= |t_{earliest}(n) - t_{start}(n)|, \textbf{ when } t_{res}(n) < t_{start}(n), \\ &= |t_{latest}(n) - t_{start}(n)|, \textbf{ when } t_{res}(n) \geq t_{start}(n), \end{aligned} \tag{4-7}$$

$$\begin{aligned} C(n) &= \frac{1}{N_{actual}}\left[p(n) \cdot \frac{t_{start}(n) - t_{res}(n)}{\tau}\right]^2, \textbf{ when } t_{earliest}(n) \leq t_{res}(n) \leq t_{latest}(n), \\ &= \frac{1}{N_{actual}}\left[p(n) \cdot C_{dp}\right]^2, \textbf{ otherwise,} \end{aligned} \tag{4-8}$$

where τ is the time difference between either $t_{earliest}$ or t_{latest} and the original t_{start}. C_{dp} is a scalar that represents the task drop penalty.

4.8.3 Reinforcement Learning Approach

The reinforcement learning approach involves two steps. In the first step, the original start time of each task is randomly shifted within its time window. The shifted tasks to the EST would result in a solution that is different from the solution previously done by the EST. By repeating this random shift then EST scheduling many times, a best solution among all could be found [135], [136]. This method is termed a Random Shifted Start Time – EST (RSST-EST) scheduling method. The details of this work have been documented in a conference paper [137].

In the second step, a machine learning radar task scheduling method is incorporated to further enhance performance. Since the prior knowledge of the global minimal cost of the task schedule is unavailable, a radar scheduler has to find a solution with less cost, which is what reinforcement learning does [138]. The proposed method is termed as Reinforcement Learning EST Scheduling (RL-EST) method, in which we establish a reward-punishment policy, and the scheduler will decide either staying at the current exploitation or switching to a new exploration. When the strategy is to exploit, the gradient descent algorithm is used to attempt to reduce the cost [139], and if the cost could be further reduced, a reward would be given, otherwise the punishment would be applied. Whenever the reward value becomes zero, the exploitation stops, then the RSST-EST will be conducted to explore new solutions, and the reward value will be reset.

The same process is repeated several times and the schedule yields the minimum cost among all will be considered as the final solution of the RL-EST scheduling. In the numerical simulation, we assume that the radar is designed for handling N tasks, while the actual number of tasks is varying from 50 % (under-loaded) to 200 % (over loaded) of N. The cost of the solution done by the RL-EST is compared with that of the EST at each loading rate of every N value, and the results are shown in Figure 4-12(a). It can be seen that the proposed RL-EST method has about 1.3 to 10.5 times less cost than the EST, while the computational time is between 20 and 90 ms as seen in Figure 4-12(b), so that the method is also considered practical for real radar missions. The outcome has been summarized and submitted in Qu et al., 2019 [140].

4.8.4 Supervised Learning Approach

We have also developed heuristic methods as well as the optimal Branch-and-Bound (B&B) technique, an as-effective-as-possible approach to solve an NP-hard problem [141]. It is shown that heuristic methods in the literature (such as "earliest start time first") have poor performance, and the B&B algorithm can have high computational complexity. We proposed that the radar could use cognitive concepts to reduce the complexity of the B&B algorithm by using Machine Learning (ML) methods. ML methods eliminate nodes from the search tree without compromising much on the performance. However, the complexity still remains rather high. The focus has two aspects:

1) We consider the practical implementation of the above methods, and

2) We also introduce new Machine Learning techniques for training the neural networks.

We proposed to further reduce the complexity using the Monte Carlo Tree Search (MCTS) method [142]. Along with using bound and dominance rules to eliminate nodes from the search tree, we used a policy network to help to reduce the width of the search. The neural network was trained using labeled data obtained by running the B&B method offline on problems with feasible complexity. We showed that the proposed method has near-optimal performance, while its computational complexity is orders of magnitude smaller than the B&B algorithm.

We investigate the performance of the proposed method for different number of tasks, N. The number of Monte Carlo rollouts is fixed to $M = 50$. We compare the MCTS, B&B, and the heuristic methods (the task switching version of the original EST and ED algorithms) with respect to their ability of scheduling all the tasks without dropping any of them. The probability that no task is dropped versus the number of tasks is depicted in

Figure 4-13. As can be seen, the performance of the proposed MCTS method is very close to the B&B algorithm and significantly better than the heuristic methods. The average numbers of visited nodes of MCST and B&B are compared in Table 4-2. MCST is significantly faster than B&B.

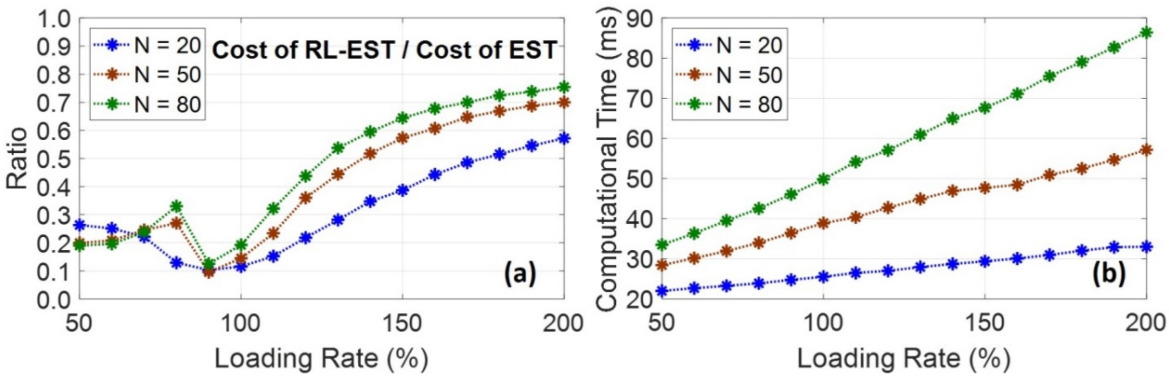


Figure 4-12: (a) Ratio of the RL-EST's Cost to the EST's, and (b) Time Consumed of the RL-EST Method, with *N* = 20 (Blue), *N* = 50 (Brown), and *N* = 80 (Green).

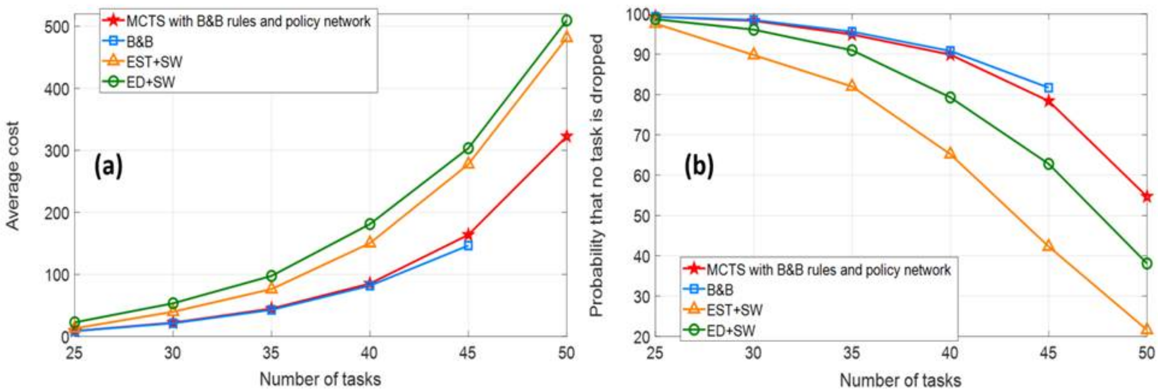


Figure 4-13: Comparison of Average Cost and Probability Without Task Dropping.

Table 4-2: Average Numbers of Visited Nodes Versus the Numbers of Tasks.

	25	30	35	40	45	50
MCTS	140	425	1266	3991	11274	25699
B&B	173	1031	27068	669738	13622348	NA

4.8.5 Conclusion

We have applied both reinforcement machine learning and supervised machine learning for the radar resource management problem. In the reinforcement learning approach, random time shifts are used for initial solutions, following by performance enhancement through reinforcement learning. This approach is sub-optimal in nature, but it significantly reduced the computation comparing with that of the optimal solution. Simulation results show that the reinforcement learning scheduler is practical in terms of the execution time and the new scheduler performs a lot better than either EST or earliest deadline.

The supervised machine learning approach is based on an optimal B&B and Monte Carlo Tree Search algorithms. It is found that the solutions obtained from the offline B&B method can be used to train neural networks which can help reduce the complexity of the search. The proposed method has near-optimal performance, while the computational complexity is significantly lower than the optimal B&B method.

Comparing the above two machine learning approaches, the reinforcement learning approach is faster than the supervised learning approach; however, the supervised learning approach has better performance, near-optimal. Our on-going work focuses on either improving performance of reinforcement learning approach or further speeding up the supervised learning approach.

4.9 PERCEPTION-ACTION CYCLE, SITUATIONAL AWARENESS AND FEEDBACK

4.9.1 Introduction

Cognition is defined as "the mental action or process of acquiring knowledge and understanding through thought, experience, and the senses". It is a complex process used by humans and animals in order to sense their environment and interact with it. The foundation of cognitive radar is based on machine learning and adaptive algorithms developed in 1940's. The term cybernetics was defined in 1948 by Norbert Wiener as "the scientific study of control and communication in the animal and the machine". It refers to intelligent systems stemming from operations research, statistics, information theory, control systems and pattern recognition.

Radars may classified as Traditional Active Radar (TAR), which operates in a feed-forward manner, and Fully Adaptive Radar (FAR), which operates in a closed feedback loop connecting the receiver to the transmitter, and as Cognitive Radar (CR), which on top of FAR can learn from the observations and develop policies and rules for adjusting its behavior in a self-organized manner. A cognitive radar system that tries to emulate the way the human brain observes the environment with a goal to bridge the gap between neuroscience and engineering.

There is no unique and universally accepted definition for a cognitive radar system. There are, however, a number of definitions that describe the main properties. For example, the definition by Bell is the following: "*While a fully adaptive radar may employ feedback and use prior knowledge stored in memory, a cognitive radar predicts the consequences of actions, performs explicit decision-making, learns from the environment, and uses memory to store the learned knowledge*". Another definition generic to all cognitive systems operating in radio frequencies is given by the ITU (International Telecommunication Union): "*A radio or system that senses and is aware of its operational environment and can dynamically , autonomously and intelligently adjust its radio operating parameters*". It does not consider any radar specific tasks. Another definition is given by the IEEE P686 Standard for Radar Definitions as: "*A radar system that in some sense displays intelligence, adapting its operation and its processing in response to a changing environment and target scene. In comparison to adaptive radar, cognitive radar learns to adapt operating parameters as well as processing parameters and may do so over extended time periods.*"

The word cognitive refers to the fact that for agile use of resources such as radar spectrum one should be able to get feedback and learn from the radio environment, i.e., create awareness about radio operation and target environment. The cognitive radar may then adapt its Degrees of Freedom (DoF) in order to optimize its performance. In practice parameters such as power, antenna selection, beampatterns, waveforms, and frequency are adjusted dynamically in order to obtain the best achievable performance in the current radar tasks. Moreover, multiple tasks may be performed simultaneously and the resource allocation among the tasks can be optimized based on the acquired awareness.

Essentially, cognitive radar may be presented as a dynamic closed-loop system employing three key steps: Sense, Learn, Adapt (SLA). These three stages form a Cognitive Cycle, a key feature in any cognitive system. This structure is common to all cognitive systems, including cognitive radios. These steps are performed cyclically, as shown in Figure 4-14 in order to satisfy a certain goal in an optimal manner.

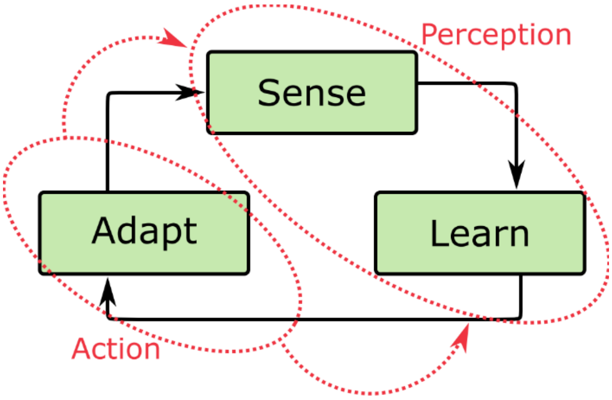


Figure 4-14: Cognitive Sense-Learn-Adapt (SLA) Cycle Containing Perception and Action Stages. Situational awareness is built and learned in the perception stage and adaptation taking into account the awareness takes place the action stage.

This cycle uses the concept of Perception-Action Cycle (PAC). The system builds situational awareness by sensing its environment and constructing a model and learning how the operational environment behaves and evolves. This acquired awareness is then used to adapt and optimize the operational parameters of the system for a specific goal, task or mission.

4.9.2 Situational Awareness

Situational awareness is crucial for cognitive radars. Based on built awareness the radar is able to adapt to the evolving operational environment. Most of the cognitive radar literature is focused on the adaptation (action) part of the cognitive cycle. In general, it is assumed that the required situational awareness about the state of the radar spectrum and target scenario has already been acquired. Building situational awareness requires sensing the operational environment or obtaining such information from other collaborating agents. Sensing may be active (probing) or passive. One may obtain information about the instantaneous state of radar spectrum and targets as well as learn their long-term behavior patterns and dynamics.

Situational awareness can be presented in many different ways. It may be in the form of:

- Instantaneous channel state information (channel impulse or frequency responses);
- Modes (e.g., singular vectors and singular values), rank and statistics of channel matrices;
- Interference awareness as a function of time, interferences between each transmitter-receiver pair, Signal to Interference and Noise Ratios (SINR), Received Signal Strength (RSS) values;
- Spatial locations and employed frequencies of transmitters and receivers;
- Spectrum cartography and radio environment maps; and
- Prior and posterior probability models for spectrum and target related parameters, and state space models capturing the dynamic behavior.

Furthermore, situational awareness may contain information about presence of other signals (jamming, interference, other friendly radars), target scenario, target RCS, local geography (terrain map, elevation, radar horizon), local propagation characteristics, atmospheric conditions. All these features are dynamic in a sense that they vary depending on the location, time and frequency. Reciprocity of the radio spectrum may also be exploited if two-way transmissions take place using the same spectrum resources in quasi-stationary scenarios. Because of the dynamic nature of radar operational environments, it is important to understand the coherence times, coherence bandwidths and coherence distances in the radio spectrum. These quantities describe how rapidly the state of the radar spectrum changes and how long feedback and estimated quantities remain sufficiently accurate to be used for adaptation at the transmitter and receivers. Similarly, target RCS looks very different depending on the illumination and observation angles and whether monostatic or multistatic radar is used.

Situational awareness may be learned using statistical methods or machine learning. In statistical approach either deterministic or stochastic models can be employed. The awareness is then expressed in terms of probability models and their parameters, confidences and how they evolve over time. In Bayesian approach the prior knowledge on the radar spectrum, channels and targets, for example, is expressed in terms of *a priori* distributions. The acquired observations, feedback and information from other sensors or nodes in the system are then used to update the prior information using Bayesian methods. Update quantities include the parameters of the probability models and associated uncertainty. Consequently, the situational awareness will be updated and learned. Sometimes it may be difficult to define a compact rigorous model for the awareness or express it using a well-known probability model. In such cases, machine learning provides powerful tools. The learning may be supervised which requires collecting large number of training data followed by a tedious training stage where correct labels are given to all data instances. The training data should exhibit all the variations that are present in the actual data in the operational stage. Moreover, one needs to ensure that the machine learning system is able to generalize, for example, through cross-validation. A widely used example of supervised learning is radar target recognition using deep learning and High Resolution Range Profiles (HRRP), see Figure 4-15. In unsupervised learning, learning and choosing optimal actions takes place through trial and error, by balancing exploration and exploitation stages.

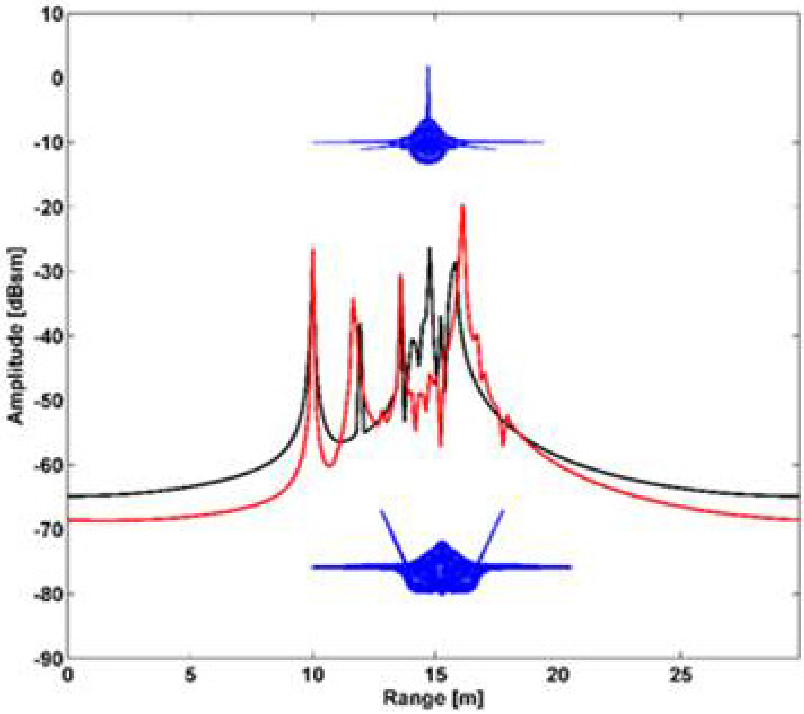


Figure 4-15: Machine Learning Based Target Recognition Using Supervised Deep Learning Network, High Resolution Range Profiles (HRRP) and a MIMO Radar Configuration to Acquire HRRPs.

Feedback from other collaborating agents is extremely valuable in the process of building awareness. If the transmitter and receiver are co-located, the use of feedback from the receiver is straightforward. In a distributed or multistatic radar system, other cooperating receivers may possess information, for example, about the channels and target responses or RCS characteristics, information about the quality of the radar channel in different time, frequency and location, level of interference and jamming they are experiencing, which signals are friendly and adversary, and their own use or resources. In order to provide feedback, collaborating agents have to be networked and often time-synchronized so that the sharing of information may take place. They can directly exchange information, or the information may be sent to a fusion center that processes, combines and analyzes information and shares it among all the agents in the system. There needs to be a low latency and secure way of providing feedback. Low latency is necessary in order to ensure that the feedback is up to date. Security and LPI communication are needed to ensure that the system and the information content are not exposed to adversary signal intelligence. Both protocol and waveform design are needed for the feedback system.

Spectrum Cartography (SC) is a particularly attractive way of presenting awareness. In order to characterize the state of the spectrum in a broader geographical area, cooperative sensing using multiple spatially distributed sensors could be employed. Especially, in highly dynamic, densely used, hostile or contested radio environments distributed sensing the state of the spectrum is necessary. The goal of spectrum Cartography is to create a Radio Environment Map (REM) which describes the state of spectrum at any desired location, time instance and frequency band. This yields a total of five dimensions but depending on the use case of a map and clarity of the presentation, one typically visualizes only two or three of them. Actual measurements are obtained only in distinct sensor locations, but SC interpolates, estimates or predicts the state of the spectrum in between the sensing points. Most commonly a 2D or 3D map presents the RF power levels as a field at one frequency band over a geographical area assuming the spectrum state is quasi-stationary over time, i.e., stationary over the observation period. Alternatively, multiple frequencies can be presented as one additional dimension of the map. Another important design choice is the selection of resolution of the map. A continuous field may be made discrete and quantized in different dimensions. The impact of sampling time is especially critical and depends on the dynamic nature of the operational environment (velocity of the targets, channel coherence time, frequency selectivity of the channel). In cognitive radar systems, the spectrum maps may be utilized, for example, in optimizing the use of Degrees of Freedom for the radar task at hand, resource allocation, avoiding unintentional and intentional interference, and mission planning. For example, one could plan a path for a platform to a desired destination such that there is minimal exposure to adversary radars. The REM is the considered as a virtual potential field where the destination is an attractive forces and adversary radars are repulsive forces and the field varies obeying commonly used propagation models.

For a multifunction radar, situational awareness can provide reasoning to switch and allocate or share resources among different tasks. The situational awareness is built based on continuously sensing the operational environment and learning from these returns. It is also acquired based on other types of sensors, as well as past data and experiences stored in a memory. The radar spectrum and hence the associated awareness depend on the time, frequency band, location and target scenario. Hence the radar environment needs to be sensed in a distributed manner, over different frequency bands and at sufficient rate to capture the dynamic behavior. In a combat situation, situational awareness is extremely important. Based on the situational awareness the radar is capable of maintaining a mission specific quality of service, for example a desired detection probability in a surveillance volume or accuracy in target tracking. This enables the radar to optimize the necessary parameters for each individual radar task. Such optimization pertains to the so-called effective resource management, which aims to optimize the resource allocation in a more general manner, based on the mission rather than the task at hand. This is a form of high-level cognition.

4.9.3 Transmitter and Receiver Adaptation Using Situational Awareness

Knowledge of the scattering coefficients and the radar channel may be utilized in optimizing waveforms, power allocation, as well as selection of subset of active transmitters and receivers, for example. Estimating the scattering coefficients essentially means estimating the instantaneous channel matrix of the radar system after compensating for the transmit power and the propagation losses. Naturally, the estimation performance is limited by the signal power, interference plus noise power at the receiver and the number of observations the radar system has acquired. If the radar operates in a highly dynamic environment, the channel may vary very rapidly as a function of time, location and frequency and the estimates may become outdated in a short period of time. This topic is addressed in more detail in the context of waveform design and optimization.

Similarly, Reinforcement Learning, may be used to model the operational environment and to take advantage of the situational awareness. The system models the states of the environment and participating agents. In such an approach one defines a reward function and the participating agents choose their actions in order to maximize it over time. The agents are able to observe the state of their environment, i.e., have access to situational awareness. The reward could be associated with high performance in a radar task, for example, target detection while operating in a hostile environment where jamming and other sources of intentional and unintentional interference is present. The state of the environment would then be associated with interference awareness. The reinforcement learning system would learn how to avoid interfering signals while maximizing its rewards since detection performance that is used as a reward depends heavily on the SINR values. Reinforcement learning is comprised of exploration and exploitation stages. Exploitation stage takes advantage of current knowledge or awareness in maximizing the rewards whereas exploration stage takes a look in unexplored resources (unknown territory) to find out if higher rewards would be available. Unexplored resources could mean, for example, employing other subbands in frequency, using different antenna array beampattern, or different radar code. Reinforcement methods need to find a balance between these two stages. For example, in the middle of exploitation, the method could randomly start an exploration stage with a small probability, for example $p = 0.05$. Reinforcement learning methods are often based on MultiArm Bandit (MAB) problem formulation and Partially Observable Markov Decision Processes (POMDP).

Chapter 5 – PERFORMANCE ANALYSIS AND VERIFICATION

In this chapter, the Cognitive Detection, Identification, and Ranging (CODIR) testbed is introduced. Its development and capabilities are presented, and some recent results from outdoor experimentation are reviewed.

5.1 THE COGNITIVE RADAR TESTBED CODIR

The Cognitive Detection, Identification and Ranging (CODIR) testbed consists of a waveform agile X-Band radar sensor and a controller with an implemented perception-action cycle. The sensor perceives the environment using the radar parameter settings defined by the controller. It includes the radar frontend, the sensor backend with waveform generator and A/D convertor and a real-time signal processor with an optional display. The controller segment tracks the target and selects the optimal radar settings at each new track update. It includes the Kalman filter tracker and the optimizer. A functional block diagram is provided in Figure 5-1. The black arrows show the data flow and represent the scheduling of the cognitive feedback loop.

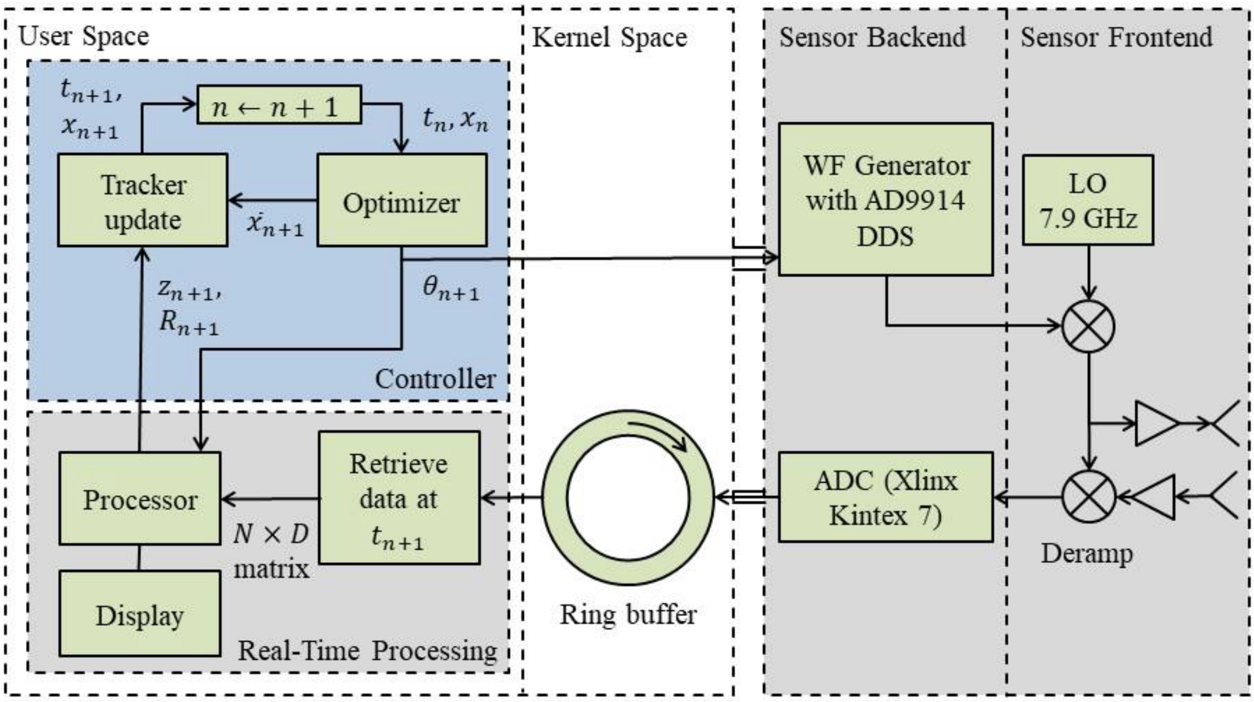


Figure 5-1: CODIR System Functional Block Diagram. The system consists of the sensor and controller segment (colored in blue). The sensor is comprised of signal generator, HF frontend, AD conversion and data processor while controller (colored in blue) is comprised of the optimizer and the tracker. The black arrows represent the data flow and the scheduling of the cognitive feedback loop.

The development of the two segments has been done in parallel. The sensor has been designed and tested with fixed radar parameters and the adaptation capability has been tested with parameter sets that could be changed with an external trigger [143]. The development of the controller has been supported with a sensor simulator which has been adapted to the sensor characteristics [144] and with recorded sensor data with fixed radar parameters and a reproducible test setup [143], [145]. For the last development stage, the two segments have been integrated to synchronize the cognitive feedback loop with the continuously running transmit/receive loop of the sensor.

The CODIR system is similar in many respects to the Cognitive Radar Engineering Workspace (CREW) developed at the Ohio State University [146]. Both sensors have the key capability to adapt transmit and processing parameters such as Pulse Repetition Frequency (PRF) or number of pulses per Coherent Processing Interval (CPI) in real-time on the fly, based on the current radar returns. The two systems are complementary in the sense that the targeted scenario of CODIR aims at outdoor small target detection at X-Band, while CREW aims at indoor detection/tracking/classification at W-Band.

5.1.1 CODIR Sensor

The heart of the CODIR sensor is the waveform generator module which consists of an AD9914 Direct Digital Synthesis (DDS) evaluation board generating Linear Frequency Modulation (LFM) pulses, a small FPGA that triggers the DDS with a given Pulse Repetition Frequency (PRF) and a Raspberry Pi that controls and adapts both components. This module is controlled via an Ethernet network interface is able to adapt the chirp bandwidth B, chirp length T_p and the PRF of the transmitted waveform on the fly within microseconds. The signal is up-converted to X-Band, amplified and transmitted.

On the receiver side, the target signal is first mixed with the outgoing transmit signal in order to deramp the signal and convert it to the Intermediate Frequency (IF) band. The Analogue-to-Digital (A/D) conversion is done with a Xlinx Kintex7 FPGA and the digitized signal is finally stored on a ring buffer storage on a RAM disk, where the raw data is passed to the processor for further processing.

The signal processing chain starts with a Moving Target Indication (MTI) filtering step. Then, the target range and velocity is estimated with a FFT based Range-Doppler (RD) processing with a CPI length defined by the controller. Finally, a detector searches for the maximum amplitude in the RD map and the corresponding range and velocity measurement is passed on to the tracker. Optionally, a monopulse Direction of Arrival (DoA) estimation can be performed by comparing amplitude and phase of the data of two out of the four receive channels. A real-time display with RD map, current measurement and track update and with the current radar parameter settings are available.

5.1.2 CODIR Controller

The controller segment is responsible for tracking a single target and for selecting the optimal radar parameter at each track update. The development of the CODIR controller follows the framework described by Bell et al. [62], where a mathematical framework to implement a perception-action cycle for single target tracking is presented.

A standard Kalman filter with a constant acceleration tracking model is used. If the sensor provides a DoA estimation, an Extended Kalman Filter (EKF) is used and tracking in done in Cartesian space. The track update loop starts at the optimizer with the estimation of the new update time t_{n+1}, the a priori state $\bar{x}_{n+1}$ and the new optimized radar parameter set θ_{n+1} which is sent to the sensor waveform generator to trigger the change in radar parameters (see Figure 5-1). With the a priori state $\bar{x}_{n+1}$ and the measurement update (z_{n+1}, R_{n+1}) from the processor the a posteriori state estimation x_{n+1} is finally calculated by the tracker.

The optimization scheme is based on the cognitive radar optimization framework developed in Bell et al., 2015 [64] and on its adaptation to the CODIR testbed described by Oechslin [143]. The optimization is done at every track update and consists of the evaluation of the predicted track accuracy and the estimated measurement and quality cost for each possible radar parameter set θ in consideration. The minimization of the cost function leads to an optimized radar parameter set θ_{opt} that is passed to the sensor. In the case of CODIR, a radar parameter set is a 4D vector (B, T, D, N), where T = 1/PRF is the pulse repetition interval, N is the number of samples per pulse and D is the number of coherent pulses to be integrated. For simplicity, discrete radar parameter values have been adopted. Typically, the list of allowed radar parameter sets contains 100 – 200 items.

5.1.3 Choice of Cost Function

The choice of cost function and optimization objectives is crucial and determines the optimization outcome. In a single tracking scenario, several, often conflicting, objectives such as tracking accuracy, minimal time effort, minimal energy consumption or minimal spectral footprint are of interest.

During the development of CODIR several cost function formulations have been tried. Phenomenological approaches which were tailored to the sensor capabilities and limitations are tried first. In order to both minimize sensor resources and to assure a given track accuracy, the cost function has been modelled as a sum of sensor resources and accuracy costs. For example, for the sensor cost $S(\theta) = B$ (to minimize bandwidth usage) or $S(\theta) = D * T$ (to minimize time effort) has been adopted. The accuracy cost has been modelled as a penalty term which zero for all radar parameter sets θ with a predicted track uncertainty within a given accuracy threshold [143], [145]. Recently, a generalized cost function is implemented that is modelled as a weighted sum of single objective costs [147]:

$$C(\theta) = \sum_i w_i C_i(\theta) = \sum_i w_i \frac{X_i(\theta) - X_{i,0}}{X_{i,1} - X_{i,0}}. \tag{5-1}$$

Such an approach to Multiple Objective Optimization (MOO) with a linear combination of single objectives has been first considered in Ref. [71] in the context of cognitive radar optimization. In Eq. (1), $\mathrm{X_i} = (\mathrm{B, T, D, N}, \alpha_\mathrm{R}, \alpha_\mathrm{v})$ is the single objectives vector consisting of the adaptable radar parameter and track uncertainties in range and velocity direction, respectively. $\mathrm{X_{i,0}}$ is the corresponding single objective goal vector and $\mathrm{X_{i,1}}$ is the corresponding least favourable values. The normalization of the single objective cost to the unit interval [0, 1] enables a comparison between different single objective costs. The choice of the normalized weight vectors $\mathrm{w_i} = (\mathrm{w_{B,} w_T, w_D, w_N, w_R, w_v})$ enables us to define top level objectives by tuning the relative importance of the single objectives. For example, $\mathrm{w_i} = (1, 0, 0, 0, 0, 0, 0)$ corresponds to minimizing the bandwidth usage (spectral footprint minimization) while $\mathrm{w_i} = (0, 0, 0, 0, 0, 0.5, 0.5)$ corresponds to minimizing the track uncertainty in both range and velocity. This flexibility in weighting the single costs can be used to optimize multiple objectives simultaneously. For example, with $\mathrm{w_i} = (0.5, 0, 0, 0, 0, 0.25, 0.25)$, we minimize the spectral footprint while optimize the track accuracy with equal prioritization.

5.2 SUMMARY OF RECENT RESULTS

5.2.1 Generic Scenario with Clutter

In Oechslin et al., 2016 [143], we considered a simple test scenario with a single target (motor car) in an outdoor range without moving clutter. Tests with two optimization goals, time effort minimization and bandwidth minimization, have been performed. The controller was able to tune the sensor to different conditions in the scene and to different goals. At good detection conditions, the controller saved sensor resources by minimizing the time effort (in case of time effort optimization, see Figure 5-2) or the chirp bandwidth (in case of bandwidth usage optimization) of the transmit waveform. At difficult detection conditions (large target ranges, small SNR, moving clutter, small target velocity) the controller allocated more radar resources to the sensor in term of time effort or bandwidth in order to fulfil the track accuracy goal. Therefore, the controller only allocated the resources the sensor needed to do its task and released unused resources. If the time effort for measurement was smaller than the minimal tracker update time, this spare time could be used for other measurement task such as a micro-Doppler or a high range-resolution profile measurement for classification purposes. On the other hand, if the optimized bandwidth is smaller than the maximal allowed bandwidth, the unused spectrum could be used by another participant in this spectral band.

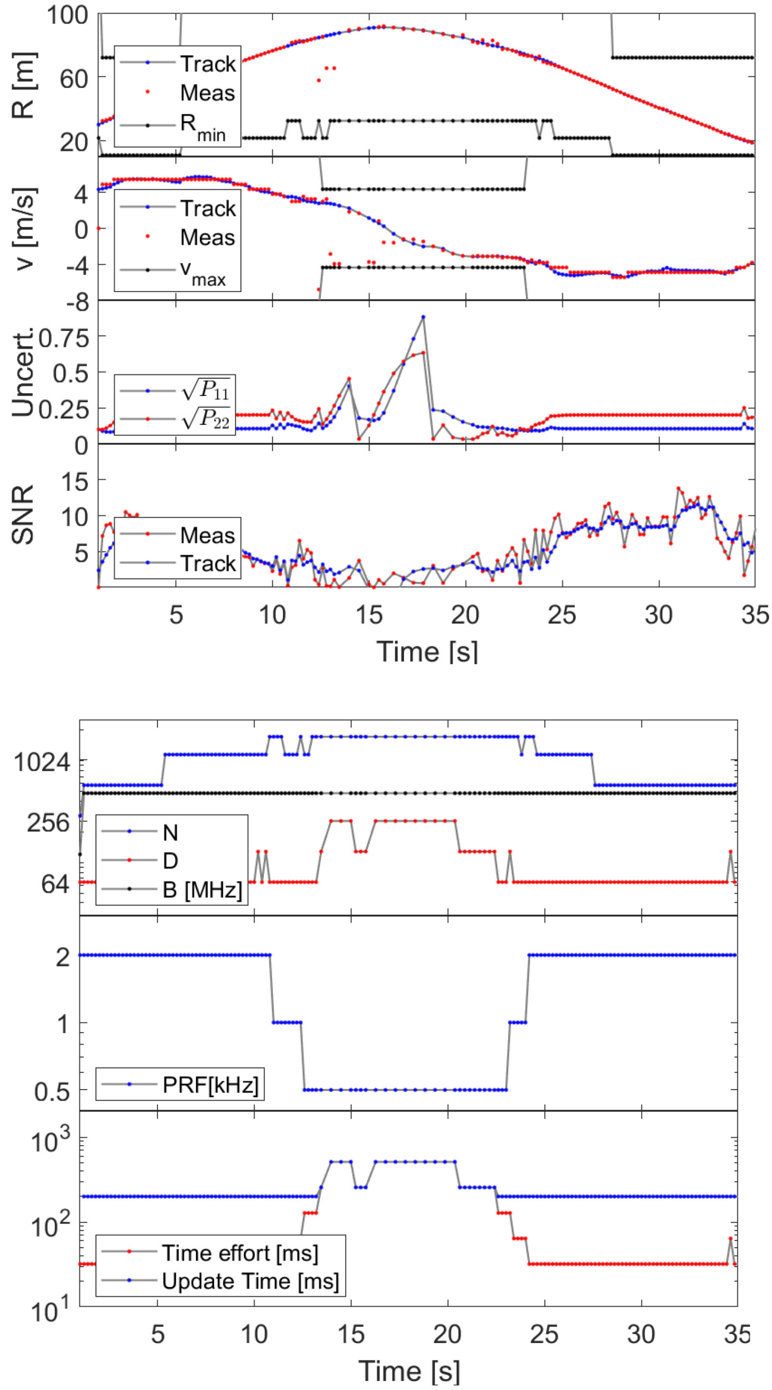


Figure 5-2: CODIR Controller Optimization with Time Effort Minimization. The following quantities (top left to bottom right) are described:

- **Range and velocity evolution (red: measurements, blue: track, black: range limits).**
- **Track uncertainty given by the a posteriori tack covariance matrix P.**
- **SNR (red: measurement from RD map, blue: track).**
- **Radar parameter selection (B, N, D and PRF).**
- **Time effort to do measurement (red), tracker update time (blue).**

5.2.2 Moving Clutter Environment

In the same work, we have also considered a scenario with moving clutter that contaminates part the RD plane. Here, a Maximum Posteriori – Penalty Function (MAP-PF, see Ref. [143] where a tracking scheme is applied to guide the track through the moving clutter region). The controller was able to adapt the sensor such that the target could be successfully tracked through the moving clutter region, even though a smaller PRF (i.e., more time effort) is needed.

5.2.3 Spectrally Congested and Jammed Environment

In Oechslin et al., 2018 [145], we considered a more challenging environment, with part of the spectrum is not available to the sensor and with a broad band jamming with different intensity. For this, the list of waveforms has been enlarged with a set of gapped LFM waveforms to avoid the spectral band not available to the sensor. The noise level with each waveform and jamming intensity were recorded prior to the measurement and fed back to the controller to favour waveforms with sufficient SINR for the required detection and tracking capability. With this input, the controller was able to adapt the sensor to different target conditions and to different jamming environments. While the standard LFM waveforms are preferred in the no-jamming environment, gapped waveforms were selected by the controller in jammed environments.

5.2.4 Generalized Cost Function

In Oechslin et al., 2019 [147], the generalized cost function formulation has been adopted to explore the dependency of the system performance on the chosen objective, cost function and target dynamics. The system performance in term of track accuracy has been analysed by comparing the radar tracks to DGPS ground truth data. The system was able to adapt its radar parameter in real-time to meet one or a combination of objectives. In the case of optimizing multiple conflicting objectives the relative prioritization could be adjusted and the system adapted its radar parameters accordingly.

5.3 EXPERIMENTAL DEMO OF COGNITIVE SPECTRAL SENSING AND TRANSMIT NOTCHING

Spectrum sensing and transmit notching is a form of cognitive radar that seeks to reduce the mutual interference between a radar and other spectrum users in the same band. This concept was experimentally examined for the case in which other spectrum user(s) move in frequency during the radar's Coherent Processing Interval (CPI) [148]. The structure of the physical radar emission was based on a Recent Frequency Modulated (FM) noise waveform [149], [150], that is robust to the degradation of sidelobes that otherwise arise when transmit spectral notching is introduced [151].

Due to the increasing likelihood of spectrum sharing with 4G and 5G communications, the Radio Frequency Interference (RFI) considered took the form of in-band Orthogonal Frequency Division Multiplexed (OFDM) signals that frequency hops around the band. The interference was measured each Pulse Repetition Interval (PRI) and a recently developed Fast Spectrum Sensing (FSS) algorithm [152] was applied to determine where notches are required, thus facilitating a rapid response to dynamic interference environments.

To demonstrate practical feasibility and to understand the performance trade-space, free-space experimental measurements based on the resulting notched radar waveforms were collected and then synthetically combined with the separately measured hopping interference. A variety of conditions were examined, including the impact of hopping RFI during the radar CPI, the effect of latency in the spectrum sensing/waveform design process, notch tapering to reduce range sidelobes, notch width modulation arising from variations in spectrum sensing, and the impact of digital up-sampling on notch depth (details are provided in Ref. [148]).

5.3.1 Spectrally Notched FM Noise Waveforms

This cognitive radar framework takes advantage of a recently developed FM noise radar waveform denoted as Pseudo-Random Optimized (PRO) FM [149], [150]. These waveforms are unique and change on a pulse-to-pulse basis, with each individual waveform possessing relatively low range sidelobes by realizing an approximate Gaussian shape for its power spectrum [153] (though the spectrum shape is arbitrary in general). In this context the utility of these waveforms arises from 1) being FM, so that they are readily amenable to the rigors of the radar High-Power Amplifier (HPA), and 2) when combined in Doppler processing after pulse compression, where their unique range sidelobe structures combine incoherently to achieve further sidelobe suppression. Due to a spectral shaping construction, this type of waveform has been shown to readily permit the inclusion of spectral notches [154], [155].

Consider the design of a pulsed FM waveform with duration T and 3-dB bandwidth B for which relatively low autocorrelation sidelobes is desired. The FM structure provides a constant amplitude envelope and relatively good spectral containment (compared to phase codes [156]). The mth pulsed waveform is initialized with a random instantiation of a Polyphase-Coded FM (PCFM) waveform [157], denoted as $s_{0,m}(t)$. To enable optimization, the length-N discretized version $s_{0,m}$ is used, which is "over-sampled" with respect to 3-dB bandwidth to provide adequate fidelity (i.e., minimal aliasing) by including a sufficient portion of the spectral roll-off region.

This discretized waveform undergoes K iterations of the alternating projections

$$\boldsymbol{r}_{k+1,m} = \mathbb{F}^{-1}\{\boldsymbol{g} \odot exp(j\angle\mathbb{F}\{\boldsymbol{s}_{k,m}\})\}. \tag{5-2}$$

$$\boldsymbol{s}_{k+1,m} = \boldsymbol{u} \odot exp(j\angle\boldsymbol{r}_{k+1,m}) \tag{5-3}$$

where $\mathbb{F}$ and $\mathbb{F}^{-1}$ are the Fourier and inverse Fourier transforms, respectively, $\angle(\bullet)$ extracts the phase of the argument, and ʘ is the Hadamard product. The length-N vector **g** is likewise a discretization of the desired spectrum $|G(f)|$, while the length-N vector **u** is a discretization of the rectangular window $u(t)$ that has the same duration T as the pulse. Per Ref. [148], based on the observed in-band RFI, notches can be placed in the desired spectrum of each waveform via direct manipulation of $|G(f)|$ and/or through application of nulling approaches such as Reiterative Uniform Weight Optimization (RUWO) [158]. In fact, the very recent development of the Analytical Spectral Notching (ASpeN) approach has been used to experimentally demonstrate notches achieving a depth of -57 dB relative to the spectrum peak [159].

5.3.2 Assessment of Spectrally Notched FM Noise Waveforms

While notching a radar's transmit spectrum to mitigate mutual interference between the radar and other in-band users is certainly theoretically possible, it is necessary to consider the practical feasibility and corresponding performance trade-space. For example, it was shown in Ref. [155] that enforcement of a sharp-edged spectral notch realizes a sin(x)/x roll-off in autocorrelation sidelobes, which tends to be undesirable (see the "Notch w/o Taper" case in Figure 5-3). However, the inclusion of an appropriate taper at the notch edges can greatly alleviate this spreading sidelobe effect.

Another factor that significantly impacts notching performance arises when the RFI moves within the radar band during the CPI. Notwithstanding the degradation that can occur when the spectrum sensing and waveform notching procedure have too high a latency to "keep up" with such changes in the RFI spectral locations (see Ref. [148]), the moving notch locations themselves introduce a nonstationary effect that can degrade clutter cancellation on receive. For example, compared to the "thumbtack" delay-Doppler point spread function that is observed for random FM waveforms when no spectral notching is performed, Figure 5-4 illustrates the spreading that occurs for two different cases. Clearly the spreading gets worse as the rate of notch movement increases (assuming it can precisely keep up with the spectrally hopping RFI).

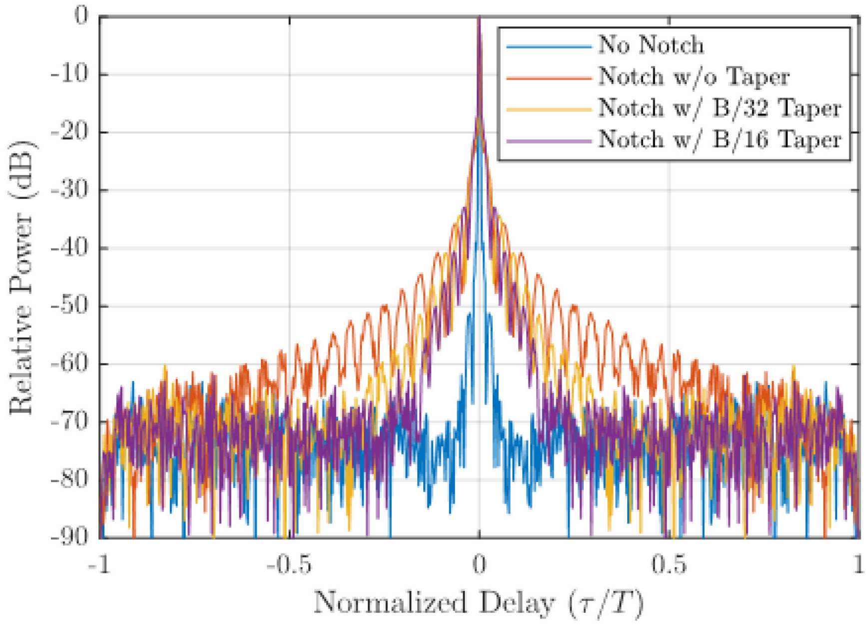


Figure 5-3: Measured Aggregate Autocorrelation (for 2500 Unique FM Noise Waveforms) Comparing Spectral Notch Tapering to the Case Without Tapering and the Absence of a Notch [148].

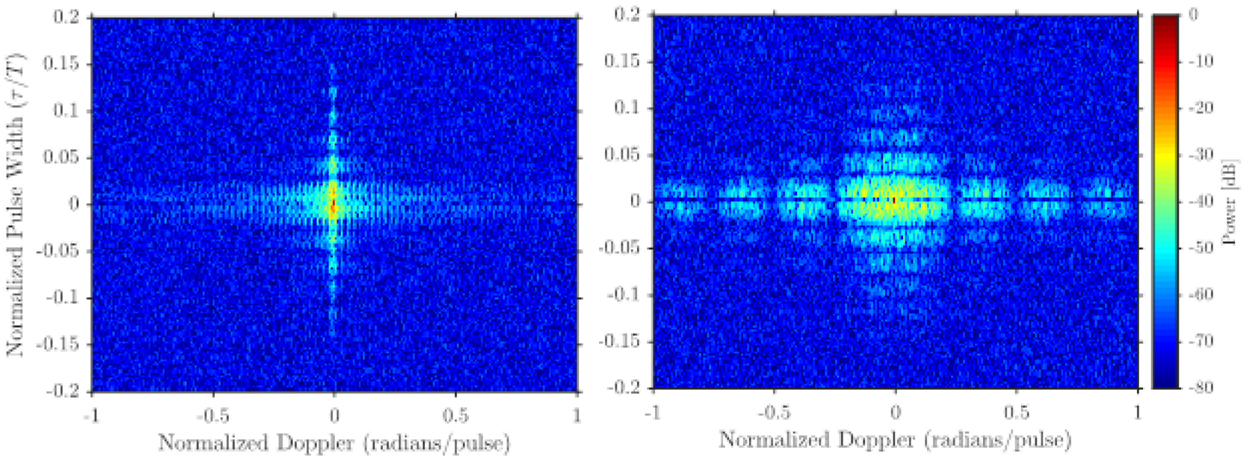


Figure 5-4: Delay-Doppler Point Spread Function When a 10% Bandwidth Spectral Notch Randomly Moves 10 Times (Left) or 100 Times (Right) During a 100 ms CPI [148].

5.3.3 Free-Space Experimental Evaluation of Spectrally Notched FM Noise Waveforms

An experiment was performed in which OFDM-based RFI was generated, measured, and then used to drive subsequent spectrum sensing and notched waveform generation. The resulting waveforms were then transmitted via open-air from a rooftop on the University of Kansas campus to illuminate a nearby traffic intersection in Lawrence, KS to evaluate Moving Target Indication (MTI) performance. In this manner the measured RFI could be combined synthetically with the measured radar responses to assess the impact with and without spectral notching of waveforms separate from RFI suppression capability.

Figure 5-5 shows the measured results after performing pulse compression, Doppler processing, and clutter cancellation, where the latter involves a simple projection (due to the stationary platform) and the full-band and (stationary) notched waveforms were interleaved to permit direct comparison of the results. While each waveform's spectral notch does employ tapering, there is still some broadening in range that can be observed in the right panel relative to the full-band result in the left panel. Of course, the synthetic injection of RFI at -20 dB Signal-to-Interference Ratio (SIR), as illustrated in Figure 5-6, reveals that spectral notching does provide a significant benefit when performing matched filtering in the radar receiver (in addition to reducing the interference caused to other spectrum users). It should be noted that RFI in this case had rather poor spectral containment, which is the reason why residual interference is still observed despite notching.

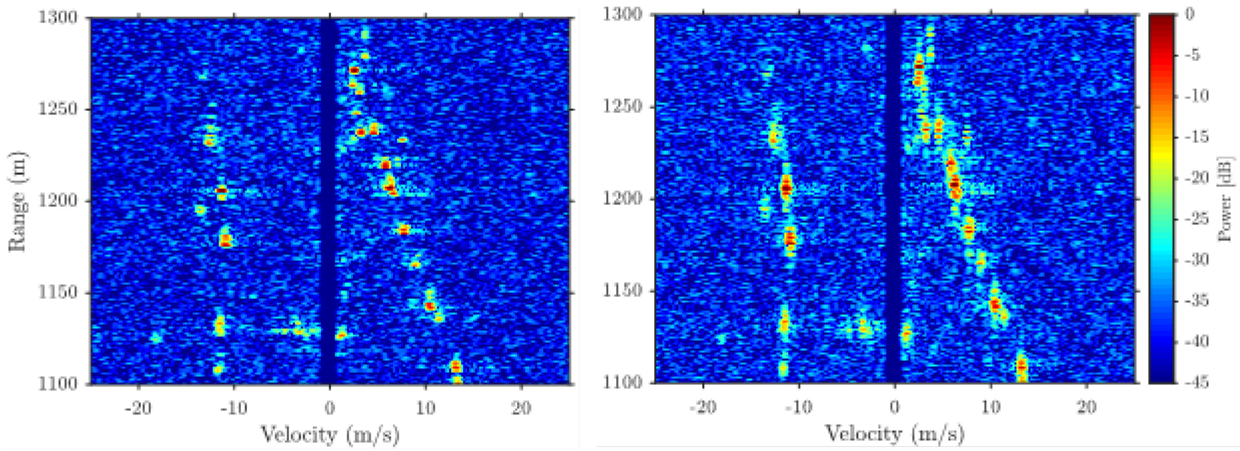


Figure 5-5: Free-Space Range-Doppler Response Without RFI for Full-Band Random FM-Waveforms (Left) and Stationary Notched Random FM Waveforms (Right) [148].

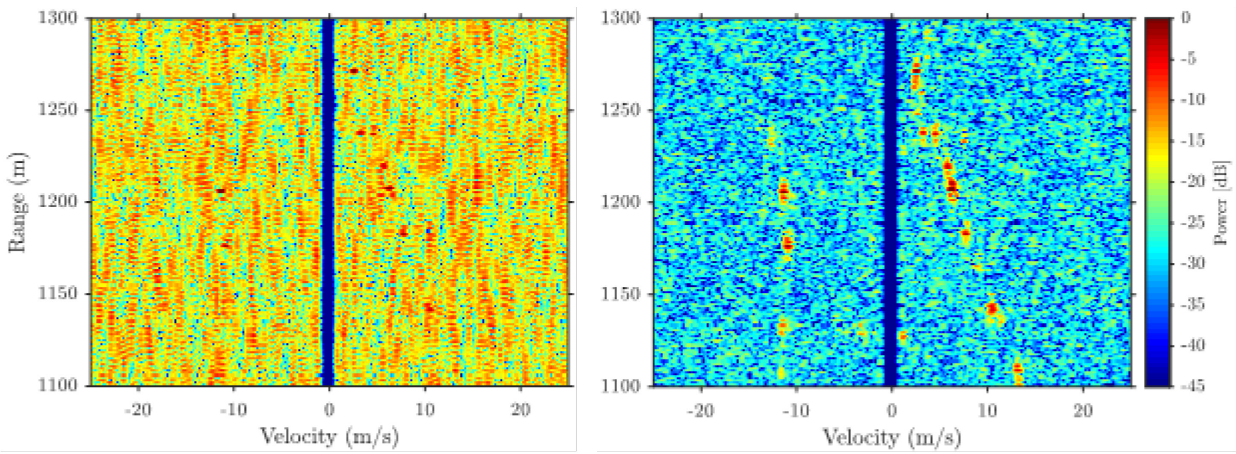


Figure 5-6: Free-Space Range-Doppler Response with Injected RFI (at -20 dB SIR) for Full-Band Random FM Waveforms (Left) and Stationary Notched Random FM Waveforms (Right) [148].

Finally, it is rather interesting to consider the impact that moving notches during the CPI, in response to spectrally hopping RFI, has on radar clutter cancellation. Figure 5-7 illustrates this case when no RFI is present and when synthetic RFI has been injected. The left (no RFI) clearly shows that standard clutter cancellation is insufficient to address this nonstationary effect, resulting in residual clutter that is smeared across Doppler. It is been very recently determined that this result is a combination of:

1) The Range Sidelobe Modulation (RSM) that arises whenever non-repeating waveforms are employed; [160] and
2) A modulation of the pulse compression mainlobe due to the changing notches [161], with new techniques being developed that in preliminary trials are showing good effectiveness at compensating for this source of degradation.

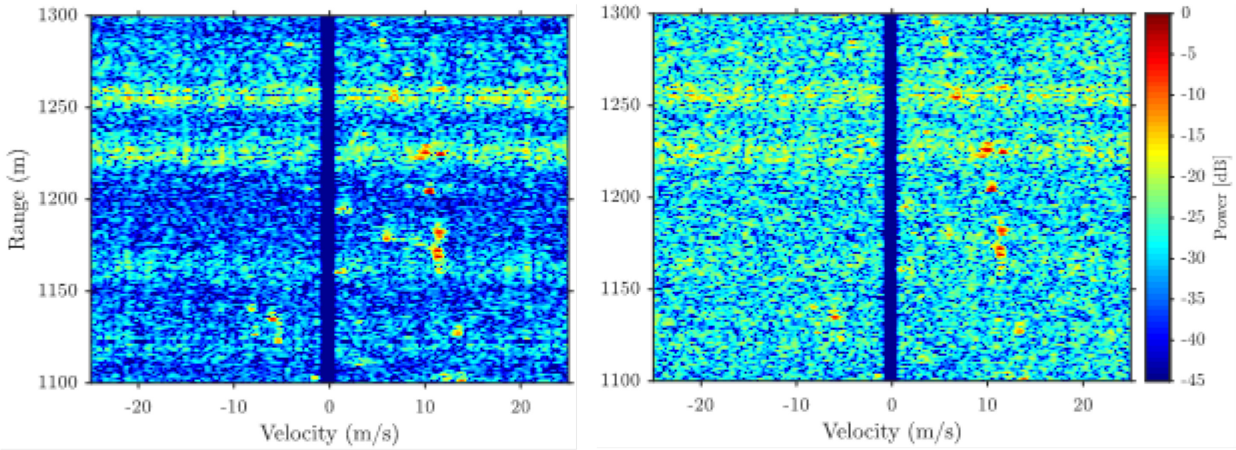


Figure 5-7: Free-Space Range-Doppler Response for Hopping Spectral Notches Without RFI (Left) and with Injected RFI at -20 dB SIR (Right) [148].

Chapter 6 – APPLICATIONS

6.1 OVERVIEW

Over the past 15 years, research into cognitive radar system design has covered a wide range of applications, using many different techniques that draw on prior advancements in Bayesian decision theory, information theory, decision theoretic approaches (including fuzzy logic, rule-based systems, metaheuristic algorithms, and Markov decision processes), dynamic programming, optimization (including maximization of Signal-to-Noise Ratio (SNR), convex optimization, and use of the Cramer Rao Lower Bound (CRLB), among others), and game theory. Thanks for the steady increase in conference and journal special sessions as well as conferences focusing on cognitive sensing, there has been a dramatic increase in publications over the last few years, as shown in Figure 6-1. These papers (83 journal papers and 238 conference papers) were identified based on a keyword search over "cognitive radar" and "fully adaptive radar" in the IEEExplore and SPIE Digital Libraries.

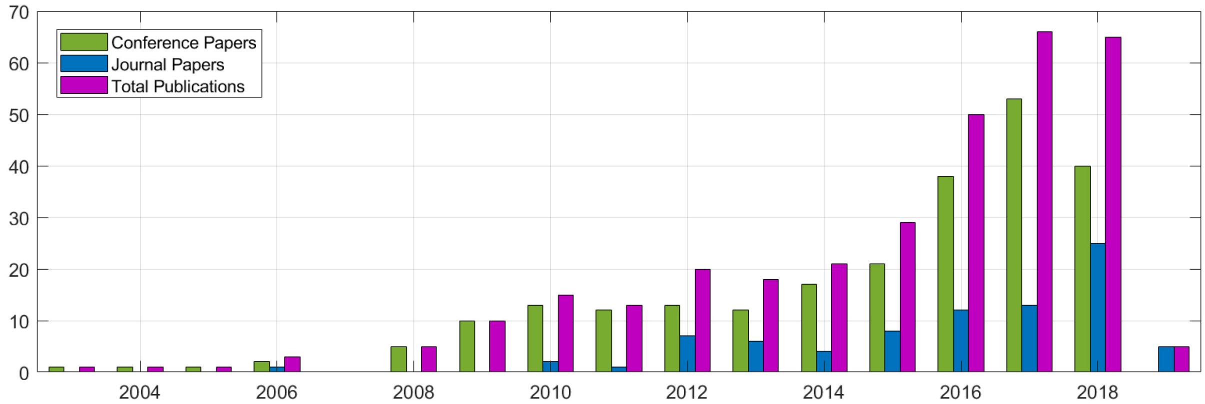


Figure 6-1: Publications on Cognitive Radar (2003 – March 2019).

A sense of the focus of these research efforts can be gained through examination of these works in terms of the techniques exploited and applications targeted. The results of this survey are provided in Figure 6-2 as a histogram of applications and techniques. This histogram reveals that while a wide range of applications are being investigated, research has focused on just several applications; namely, conceptual studies investigating Architectures and Mechanisms for Cognitive Processes in Engineering Systems (ARCH), Radar Resource Management (RMG), Target Detection (DET), Localization/Direction-Of-Arrival Estimation (LOC) and Tracking (TRK), Radar Networks (RN), and Spectrum Sharing (SS). Most works involve some form of Waveform Selection, Optimization and Design (WD), while Adaptive Control of Antenna Beam Pattern and Design of Adaptive RF Components (ADPTHARD) as well as Experimental Testing of Cognitive Systems (EXP) have also been explored.

Spectrum sharing has been a topic of focus due to the urgent challenges presented by a congested RF spectrum to military and civilian systems alike. The availability of frequency spectrum for multi-function radar systems has been severely compromised and the available frequency bands are continuously diminished. The growth of activities in the area of civil communications, the emergence of new technologies and new services that involve a strong demand for spectrum allocation induce a very strong pressure upon the frequency channels currently allocated to radars. In the VHF (30 – 300 MHz) and UHF (300 – 1000 MHz) bands, where for instance Foliage Penetrating (FOPEN) radars are active, interference can come from broadcast and TV services. Recently, these bands have seen the introduction of the IEEE802.11ah and IEEE802.11af protocols for Internet of Things (IoT) and Cognitive Radio Technology, respectively. Recently, in the United States, the National Telecommunications and Information.

Application Codes

ARCH: architecture/general
RMG: resource management
DET: detection
TRK: tracking
EST: estimation
LOC: localization
PASSR: passive radar
RN: radar networks/MIMO
WD: waveform diversity
SAR: SAR imaging
SS: spectrum sharing
CC2: command & control
OTHR: over-the-horizon radar
LPI: low probability intercept
EW: electronic warfare
THR: threat assessment
BF: beamforming
NLR: nonlinear radar
REMS: remote sensing
HLTH: health
TRAN: transportation
TESTM: testing methodology

APPLICATIONS	TECHNIQUES																			
	CONCEPT	KA	BAYES	MARKOV	DYNP	CONVOPT	CS	OOPT	SINRMAX	IT	FUSION	FRFT	MODEUPT	MACHLRN	ITER	ADPTHARD	ANTENCON	GAME	EXP	TOTAL
ARCH	23		2	3	2			1		1				2		3	1		1	39
RMG	2		5	1	2			4					1	2				2	1	20
DET	5	7	6		2	2	2	8	7	4	2	1	1	3	4		1		1	56
TRK	4	1	21	3	3			13	4	4	3		4	3	1	3	2		12	81
EST	1	1	6	1			4	6	1	1				1	4	2				28
LOC	5		4			2	2	7					1		2	4	1		2	30
ATR	1		3	2			1	1	1	2			2	4	1					18
PASSR	5			1				4												10
RN	10	2	10			2	2	11	5	4	2		1	2	2	1	1	2	3	60
SAR	1	1					1	2					1						1	7
SS	6		1	5		1	10	10	7	5	1		2	6	3	7	1		12	76
WD	4	2	12	3	2	6		34	21	15	1	2	2	2	11	2			6	115
CC2	1												2		1				2	6
OTHR	2							1	1		1		2		1					8
LPI													1							1
EW	7					1	1	5	4	2			1	4		1	1	1	1	29
THR														2			1			3
BF			2					3		1			1							7
NLR	1																		1	2
REMS														1		1				2
HLTH			1						1		1									3
TRAN	1		1				1	2	1	1				1						8
TESTM																			1	1
TOTAL	82	14	74	19	9	14	24	112	53	40	11	3	22	32	30	24	9	5	44	

Technique Codes

CONCEPT: concept/general/ad hoc
KA: knowledge-aided
BAYES: Bayesian framework
MARKOV: Markov processes/models
DYNP: dynamic programming
CONVOPT: convex optimization
CS: compressive sensing
SINRMAX: SINR maximization
OOPT: other optimization methods
IT: information theory
FUSION: fusion
FRFT: fractional fourier transform
MODUPDT: model updating
MACHLRN: machine learning
ITER: iteration
ADPTHARD: adaptive hardware
ANTENCON: antenna control
GAME: game theory
EXP: experimental work

Figure 6-2: Techniques/Applications Investigated in Cognitive Radar Publications (2003 – March 2019).

Administration (NTIA) has devoted efforts on identifying frequency bands that could be made available for wireless broadband service provisioning, resulting in allocation of 115 MHz of additional spectrum (1695 – 1710 MHz and 3550 – 3650 MHz bands) and a conflict with L-band (1 – 2 GHz) radars. An example is the air route surveillance radar used by the Federal Aviation Administration (FAA) that shares the spectral band with Wireless Inter-Operability Microwave Access (WiMAX) devices. The majority of the LTE services, e.g., WiMAX LTE, LTE Global System for Mobile (GPS) are operative in the S-band (2 – 4 GHz), where they interfere with surveillance radars. In C-band, the spectrum has been eroded by allocation of the 5 GHz band to 802.11a/ac wireless LAN technology. X-band is still free from communication services interference, but when 5G systems become fully operative, even the Ka, V and W bands will be “dense”.

Thus, in a near future, radars will likely be required to share their bandwidth with communication systems, where the latter ones, quite often, are the primary users. Yet, this problem cannot be addressed only by traditional modes of operation, such as antenna beamforming or interference cancellation on receive. Future systems require the ability to anticipate the behavior of radiators in the operational environment and to adapt the transmission to it in a cognitive fashion based upon the spectrum availability. The radar cognition in this case is based on two main concepts: spectrum sensing and spectrum sharing. Spectrum sensing aims at recognizing frequencies used by other systems occupying the same spectrum in real time, while spectrum sharing tries to limit interference from the radar to other services and vice-versa.

Furthermore, battlespaces of the future will not involve isolated geographical regions with limited technological resources, but will require integration of networked ground-based, airborne, and space-based sensors at different levels, seamlessly integrated and automated to find, identify and track threats in increasingly complex and diverse environments. The challenge of spectrum congestion is but one dimension of this broader battlespace. Technological advancements have not just benefited modern society but have also made it easier for adversaries to make their forces both mobile and elusive, such through use of small drones to attack a diverse set of tactical targets, previously not exposed to any threat. Both force protection and forward operations require pervasive, robust, and agile sensing that can optimize multiple missions in a dynamic environment.

This operational requirement directly maps to the definition of what a cognitive radar strives to accomplish, and indeed, the generalized notion of a cognitive sensor network, empowered with multiple-layers of hierarchical cognitive processing. As the capabilities of radar transceivers advance to jointly sense, learn, and adapt on both transmit and receive, new opportunities and vulnerabilities will become part of the changing dynamics of Electronic Warfare (EW). While boosting sensing capabilities so that friendly systems can defend against jamming and other counter-measures, and leaving adversaries no place left to hide, cognitive radar nonetheless retains the risk that it could be beguiled into poor decisions, much akin to the human counterpart that has inspired its design. Thus, the key will be how to construct such a radar so that it can learn from past mistakes that have occurred as a result of poor decisions, and thereby enable it to gain the ability of making informed decisions in the future.

In the following sub-sections, discussion of the role of cognitive radar in specific application examples is given; namely, spectrum sharing, imaging radar, and jammer deception.

6.2 COGNITIVE RADAR IN SPECTRUM SHARING SCENARIOS

In this sub-section, we will provide an overview of some the cognitive radar technologies which can be utilized to provide efficient spectrum sharing and coexistence among radars and other radio systems. These technologies are in the core of cognitive radars since they require knowledge of the radar channels, interference and jamming awareness as well as adaptation of both transmitters and receivers to achieve desired quality of service for all subsystems while managing the mutual interference. Such situational awareness may be built via sensing, feedback and exchange of information among different radios and subsystems. Consequently, a full Sense-Learn-Adapt cognitive cycle will be employed since sensing of the spectrum, building and learning situational awareness from the observations as well as adapting both the transmitters and receivers is taking place.

6.2.1 Spectrum Sensing

Some of the spectrum sensing techniques proposed for the radar systems, are reminiscent of those already operative in cognitive radio systems. The open literature on spectrum sensing focuses on primary transmitter detection based on the local measurements made by the secondary users, since detecting the primary users that are receiving data is in general very difficult. According to the a priori information they require and the resulting complexity and accuracy, spectrum sensing techniques can be clustered into the following main categories [60]: Energy Detector (ED), Feature Detector (FD), and Matched Filter (MF) detector techniques.

The ED is the most common spectrum sensing detector because of its low computational cost and implementation complexity. In addition, it does not need any a priori knowledge on the signal emitted by the primary users. Detection is performed by comparing the output of the energy detector with a threshold, which depends on the noise floor. Some of the drawbacks of the energy detector are the inability to differentiate interference from primary users and noise, inefficiency for detecting spread spectrum signals, and poor performance in low signal-to-noise ratio situations.

Another type of spectrum sensing detector is the FD. There are specific features associated with the signal transmitted by a primary user. For instance, the statistics of many communication signals show some inherent periodicities such as the modulation rate or the carrier frequency. Such features are usually viewed as cyclostationary features, based on which a detector can distinguish cyclostationary signals from stationary noise. Compared with energy detectors that cannot detect weak signal in noise and are subject to high false alarm rate due to noise uncertainty, cyclostationary detectors are good alternatives because they can differentiate noise from primary user's signal and have better detection robustness in a low-SNR regime. However, the computational complexity and the significant amount of observation time required for adequate detection performance prevent a wide use of this approach.

The last kind of detector is the MF detector. Matched filtering is known as the optimum method for detecting primary users when the transmitted signal is known. The main advantage of matched filtering is the short time to achieve a given probability of false alarm or a given probability of missed detection as compared to the other methods discussed in this section. However, matched filtering requires a perfect knowledge of some primary users signaling features, such as bandwidth, operating frequency, modulation type, pulse shaping, and frame format. Moreover, since cognitive radio needs receivers for all signal types, the implementation complexity of sensing unit is impractically large. If the MF design relies on wrong information, the detection performance will be largely degraded. Advantages and disadvantages of these three classes of spectrum sensing techniques are summarized in Table 6-1.

On the other side, multiple spectrum sharing techniques ad policies have been proposed in literature for guaranteeing radar and communication system coexistence. Some of them are cooperative, and suppose some form of information exchange between radar and communication devices [162], some of them are non-cooperative, then radars do not communicate with the other RF sources and adapt their transmit waveforms in order to avoid interferences. One of this strategy is to add spectral notches to the radar waveform. These spectrally compliant waveforms have the capability to mitigate RFI to other RF emitters and maximize the available bandwidth [152].

Table 6-1: Summary of Main Spectrum Sensing Techniques.

Type	Test Statistics	Advantages	Disadvantages
Energy Detector (ED)	Energy of the received signal.	• Easy to implement. • Does not require prior knowledge about primary signals.	• High false alarm rate due to noise uncertainty. • Very unreliable in low-SNR situations. • Cannot differentiate a primary user from other signal sources.
Feature Detector (FD)	Cyclic spectrum density function of the received signal.	• More robust against noise and better detection in low-SNR than energy detector. • Can distinguish among different types of transmissions and primary systems.	• Specific features must be associated with primary signals. • Higher complexity than energy detector.
Matched Filtering (MF)	Projection of the received signal in the direction of the known primary signal.	• More robust against noise and better detection in low-SNR than feature detector. • Require fewer signal samples to achieve good detection.	• Require prior information about certain waveform patterns of primary signals. • High complexity, mostly unpractical.

6.2.2 Spectrum Sharing

Spectrum sharing has been broadly categorized into three approaches: coexistence, cooperation and co-design [163]. In this report, we denote coexistence as a more general term which covers all different aspects of spectrum sharing (see Figure 6-3). In the simplest form, coexisting systems try to avoid mutual interference by sensing the spectrum and accessing it only if the spectrum is found to be idle or underutilized. No sharing of information or cooperation among subsystems, such as radar and communications systems, is necessarily required and the participating systems are typically distinct and in different locations. Hence, the term non-cooperative spectrum sharing in used in Figure 6-3. Different radio systems are competing for the spectrum resources, while following some kind of etiquette in spectrum access and regulations on the power usage. In some cases, certain radio system may be a primary system with higher priority and the other systems are secondary systems that may access the spectrum only if the primary system is not active or if they do not exceed certain interference level (underlay). As an alternative to these hierarchical systems, all the systems may be equal as in the case of ISM bands. Since no cooperation is taking place, this approach does not necessarily require changes in standardization if subsystems are wireless communications systems.

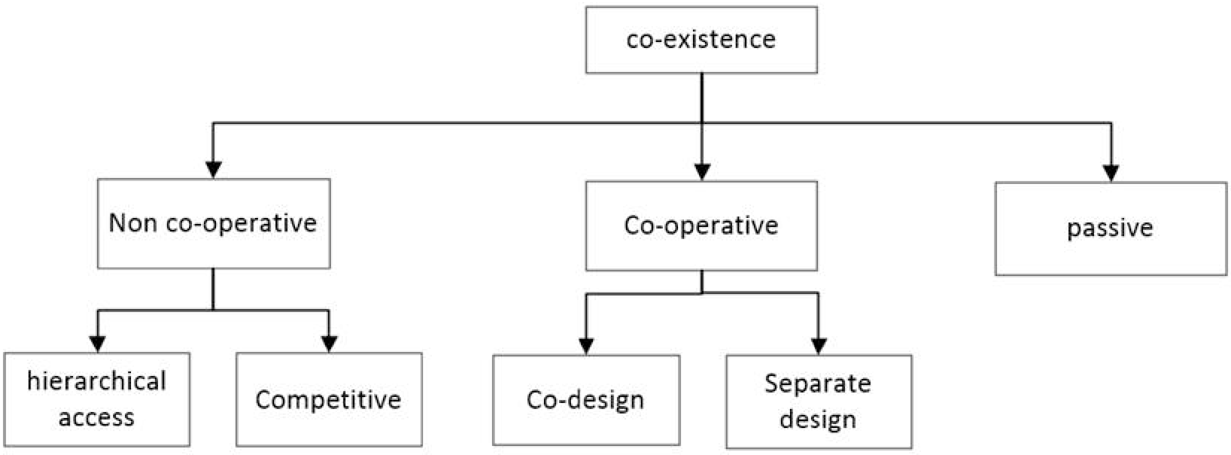


Figure 6-3: General Categorization of Spectrum Sharing System.

In cooperative scenarios different radio system may exchange information about the state of the radio spectrum, channel quality information as well as interference awareness. They may also take advantage of knowledge of the waveforms and pilot signaling used in different subsystem to estimate channels and levels of interference. The reciprocity of the radio channels may be also exploited if the systems use the same frequencies in both directions of a link within a coherence time. The acquired awareness on the state of the spectrum may be used, for example to optimize the waveforms in different subsystems for a specific task or scenario. As an example result, the desired detection performance in the radar subsystems could be achieved while ensuring that the communications users get their required Quality of Service (QoS). In a radar-centric optimization of the waveforms the radar performance is used as an objective function and the constraints ensure sufficient performance for the communications subsystems as well as impose constraints on the use of resources such as power or bandwidth. Alternatively, a communications centric optimization may take place in which the objective could be the sum rate of communication users or some QoS level. Furthermore, a pareto-optimal solution might be of interest where both radar and communication system performance are used in the objective function and increasing the performance of the radar subsystem would deteriorate the performance of communications subsystem and vice-versa. Cooperative systems may operate in distinct locations or they may be co-located. This kind of cooperation usually requires changes in standardization since the formats of information exchanged and protocols for cooperation need to be agreed upon.

Co-designed radar and communications systems would typically be co-located as well. Then sharing the knowledge on channel state and interferences is simple. Moreover, optimizing waveforms, scheduling, resource allocation and synchronization would be easier to achieve. Reduced control information exchange among different subsystems would be required. The waveforms could be designed so that they share the resources (antennas, beams, subbands) or the employed waveforms could be designed so that sensing and communications are embedded in the same waveform. One of the systems can be a primary system whereas the other system is guaranteed some minimum performance level.

The concept of Dual-Function Radar-Communications (DFRC) is an example of an approach which performs the communications as a secondary task in addition to the primary radar operation while sharing the same spectral resources [164]. A secondary communications function may embed information symbols in radar waveforms such that the radar achieves its desired performance. The popular techniques embedding communications into radar signaling include waveform diversity-based methods, sidelobe amplitude modulation method, multi-waveform Amplitude Shift Keying (ASK) method, and Phase Shift Keying (PSK) method. The waveform diversity-based method uses a dictionary of waveforms such that each waveform corresponds to one communication symbol [165]. A multi-waveform ASK-based scheme exploiting sidelobe control and waveform diversity was proposed in Ref. [166] which can transmit different communication symbols to different users during one radar pulse instead of broadcasting to all users.

The last category of coexistence are passive radars that take advantage of broadcast signals such as digital TV signals (DVB-T, DVB-T2), FM radios or Wi-Fi signals as signals of opportunity in performing radar tasks instead of actively transmitting radar waveforms. Similarly, adversary radars could be used as a signal of opportunity.

There are a couple of topics that need to be addressed prior spectrum sharing can alleviate the spectrum congestion. First, the spectrum regulation needs to allow spectrum sharing. Efficient sharing requires learning and understanding how the time-frequency-location varying state of the spectrum evolves (situation awareness), how different subsystems operate, their performance criteria and how they impact each other in terms of interference and use of resources. Then methods, protocols and policies are needed to design the coexistence and cooperation of the subsystems, or co-designing radar and communication systems. Finally, advanced technologies, such as waveform optimization, precoder-decoder designs, subspace projections, beamforming, interference mitigation, resource allocation or task scheduling needs to be deployed. Addressing the topics separately simplifies the discussions, even though they all influence each other.

One major obstacle that has slowed down agile use of spectrum is the current rigid regulation of frequency bands. The spectrum can be used more efficiently by allowing more users to use the spectrum in an agile manner. Other users may have equal rights to use the spectrum or the systems may be hierarchical wit licensed primary users and secondary unlicensed users when accessing underutilized frequency bands. Hence, overall higher data rates, improved QoS or better radar performance may be achieved. This requires better understanding how the different radio systems impact each other if they coexist and share the spectrum.

The awareness of the spectrum state can be exploited to efficiently utilize the scarce resources. This awareness is constructed through sensing followed by estimating, learning the state of the spectrum and having memory that captures information from past experiences. Knowledge of active radio system parameters would be useful, if available. Some radio system, for example, cognitive radio systems, are able to sense and access the identified idle spectrum in a flexible and opportunistic manner. In the special case of radar systems, the spectrum state is more dynamic which makes the spectrum state estimation more challenging.

Finally, all coexistence of different radio systems means also that new advances in technology are needed in order enhance the spectrum usage further. For example, joint system design, optimizing the transmitted waveforms and receiver processing, designing precoders and decoders and interference mitigation have been proposed to maintain or even improve the performance in coexisting system scenarios.

6.2.3 Spectrum State Awareness / Spectrum Maps

Awareness of the state of radio spectrum is a key enabler for efficient and agile spectrum use and coexistence of different radio systems. Acquiring such awareness is a challenging task because the state of the spectrum varies depending on time, frequency and location, [ARF][1]. Prior knowledge of spectrum allocations, different types of potential users and employed waveforms as well as surveillance information may be available. Sensing, which is a crucial component in any cognitive processing, is also necessary in acquiring the spectrum awareness. For example, in order to characterize the state of the spectrum in a broader geographical area, cooperative sensing using multiple spatially distributed sensors could be employed. Especially, in highly dynamic, densely used, hostile or contested radio environments sensing the state of the spectrum is necessary.

A convenient way to represent spectrum awareness is Spectrum Cartography (SC). The goal is to create a Radio Environment Map (REM) which describes the state of spectrum at any desired location, time instance and frequency band. This yields a total of five dimensions but depending on the use case of a map and clarity of the presentation, one typically visualizes only two or three of them. Most commonly a 2D or 3D map presents the RF power levels as a field at one frequency band over a geological area assuming the power is quasi-stationary over time, i.e., stationary over the observation period. Alternatively, multiple frequencies can be presented as one dimension of the map. Another important design choice besides the dimensions is the selection of resolution of the map, i.e., grid size. The impact of sampling time is especially critical and depends on the dynamic nature of the operational environment (velocity of the targets, channel coherence time, frequency selectivity of the channel) and use case of the map. In cognitive radar systems, the spectrum maps may be utilized, for example, in resource allocation (optimization of transmitted waveforms, allocation of power, sensor selection, task scheduling), avoiding unintentional and intentional interference, and mission planning.

There are two fundamentally different approaches to create a spectrum map. The parametric approach is based on knowledge (or estimation) of the system parameters, such as location, power etc., and usage of different parametric models such as propagation models for certain frequency bands and operational environments. An alternative approach, sometimes called non-parametric approach, utilizes measurements from a distributed sensor network to estimate the spectrum state in the other locations (or frequency) in between the measurement points without estimating the system parameters explicitly. This can be done with multiple different spatial interpolation and regression techniques. The proposed methods include Kriging interpolation [167], dictionary learning [168], basis expansion [169], matrix completion [170] and Reproducing Kernel Hilbert Space (RKHS) regression [171]. In practice, a hybrid method of these two seems most promising. Terrain information, including elevation, should be also be taken into account.

Spectrum cartography has been widely exploited in cognitive radios with different techniques, for example packet forwarding, scheduling and interference management. However, there are some significant differences how radars use the spectrum in comparison to communication systems. Radars typically form very narrow beams in order to illuminate targets and significantly higher transmit powers are used as well. Radars may also scan the operational environment using a mechanical rotating antenna which introduces a periodic variation in the state of the spectrum. Alternatively, an electrically steerable antenna system such as Active Electronically Scanned Array (AESA) may be used and the beampatterns exhibit more irregular variations and rapid changes then. Some of the radars may be on a moving platform. Moreover, jamming and clutter can be time-frequency-location varying. Consequently, a spectrum map describing how the state of the spectrum evolves in radar scenarios will be highly dynamic.

To capture the dynamic part of the spectrum state properly the construction of a spectrum map can de-coupled into static and dynamic parts, [172]. The static part of the maps can be estimated similarly as in the case of

[1] Advanced RF Mapping (Radio Map): http://www.darpa.mil/program/advance-rf-mapping.

cognitive radios, for example, with Kriging interpolation method. The dynamic part of a map needs to be separately constructed, for example, by using a parametric approach. The measurements must be preprocessed such that possible strong temporal variations will not impact the modeling of the stationary part. This can be achieved, for example, by using median values instead of mean values in describing the expected value of the field over time. The temporal peaks can then be used to estimate radar operational parameters. Figure 6-4(a) illustrates an example of how two scanning radars impact the mean of the measured field and hence the whole spectrum map. In Figure 6-4(b), the strong temporal peaks are removed from the measurements. Finally, in Figure 6-4(c), a temporal snapshot of the spectrum map with two scanning radars is depicted. This is only a snapshot and if the radar is scanning in it may make more sense to draw the complete scanning sector to the map, as seen in Figure 6-5. In this figure, the static and dynamic parts are first separately modeled, but the final RF power values are calculated as max over the interpolated values and the modeled radar over the entire scanning period.

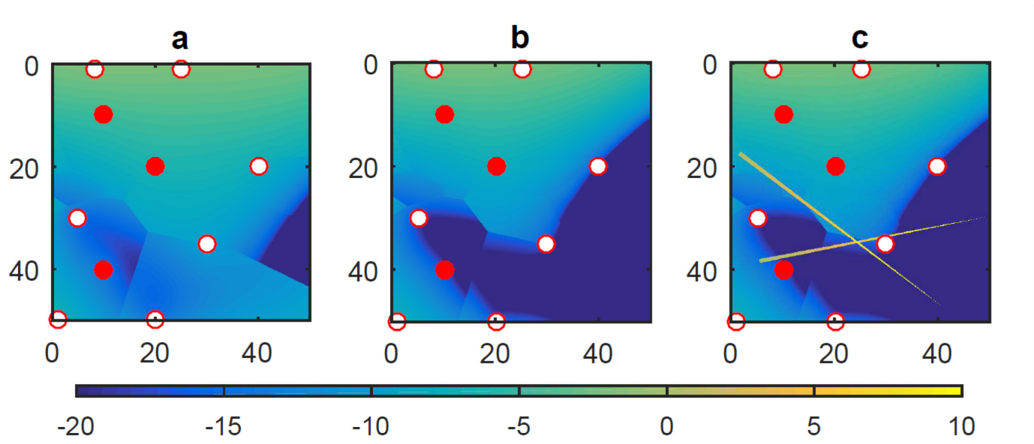


Figure 6-4: Impart of Dynamic and Static Spectrum Map Components [172]. Red and white circles are surveillance and ordinary sensors. (a) Average measurement results with Universal Kriging method. (b) Impact of strong temporal peaks are removed. (c) The scanning radars are modeled based on surveillance sensor parameters estimation.

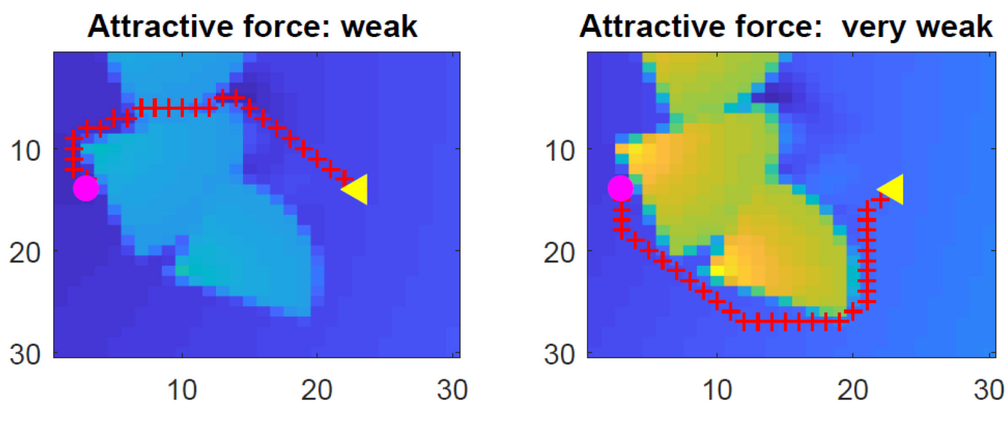


Figure 6-5: Example of Using Spectrum Maps as a Repulsive Force in Path Planning. A combination of spectrum maps, and an attractive force, forms a potential field where the platform navigates to the target. Different scaling of the attractive force can yield different results.

Besides optimizing resource allocation spectrum maps can also be utilized in other task, for example in surveillance avoiding path planning for platforms such as aircrafts, as well as scheduling and selecting transmitters and receivers. In Melvasalo and Koivunen, 2018 [173], such maps are used to create virtual potential fields where adversary surveillance signals are modeled as repulsive forces and the desired destination as an attractive force. The attractive force is proportional to the square distance from the target. Combination of the two forces form further a virtual potential force field where the platform can navigate to find a safe route to the target. Since in practice, surveillance by radars cannot be totally avoided, the goal can be minimizing the treat or finding the shortest path while keeping the threat in a tolerable level. Other constrains such as maximum length of the path (flight time) can also be taken into account.

6.2.4 Waveform Design and Optimization

Waveform design and optimization play a central role in facilitating the coexistence and spectrum sharing. These problems have been addressed in a variety of scenarios, see Refs. [163], [174], [175], [176], [177]. The most common case is one communication and one radar systems sharing the frequency resources. The simplest design problem is faced when the two systems are co-located and they can be co-designed to achieve desired performance for both subsystems. The joint radar-communications system can be considered cognitive, if the waveforms and the use of resources are optimized by taking into account the channel state information and awareness of the radio spectrum, including interference awareness. A broader view is obtained by optimizing the use of Degrees of Freedom (DoF) in transmitters and receivers instead of just waveforms. The degrees of freedom include frequency, polarization, time, space (antenna or sensor location and selection) and waveforms (code and power allocation). Furthermore, the optimization can take advantage of some known dictionary of waveforms designed in advance, or it can find a numerical solution to an optimization problem. Both the transmitters and receivers need to be adaptive in cognitive processing. In case of radar subsystems, also the target scenario and the radar task and mission need to be taken into account in the optimization. For a coexisting communications subsystem, the goal is usually to ensure the desired Quality of Service (QoS) for the wireless users. It can be defined quantitatively in terms of data rate, error or outage probabilities or delays, for example. In more general cooperative design where the subsystems are not necessarily co-located, the two systems may exchange information, for example channel state information or level of observed interference (e.g., SINR value), but the design is done independently for both systems. In this case, the design can be called either radar-centric or communication centric, depending on which waveform is optimized based on the shared information. The performance requirement of the other subsystem is then imposed as a constraint to the optimization problem. An example of radar-centric optimization problem formulation, see Ref. [178], is:

$$\underset{P_k,\eta}{\text{maximize}}\ p_{\mathrm{D}}\ \text{ subject to } p_{\mathrm{FA}} \leq \alpha,\ \log\left(1 + SINR_k\right) \geq t_k,\ \forall k,\ \text{and} \sum_{k=0}^{N-1} P_k \leq P_{\mathrm{T}}, \tag{6-1}$$

in which radar's probability of detection p_{D} is maximized under constraints of false alarm rate (p_{FA}) as in Neyman-Pearson detector with threshold value η, minimum rate constraint t_k for kth wireless user and total power constraint P_T. One could impose additional constraints on the shape of the ambiguity function (small departure from the ideal thumbtack ambiguity function) and constant modulus of the transmitted radar signal.

The desired performance of both subsystem can also be described in a joint objective function and a pareto-optimal solution is found. Improving the performance of one subsystem may then decrease the performance of other subsystems.

The formulation of the optimization problems and employed methods for solving them depend on how much information or prior knowledge is available and what kind of constraints are imposed. Furthermore, the objective function of the waveform design is different for different radar tasks and communications. A common objective, however, is to control the interferences caused to other systems. In practice, this can mean e.g., maximizing the Signal to Interference and Noise Ratio (SINR) since it will impact probability of detection, target estimation variance as well as achievable data rate. Another objective is to take advantage of the non-contiguous spectral allocation and non-continuous use of spectrum and maximize the spectral efficiency.

In scenarios where radars have to coexist and share spectral resources with other radio systems, managing interferences is a key task. Typically, this requires sensing the state of the shared spectrum and adjusting transmitter and receiver parameters so that the impact of interference is sufficiently reduced. Transmitters and receivers can use all of their DoFs such as different antennas, frequency, coding or polarization to mitigate or avoid interference. Radio receivers are always victims of the interference and consequently they need to use their DoFs to attenuate interferences. A common approach is to use multiple antennas and spatial processing for nulling the interference from certain direction. Interferences may also be caused by leakage of signals from adjacent channels, harmonics or due to reuse of same frequencies in different location. Multipath and clutter would be additional potential sources of interferences. The transmitters can adjust their transmit parameters so that the level of interference is reduced at the unintended receivers. In order to do so, awareness about the dynamic state of the radio spectrum and interference experienced at receivers in different locations, different subbands at different time instances is needed. The awareness may be obtained through feedback provided by the receivers to the transmitter about the channel response and Signal to Interference and Noise Ratio (SINR) it is experiencing. Both the transmitters and receivers can then be optimized so that the SINR is maximized at the receivers. Channel reciprocity is also useful property in building awareness of interferences.

Multicarrier radar [179], is considered to be particularly well suited for coexistence scenarios, due to flexibility to adaptive spectrum usage. Moreover, it is a promising technology for RF convergence where the same transceiver platform is used both for radar or other radio frequency sensing and wireless communications. Coding of the waveform or pulse compression can be done over time or over subcarriers. In order to have an orthogonal design, subcarrier spacing may have to be adjusted. An example of a multicarrier design called MCPC waveform is given by Levanon and Mozeson [180], where pulse compression of multicarrier signal using a code of length M chips is employed.

Waveforms can be optimized for different radar tasks, such are detection or target characterization or parameter estimation. For example, in Bica, 2018 [176] different radar waveform optimization criteria, such as maximizing the Mutual Information (MI) or probability of detection or minimizing Cramer Rao Lower Bound (CRLB) criteria, have been considered. Further constraint on the total transmitted radar power and an interference mask provided by the communications system. Constraints on Peak-to-Average Power Ratio (PAPR) and shape of the ambiguity function may be imposed as well.

6.2.5 Interference Mitigation

Interference mitigation may be performed at the receiver end alone. Then there is not necessarily need to acquire channel state information or exchange information among coexisting radios. Typically, it requires multiantenna receiver structures and processing of the received signals in spatial and/or time domain, see Ref. [177]. If the interferences are impinging the receiver from different angles than the desired signal, beamforming is commonly used in the receiver. The beampattern is designed such that there is a high gain towards the desired signals and a null is steered towards the interfering signals. Subspace processing may be employed as well. Based on the array covariance matrix and its eigenvectors, the received signal space can in some cases be divided to orthogonal signal and interference plus noise subspaces. The received signal can be then projected to a subspace orthogonal to the interference and noise subspace to enhance its quality. Consequently, the receivers will process practically interference-free signals. Similarly, precoders and decoders for radar and communication systems can be designed such that all interference in the system is aligned to a low-dimensional subspace. Interference Alignment based method for precoder-decoder design was introduced for MIMO radar and communications configurations in Cui et al., 2018 [181].

Advanced interference cancellation receivers are techniques that decode desired information and then use this along with channel state information to cancel the interference part from the overall received signal. Such methods estimate the channel impulse response, use feedback about channel response or other awareness of the state of the radio spectrum. The channels are often assumed to be quasi-stationary, i.e., the coherence time of the channels should be sufficiently long so that the channel knowledge is not outdated during the interference cancellation. This class of techniques is typically applicable only for systems using digital modulation.

Adaptive beamforming method for a coherent MIMO radar has been developed to reduce interference caused by communications systems in radar-communications spectrum sharing scenarios. The conditions of the MIMO radar mainlobe interference cancellation were established [177].

Dual-Function Radar-Communications (DFRC) system using MIMO transmitter in multi-user setting cab produce a desired radar waveform in one spatial direction and an information-bearing communication signal in another direction, hence controlling the interference by using spatial degrees of freedom. The method performs antenna selection and permutation of different antenna-waveform pairs [182].

If a waveform optimization method uses maximal SINR as an objective function, the resulting transmitter and receiver will be able cancel interferences. Typically, channel or interference awareness in needed in the process. The interference may be projected into a subspace where it is causing less performance degradation [183]. If interference alignment is able to steer all interferences to a very low-dimensional subspace so that the receivers can operate practically in an interference-free scenario while maintaining the desired degrees of freedom for resolving targets, forming beams, diversity order while ensuring sufficient spatial diversity for spatial multiplexing [181].

6.3 IMAGING RADAR COGNITIVE ARCHITECTURE: IMPLEMENTATION

This sub-section illustrates how the imaging radar cognitive architecture (Figure 3-14) can be implemented to enhance radar detection and imaging capabilities [51]. The proposed architecture (Figure 3-14) appears as a whole in the example scheme depicted in Figure 6-6 [51]. The architecture has been rearranged to highlight the perception-action cycle (fully adaptive block) which is another main ingredient of CRs according to Haykin’s definition.

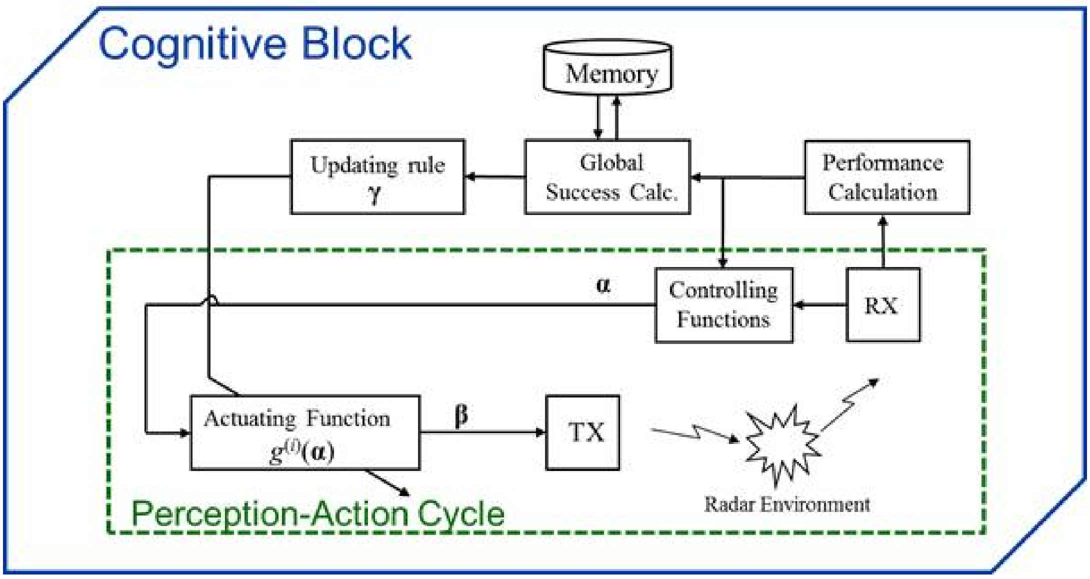


Figure 6-6: Example of the Cognitive System Block Scheme [51].

The perception-action cycle modifies the system parameters as a function of the *actuating function* outputs (**β** = *g*(**α**)) which represent the decision-making algorithm. This function is driven by some *controlling functions* (**α**) that represent a compressed measure of the information contained in the received returns and may change with respect to the mission. One problem to be solved is how the system is able to update the actuating function and, as a consequence, how to change its parameters in order to maximize the system performance in certain environment. The *updating rule* block together with the other ones in the cognitive block accounts for this purpose. Specifically, the updating rule block provides the weights (**γ**) that define **α** in the actuating function. The **γ** parameters are modified in accordance with the feedback given by the *global success calculation* block which compares the measured performance indexes (output of the performance calculation block) with those stored in memory. If the measured performance is better than those stored in memory, this is updated with both the actual weights and the actual performance values, otherwise the weights are modified throughout some rules aiming at performance improvement driven by mission prioritizing and resource availability.

To better explain the behavior of the proposed architecture, in the following a dual band (L-band and X-band) multichannel FMCW-SAR system with GMTI (ground moving target indication) and imaging capability will be considered. The GMTI function is here implemented by using the Space-Time Adaptive Processing (STAP) [52]. The system is conceived to obtain high resolution images of non-cooperative moving targets detected in the scene. For this purpose, the performance has to be measured in terms of imaging and detection capability after clutter suppression. To accomplish this objective, the architecture behavior has been characterized through the following elements:

1) **Input Parameters**, namely the signal backscattered from the environment (e.g., target, clutter, interference). These elements are not dependent on the model but affect it.

2) **Output Parameters (β)**, namely the system reconfigurable parameters (e.g., transmitted frequency, f_0, instantaneous bandwidth, B, transmitted power, P_T), which embodies the effect of the system behavior on the input.

$$\boldsymbol{\beta} = [P_L, B_L, P_X, B_X] \tag{6-2}$$

where P_L and P_X are the power allocated for the L-band and the X-band respectively, while B_L and B_X are the bandwidth allocated for the L-band and the X-band signal respectively. The power allocation must be manged by taking into account the limited amount of transmitted power (P_T).

3) **The performance indexes** which give an intrinsic representation of the system and are strictly connected to the system performance. Specifically, taking into account that the system performance relies on its capability to remove the clutter, detect the target and give well focused target images (high resolution images), the following performance indexes are defined:

- The Attenuating Factor (AF) characterized by the ratio between multichannel SAR image power before and after clutter cancellation:

$$\mathrm{AF} = \left[\mathrm{P_{Image}} \,@\,\text{before STAP} \middle/ \mathrm{P_{Image}} \,@\,\text{after STAP} \right] \tag{6-3}$$

The greater the AF, the better works the STAP filter. It is important to underline that this parameter is insufficient to establish if the STAP works well or goes wrong. In fact, it could happen that the AF is high as a strong slow-moving target was removed. Therefore, the STAP filter Null Position (DN) and the Null Doppler Bandwidth (DNB) have been introduced. These are computed from the STAP filter Doppler profile and respectively correspond to the zero Doppler point (Ratio between the notch position of the actual Doppler filter and the ideal one) and the ratio between the notch bandwidth of the actual Doppler filter and the ideal one:

$$\mathrm{DNB} = \left[\mathrm{B}_{(\text{measured Doppler profile})} \big/ \mathrm{B}_{(\text{ideal Doppler profile})} \right] \tag{6-4}$$

These parameters (AF, DN, DNB) give a measure of the STAP filter to reject the clutter and/or interferences. Then, are strictly linked to the system detection capability.

- The range resolution gives a measure of imaging performance.

4) **Mathematical laws (2)** which give the rules used to update the system reconfigurable parameters trough the controlling functions (**α**).

$$[\boldsymbol{\beta}] = g^{(i)}[\boldsymbol{\alpha}] \tag{6-5}$$

where $g^{(i)}$ namely the actuating function depends on the kind of mission (i = [1,2,3] = [imaging, detection, both]) and scenario and it is a weighted combination of **α.** Four controlling function, $\boldsymbol{\alpha} = [\boldsymbol{\alpha}_1, \alpha_2, \alpha_3, \alpha_4]$, has been identified in the considered example. The first controlling function $\boldsymbol{\alpha}_1$ (6.6), directly manages the amount of power (P_T) to be assigned to each frequency channel (X, L-band) according to the kind of clutter in the observed scene and the mission priority (6.7). To this end, a classification of the clutter in Nc classes, each one with assigned priority, $\mathbf{w} = [w_1, \ldots, w_{Nc}]$ and the percentage of pixels (**p**) for each class are needed.

$$\boldsymbol{\alpha}_1 = \frac{\mathbf{p} \otimes \mathbf{w}}{\sum_{k=1}^{N_C} [\mathbf{p} \otimes \mathbf{w}]_k} \tag{6-6}$$

$$\left\{ P_i = \sum_{k \in \Omega_i} \boldsymbol{\alpha}_1[k] \cdot P_T \right\}, i = \begin{cases} 1, L-band \\ 2, X-band \end{cases} \tag{6-7}$$

It is important to point out that for each class of clutter it is possible to identify an operating frequency that gives the best performance in terms of target detection or target imaging. For instance, the L-band has to be preferred in case of targets embedded in forest clutter while the X-band has to be better in case of targets embedded in bare soil, sea clutter. The others controlling functions steer (increase/decrease of ΔB) the amount of bandwidth for each frequency channel, according to:

$$B^{(i)} = B^{(i-1)} + \mathrm{sgn}(\alpha) \cdot \Delta B \tag{6-8}$$

where α is a weighted combination of the following controlling functions.

$$\alpha = \gamma_2 \alpha_2 + \gamma_3 \alpha_3 + \gamma_4 \alpha_4 \tag{6-9}$$

More specifically, $\alpha_2 = \{0,+1\}$, is a binary variable that suggests the actuating function to increase the instantaneous bandwidth ($\alpha_2 = +1$) when the range resolution is too poor with respect to the minimum range resolution required by the application at hand. The function α_3 is a binary function ($\alpha_3 = \{0,-1\}$) that suggests to the actuating function to decrease ($\alpha_3 = -1$) the instantaneous bandwidth to avoid co-channel frequency interference and therefore improve the SINR value. Although α_3 is a measure of the capability of the STAP filter to remove both clutter and interference, it is not sufficiently by itself to really assess the STAP filter performance. In fact, it may happen that the filter removes the moving targets as well. The controlling function α_4 is a binary function ($\alpha_4 = \{0,-1\}$) that accounts for this issue and measures the effectiveness of the STAP filter with respect to the ideal one (Figure 6-7). More specifically, it depends on both the position and the bandwidth of the filter notch in the radial velocity domain. It suggests to decrease the bandwidth ($\alpha_4 = -1$) to be sure that STAP does not remove moving targets, in fact $\alpha_4 = -1$ stands for the STAP filter does not perform well and then something went wrong probably due to some interferences.

The weights γ are positive real numbers lower of equal to one. Their values must be modified to account for environmental changes by exploiting the measured performance indexes and stored performance indexes, AF_{mem} and δr_{mem} (Table 6-2). The comparison among these indexes stands for effectiveness of the system functioning.

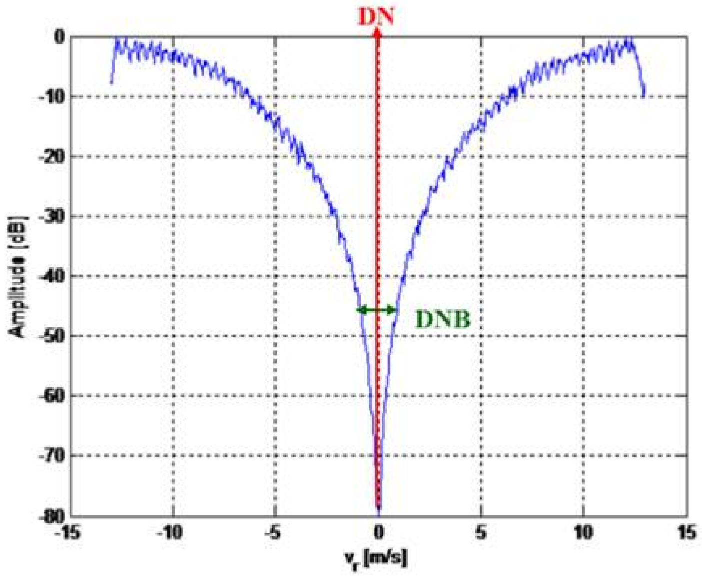


Figure 6-7: Example of Ideal STAP Doppler Profile [51] [52].

Table 6-2: Updating Rules for Controlling Functions Coefficients [51] [52].

	AF > AFmem	**AF < AFmem**
δr < δr,mem	$\gamma_2 [t] = \gamma_2 [t-1]$ $\gamma_3 [t] = \gamma_3 [t-1]$	$\gamma_2 [t] = \gamma_2 [t-1] - \Delta_p$ $\gamma_3 [t] = \gamma_3 [t+1] + \Delta_p$
δr > δr,mem	$\gamma_2 [t] = \gamma_2 [t-1] + \Delta_p$ $\gamma_3 [t] = \gamma_3 [t-1] - \Delta_p$	$\gamma_2 [t] = \gamma_2 [t-1] + \varepsilon$ $\gamma_2 [t] = \gamma_3 [t-1] - \varepsilon$

Referring to Table 6-2, when both the measured ΔF and δr are better than those stored in memory, the weights at time t remain the same of those at time $t-1$ and the performances stored in memory are updated with the actual values. In the case in which the measured ΔF is worse than the one stored in memory (STAP performance degrades) the weight γ_3 is increased of a quantity Δ_p, which is a positive real constant quantity. As a result, γ_2 is decreased by the same quantity, while $\gamma_4 = 1 - (\gamma_2 + \gamma_3)$. Similarly, when the measured δr is worse than the one stored in memory (resolution degrades), the weight γ_2 is increased of a quantity Δ_p while γ_3 is decreased of the same quantity.

Finally, when both the measured δr and AF are worse than those stored in memory, the weights γ_2 and γ_3 are perturbed by a quantity $\varepsilon<1$. This approach permits to change the actuating function so as to prioritize the target imaging or the target detection.

The proposed cognitive architecture has been tested on a SAR dataset simulated by the Institute of Electronic systems of the Warsaw University of Technology [53], [54], [55]. Table 6-3 outlines the simulation parameters.

Table 6-3: Simulation Parameters [51].

Centre Frequency	9.6 GHz
PRF	1.67 kHz
TX Bandwidth	500 MHz
Sampling Frequency	500 MHz
Integration Time	0.4 s

The terrain has been modeled by using a DEM with size 500 m × 500 m. Two moving targets were present in the scene: a large trailer truck with velocity 15 m/s along the range direction; a GAZ 66 military truck with velocity 30 m/s along the range direction. In order to assess the system capability to reconfigure itself in a context-aware manner, a monochromatic interference has been simulated and added to the received signal. For sake of simplicity only the bandwidth is considered as a free parameter to be optimized. To cope with the proposed objective, more than one acquisition of the same scene is executed by varying the interference frequency position and power and assuming that both the target and the clutter distribution do not change over time (Table 6-4).

Table 6-4: Historical Sequence of the Interference [184].

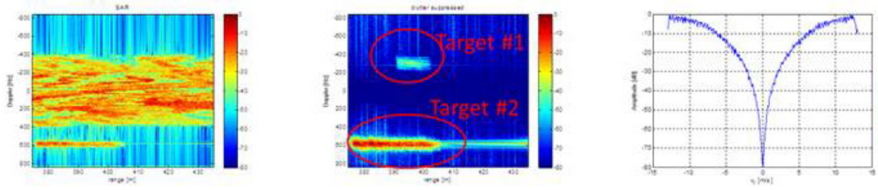
N	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Interference frequency (GHz)	9.75	9.75	9.75	9.75	9.75	9.75	9.75	9.55	9.55	9.55	9.55	9.55	9.55	9.55
Interference power	Low	Med	High	High	High	Med	Low	Low	Med	High	High	High	Med	Low

At the beginning, T_X parameters are selected heuristically in order to provide the expected performance in absence of interference (Table 6-5) and the received signal is elaborated in order to extract the performance indexes and the controlling function.

Table 6-5: Parameters Setting at the Beginning [51].

Δr_{min}	B	γ_2	γ_3	γ_4

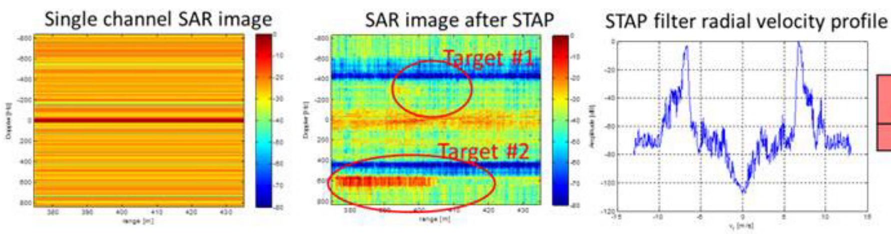
Figure 6-8 shows the STAP ability to filter out the clutter from the SAR image and the alpha values denote the preservation of the receiver requirements. Then the waveform parameters are unchanged in the second acquisition. The cycle is then repeated in light of the decision made in the previous acquisition time and new controlling functions are computed through the performance indexes extracted from the received signal. If the spectrum availability changes, a degradation of imaging capability could be evaluated by the global success calculation block as a consequence of performance degradation (Figure 6-9). For instance, in the third cycle the AF exceeds the minimum one required (20 dB) suggesting the actuating function (α_3) to reduce the instantaneous bandwidth to compensate the SINR reduction due to the presence of a strong interference. This is confirmed by α_4 that attests an anomaly of the STAP filter profile. This fact means that the new spectrum environment affects the instantaneous bandwidth used by the system. To face this issue, the system senses the spectrum to detect the interference so as the updating rule block increases of a certain quantity the weight (γ_2) related to the resolution and suggests the actuating function to increase the instantaneous bandwidth so as to exploit the largest portion of the available spectrum (Equation (6-5)).



AF [dB]	DN	NDB	δ_r	α_2	α_3	α_4
20	1	1	0.3	0	0	0

a) SAR image before STAP filtering (b) SAR image after STAP filtering (c) STAP filter Doppler profile

Figure 6-8: First Cycle (n = 1): Processing, Performance Indexes and Actuating Function [51].



AF [dB]	DN	NDB	δ_r	α_2	α_3	α_4
163	0	-	0.3	0	-1	-1

Figure 6-9: First Cycle (n = 3): Processing, Performance Indexes and Actuating Function [51].

The cycle is then repeated over time in order to update the memory and to adapt in a dynamic way the system parameters to the environmental changes and spectrum allocation. The system evolution as a function of the interference frequency is reported in the following Table 6-6.

The approach and architecture here presented are an example of how the cognitive radar paradigm allows mitigating the effect of a dynamic environment by ensuring a tradeoff between spectrum occupancy and system performance. More details can be found in Ref. [51].

6.4 Cognitive Jammer-Based ISAR Passive Radar

The idea behind the utilization of a passive radar in Electronic Warfare (EW) operation lies in its capability to remain covert within the wider EW scenario. Today, EW becomes more and more agile, intelligent and flexible. Passive radar can, without disclosing its position, detect, localize, track and make ISAR images of targets. The parameters such as bandwidth, high transmitters power allow passive radar to perform air surveillance using the civil, commercial illuminators of opportunity such as FM, DVB-T or cellphone Base Transceiver Stations.

Table 6-6: System Evolution as a Function on the Interference [51].

n	AF[dB]	DN	NDB	α_2	α_3	α_4	α	$\delta_r[m]$	B[MHz]
1	20	1	1	0	0	0	0	0.3	500
2	126	1	1	0	0	-1	$-\gamma_3$	0.3	500
3	164	0	-	0	-1	-1	$-\gamma_3-\gamma_4$	0.3	500
4	19	1	1	1	0	0	γ_2	0.4	375
5	163	0	-	0	-1	-1	$-\gamma_3-\gamma_4$	0.3	500
6	19	1	1	1	0	0	γ_2	0.4	375
7	20	1	1	0	0	0	0	0.3	500
8	20	1	1	0	0	0	0	0.3	500
9	127	1	1	0	0	-1	$-\gamma_3$	0.3	500
10	164	0	-	0	-1	-1	$-\gamma_3-\gamma_4$	0.3	500
11	19	1	1	1	0	0	γ_2	0.55	275
12	163	0	-	0	-1	-1	$-\gamma_3-\gamma_4$	0.3	500
13	19	1	1	1	0	0	γ_2	0.55	275
14	20	1	1	0	0	0	0	0.3	500

With the advent of the rapid development of computers the idea of quasi-real time target ISAR imagery became possible. It is assumed that the radar range resolution cell should be no more than 1/10 of the target size. The bandwidth B = 7.61 MHz (DVB-T) allows to obtain the monostatic range resolution of the order of 20 m (in the bistatic scenario the value will be influenced by the cos of the bistatic angle). Utilizing many adjacent DVB-T channels to improve the range resolution is possible but entails problems with the frequency spectrum holes. An alternative possibility is utilizing jamming waveforms as illuminators for the operation of passive radars. For the case of a friendly jammer, the jamming waveform can be optimized for the two objectives of jamming and imaging performance.

6.4.1 Case Study

As is often in the case with radar, there is a tradeoff between jamming efficiency and ISAR imaging. Both approaches have conflicting requirements: the jamming is the most effective when the jamming signal follows the signal signatures of the radar that is jamming. The faster the jammer can react – the better. It allows to efficiently interfere with the original signal even if the frequency-hopping technique is utilized. What's more, that kind of jammer in some scenarios (e.g., deceptive one) can record the signals and manipulate it on a pulse to pulse basis in order to deceive the radar. Rapid frequency hops during high PRF and changing modulation of the signal are problems to be solved in modern ECCM systems. On the other hand, the ISAR imagery expects long integration times (of the order of milliseconds), quite equalized bandwidth without notches. These contradictory features do not mean, however, that the simultaneous jamming and ISAR imagery are impossible to connect.

The simplest form of jamming is barrage, i.e., interfering multiple frequencies simultaneously in a given frequency span. This approach is inefficient in terms of jamming effectiveness (the radar only sees the part of its bandwidth and the jammer needs to cover much wider span of frequencies that manifests as the lower spectral density of the noise). From the operational point of view this type of jamming can jam both hostile and friendly devices. What is more, modern pulsed-Doppler radars utilize complex pulse compression techniques and coherent integration what makes wideband jammers rather ineffective even if it seems that the jammer's transmitter power is quite high. From the point of view of the ISAR imaginary that kind of signal has very good features (long integration time, wide bandwidth) provided that the SNR in the receiver is at a sufficient level. The most popular barrage jammers are noise ones.

The second type is spot jamming. Spot jamming can be similar to barrage jamming wherein it utilizes narrowed spectrum in the vicinity of the jammed signal frequency. It can be noise jamming, LFM jamming or signal-matched jamming what is the most effective one. This type of jamming can provide enough power and bandwidth to simultaneously jam and make ISAR image of the target that holds the jammed receiver.

Summarizing, from the point of view of the ISAR imagery the Illuminator of Opportunity should feed the PCL receiver with high power, wide bandwidth and continuous signal with long integration time. The requirements for jamming are quite different – the jammer should have the matched bandwidth (or extend it in jammed signal neighborhood due to power accumulation in selected frequency span), provide rapid changes in order to follow the jammed signal in case of modulation, frequency (what is not the case in the wideband noise jamming scenario).

In order to achieve the operational assumptions, the jammer should choose the emitting signal parameters in order to jam and image the target. One can imagine that the first thing that should be done is the classification of the target. Thanks to this appropriate action can be taken and further interference carried out. At the beginning when the target is detected and tracked by the Passive Emitter Tracking – Passive Coherent Location PET-PCL system (with PCL utilizing FM and DVB-T) and the signals from the target's radars are analyzed by PET. The signal parameters are passed to the jammer and the noise signal is formed in the frequency vicinity of the signal from the target.

6.4.1.1 Sample Case

Let us analyze the very general and demonstrative use case with cognitive jammer-based passive radar called C-JAMPAR (See Figure 6-10) that is composed of Passive Coherent Location (PCL) and Passive Emitter Tracking (PET) systems that work together. This system utilizes jammers as illuminators of opportunity and uses their signals in order to detect, create ISAR image and probably classify the targets. It is assumed that the signals emitted by jammers are controlled by the friendly military forces that allow adaptive signal formation. The aim of the mission is to simultaneously jam the hostile target and to make ISAR image of the target in order to extract its special features.

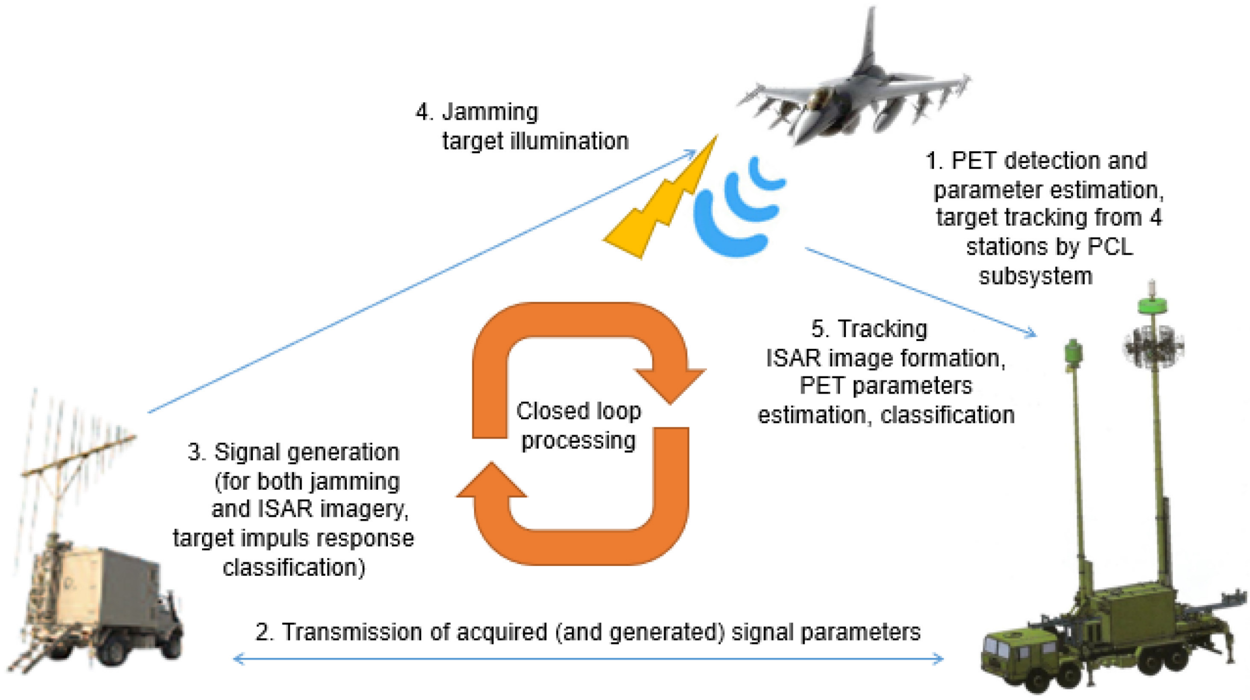


Figure 6-10: C-JAMPAR Use Case.

The first step of operation is target detection by means of PET subsystem. It allows to estimate signals emitted by onboard radars. Next, tracking by means of PET and PCL (utilizing civil illuminators of opportunity such as DVB-T, FM) fusion is conducted. After the initial radio-electronic recognition in Step 2 signal characteristics that are going to be generated in friendly jammer are synthesized and transmitted to jammer. Next, the target is being illuminated by the suitable signal, which is supposed to both jam the target as well as make it possible to extract useful features from the reflected signal. It allows C-JAMPAR to track the target, make an ISAR image and estimate the necessary parameters.

6.4.1.2 Jammer Transmitter Adaptation

The adaptation of the illuminator should follow the following steps:

1) PET (ELINT) signal capture, PET-PCL fusion target tracking;
2) Estimate the power (if possible), PRF, pulse length, modulation, bandwidth, initial target classification based on PET signals and target flight trajectory;
3) Transfer the signal description from, PET-PCL radar to jammer;
4) Perform the scenario (e.g., image target as good as possible providing sufficient parameters for jamming); and
5) Go to #1.

Two scenarios of jamming are possible – the barrage jamming that allows to hide the target's radar pulses in the noise or sending matched pulses which can jam the target in more intelligent way and allow other operations by the passive PET-PCL radar.

6.4.1.3 Requirements for Jamming Signals

The friendly jammer transmitter adaptivity should allow to simultaneously perform:

- Jamming (matched bandwidth, high power, fast changes in signal parameters i.e., modulation, frequency hops).
- Target impulse response separation (maximization of separation of target features-matching the jamming signal to the difference of target impulse responses).
- ISAR imaging (high SNR, wide bandwidth, continuous waveform with long coherent processing interval).

Summarizing, jamming signals from friendly jammers are used to obtain three different goals (jamming target's onboard radar, feature separation, ISAR image formation) so each of them can put its' own specific requirements. These differing objectives are:

- Jamming: The jammer aims to improve the jamming signal-to-noise ratio.
- Target impulse response: It is based on the Guerci's book 'Cognitive Radar: The Knowledge-Aided Fully Adaptive Approach' [32] – optimum MIMO target Identification chapter. This approach assumes the usage of the method of stationary phase to create a constant modulus non-linear frequency modulation pulse for the chosen optimal signal assigned to the max eigenvalue of the matrix that is the difference between target transfer matrices.
- ISAR: ISAR image resolution is an important factor that provides to resolve the scatterers in ISAR image. There are two types of ISAR resolutions, range and cross-range resolution.

6.4.1.4 ISAR Simulation Results

Figure 6-11 shows different ISAR images that were formed by two types of signals – linear frequency modulated signal and noise signal with different values of bandwidth and coherent processing interval parameters. One can see that both signals can provide good ISAR images.

6.4.1.5 Conclusions

The aim of the utilization of the friendly jammer is to form a waveform that can simultaneously ensure three radar operations: jamming the target, ISAR imaging and classifications. It can be obtained by creating a waveform with time intervals that provide optimal (or even sufficient) conditions in each of the intervals.

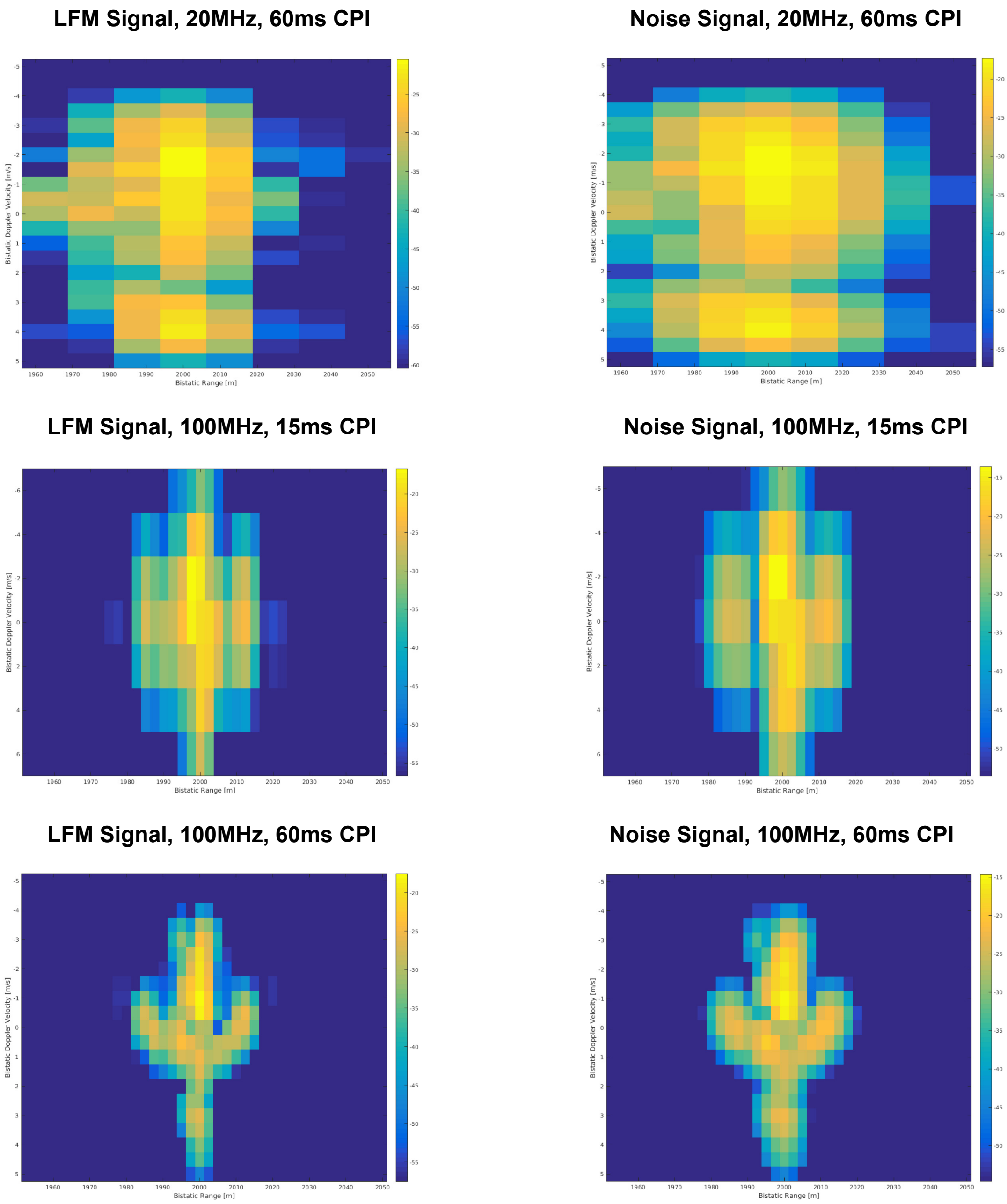


Figure 6-11: Example ISAR Images Depending on Signal Types and their Parameters.

Chapter 7 – ENABLING TECHNOLOGIES

The architectures and techniques presented in this report, as well as the applications where their implementation is envisioned, will only receive their potential if a number of enabling technologies become available and continue to mature. Many of the techniques require sophisticated processing, large-scale optimization, and/or specialized hardware. Furthermore, some require precise waveform synthesis or beamforming, such that system calibration will be critical if benefits are to be achieved. In this section, we outline several critical enabling technologies that the task group sees as essential to the deployment and success of future cognitive radar systems.

7.1 COMPUTING AND OPTIMIZATION

At its foundation, cognitive radar involves assessing the current operational state of a sensor (progress relative to objectives, propagation and interference environment, etc.), representing this state in some manner, and then applying methods to determine how the sensor should perform its future operations. Therefore, at some level, every technique or approach presented in this report requires computation to make sense of the environment, and calculations or optimizations to determine how to proceed.

As we know, radar systems produce tremendously large data sets that must be processed before the radar can make decisions related to its objectives, and in cognitive radar, we are asking the system to make decisions beyond the standard detections and parameter estimations required for detection and tracking. Cognitive radar techniques involve detailed spatial-spectral characterization [59], [148], [185], of the propagation environment in order to identify and to disrupt or avoid other sources; numerical representations of errors or uncertainty in order to optimize parameters such as pulse repetition frequency, center frequency, and/or modulation; biologically-inspired processing techniques [186] in support of intelligent decision-making or novel data collection modes; calculation of future expected rewards [69] in response to potential actions taken by the sensor; and many other examples of computationally intensive methods. Therefore, to implement cognitive radar techniques in practical systems, especially in real time, raw computing speed must continue to improve and processors must continue to become more tightly integrated via low latency connections to the Analog-to-Digital Converters (ADCs) and Digital-to-Analog Convertors (DACs) that collect and initiate the measurements. Fortunately, there are technologies such as the emerging RF System-on-Chip [187] (RFSoC – see more discussion below) where this tight integration is occurring alongside highly-agile RF front ends capable of operating over wide frequency ranges [188], [189]. Heterogeneous processor types (FPGAs, GPUs, and microprocessors) joined by high-speed interconnects can help ensure that processors best suited for specific types of calculations can be exploited while minimizing latency.

Continued research into optimization theory and techniques is needed, especially with respect to large-scale optimization problems with high dimensionality. Better understanding of effective ways to reduce multi-dimensional, continuous search spaces to smaller, discrete searches is needed. New algorithms suitable for the optimization of radar parameters and radar resource allocation over large system models are necessary, including techniques that can provide near-optimal answers on the timeline of a typical radar processing interval.

7.2 ONLINE WAVEFORM SYNTHESIS AND GENERATION

Much of the recent cognitive radar trend can be traced back to the increased availability of arbitrary waveform generators powered by high-speed DACs. This availability inspired research into optimized waveforms [102], [104], [190] for tasks such as interference avoidance and target recognition, which was then envisioned within a closed-loop process that could be considered cognitive. We expect optimized waveform design to continue as an important topic in cognitive radar, as evidenced by the emphasis on waveform design in Section 4: Techniques and Approaches.

Continued advances in waveform design are necessary. MIMO waveform designs need continued improvement, and cognitive radar may create the need for MIMO designs with specific cross-correlation properties or features that exploit knowledge of target and interference parameters. MIMO waveform designs for multi-beam and multi-function operation with varying resolution and low cross-correlation will be useful for digital arrays that can adaptively transmit different waveforms from different sub-apertures. Furthermore, many cognitive techniques envision real-time waveform adaptation to optimize performance and/or avoid interference; therefore, corresponding algorithms must be able to optimize waveform properties and compute DAC samples that can be faithfully generated to produce the desired waveform. In order to adapt waveforms in real time, waveform synthesis must be fast, and the latency between processor and DAC must be very small.

Waveform design techniques for cognitive radar also commonly produce waveforms with very specific properties that can be degraded by small errors in the physical creation of the waveform. For example, a waveform designed to have a specific range sidelobe null can be distorted by non-ideal DAC synthesis or by the power amplifier. In some cases, the benefits of precise waveform design will only be realized for highly calibrated hardware. In other cases, waveform pre-distortion [191] should be used to compute an intentionally distorted waveform that has the ideal properties once corrupted by the physical DAC and High-Power Amplifier (HPA). While waveform pre-distortion has been demonstrated to some extent, in-the-loop adaptive waveform design for cognitive radar requires pre-distortion to be applied in real time, which also requires exact characterization of the transmitting hardware.

7.3 WIDEBAND AND TUNABLE FREQUENCY COMPONENTS

One application of cognitive radar is to provide adequate performance in congested and contested spectrum environments, and spectrum agility and tunability are essential for that purpose. Spectrum agility implies the ability to tune the cognitive radar’s center frequency of operation and instantaneous bandwidth, while tunability refers to the system’s ability to shape its frequency response to match. For example, a switchable RF synthesizer can be used to change the frequency of the Local Oscillator (LO) used for up- and down-conversion, which changes the RF center frequency. Wideband mixers that can cover a wide range of frequencies on the LO and RF ports are widely available, resulting in significant frequency agility. However, the antenna operating range must also cover the full range of operation, and the radar receiver will be wide open to out-of-band interference unless front-end filters are matched to the system’s instantaneous frequency range. Filter banks could be used (switchable to a filter with suitable passband at any given time), but true frequency agility would require an enormous number of filters to cover GHz worth of operating range with varying instantaneous bandwidth. Therefore, continued improvement of tunable filters [192], amplifiers, and antennas [193], [194] will be essential to obtain frequency agility while maintaining power efficiency, low noise figure, and maximum immunity to out-of-band interference. These components must also cover wide operating frequency ranges, be capable of matching instantaneous bandwidth, have fast tuning, and must be compact and efficient themselves. Current designs are often slow to tune and may rely on tunable loads that reduce efficiency.

7.4 MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

Although early methods in cognitive radar have focused on maximizing metrics such as SNR and mutual information, many problems involve parameters and signals that are difficult and computationally intensive to represent by traditional statistical methods. In these cases, Machine Learning (ML) and other

Artificial Intelligence (AI) techniques (such as neural networks) will likely have a strong role to play [141], [195]. These techniques can be used to identify patterns and learn behaviors, which are essential knowledge for the decision-making (action cycle) aspect of cognitive radar. It has been proposed, for example, to use Machine Learning for spectrum characterization and awareness, or to use convolutional neural networks for signal identification. Therefore, it appears that these techniques will serve an important purpose for the higher levels of cognitive radar – not necessarily in detecting or tracking targets, but in characterizing the situation and suggesting actions to take.

ML and AI require significant training data, which is always in short supply for radar applications. Each scenario that a radar faces provides a unique signal environment, geometry, set of targets, and other features; thus, it is imperative that techniques be able to incorporate both supervised learning from existing datasets and online real-time learning as new scenarios are presented. How to train, implement, and protect cognitive radars employing ML/AI is still an open question. Some have expressed concern that cognitive radars, especially those employing AI, could be tricked into learning bad habits; thus, it is imperative that ML/AI techniques for cognitive radar should have some bounds on the radar's allowable behavior. Such bounds, however, could limit the potential impact of cognitive systems by restricting its ability to learn and adapt.

For now, ML/AI algorithms take data as inputs and yield a decision based on that data. Typically, this decision is some type of detection or classification, which makes the accuracy of the decision (i.e., the performance of the algorithm) easy to define. In contrast, if ML/AI algorithms are used to output a course of action, additional modeling must be performed to assess whether the proposed course of action yields an improved performance. Furthermore, this modeling must be included in the training stage to provide feedback to the algorithm. Whereas the feedback in a traditional ML/AI application might be a simple correct/incorrect assessment, in a cognitive radar application the feedback must include a figure of merit on the proposed course of action. Therefore, additional research is needed in order to use ML/AI as a decision agent in cognitive radar's closed-loop or perception-action cycle.

7.5. ALL-DIGITAL RADAR ARRAYS

All-digital arrays are defined as RF antenna arrays that possess the capability for independent waveform synthesis and analog-to-digital conversion at every element of the array [197], [198]. Such an architecture produces a huge amount of data and requires a significant amount of control, yet the potential agility and performance of an all-digital system is unmatched. The possibility for unique space-time waveform concepts, multiple transmit beams, and full digital beamforming on receive opens a wide design space for cognitive radar.

Nearly any concept of arbitrary waveform combined with adaptive-transmit aperture allocation is possible. The aperture can be divided in sub-apertures, with each sub-aperture transmitting its own unique waveform in an independently defined direction. Such a mode is useful for tracking multiple targets that don't require the sensitivity of the full aperture or for temporarily tasking a sub-aperture with performing a communication link. The aperture can also be divided into sub-apertures for MIMO operation [196] where the sub-apertures do not need to be the same size or shape. On receive, every element can receive the reflected signals due to all waveforms assuming the signals are within the instantaneous sampling bandwidth of the digitizers. Therefore, full-gain beams can be formed on receive even if the transmit beams were spoiled or low-gain due to using a fraction of the aperture. The cognitive, adaptive-transmit potential for digital arrays is nearly limitless.

A few all-digital arrays are being developed and will become operational or available as testbeds in the near future [197], [198], [199]. Synchronization across elements, coherence of LO signals, and per-channel amplitude and phase mismatches can reduce performance unless carefully implemented. Distributing a common LO signal across the array maintains coherence but requires all elements to operate within the same instantaneous band. On the other hand, independent LO signals allow the array to diversify its instantaneous operating frequency over the array but will likely reduce channel-to-channel coherence. Calibration algorithms for all-digital arrays are being researched and will be essential for achieving full performance.

The exploitation of digital arrays is also highly dependent on the implementation of the system software. Software architecture decisions can make tasking the array easier but could restrict the flexibility of the array to perform in unique configurations. As cognitive radar algorithms that can exploit digital arrays become more prevalent, the software on these systems may need to adapt to allow more creative modes. Finally, processing the data from all-digital systems is a huge effort, as digital arrays can easily produce terabytes of data per second. Real-time cognitive radar on digital arrays will require immense processing power to analyze the data, understand the situation, design or select an operating mode, and then upload desired waveforms to the DAC on every element.

7.6 RF SYSTEM-ON-CHIP (RFSoC)

RF System-on-Chip (RFSoC) [187], [188], [189] is becoming more advanced as investment by the US Defense Advanced Research Projects Agency (DARPA), other government agencies, and industry rapidly increases. In the final year of this task group, Xilinx has released an RFSoC [186] that incorporates ADCs, DACs, and a powerful FPGA on the same chip. The ADCs operate at 4 Gigasamples/second while the DACs operate at 6.4 Gigasamples/second, thereby allowing Gigahertz of instantaneous bandwidth and direct sampling up to S-band. For example, the current version of the Xilinx Zynq UltraScale+ RFSoC contains up to 16 12-bit ADC channels, up to 16 14-bit DAC channels, an ARM processor, and Xilinx FPGA all on the same chip. Because of the tight on-chip integration between ADC, DAC, and the FPGA, high-latency communication between these devices is eliminated, creating a perfect platform for real-time exploitation of data, calculation of actions in the perception-action cycle, and loading of optimized waveforms into the DACs [200]. As these types of devices begin to incorporate improved synchronization and networking across chips, as well as integrated analog up- / down-conversion to increase their operating frequency range, their potential will increase even further.

RFSoCs could enable real-time implementation of cognitive radar algorithms such as online waveform optimization (and loading to the DACs), spectrum characterization performed at the RF front end rather than back at a CPU, low latency research allocation, and even artificial intelligence algorithms that control the front-end operation.

The key for this technology is the low latency between processor and ADCs/DACs. Other technologies may emerge that also provide this low latency, but currently RFSoCs seem to be the closest enabling hardware technology for implementation of truly real-time adaptive waveforms and transmit apertures.

Chapter 8 – CHALLENGES TO THE RESEARCH COMMUNITY

The potential of cognitive approaches to enhance existing radar performance in almost all respects has led to an upsurge in research in recent years. There has been much progress in developing cognitive radars both theoretically and practically, however there remain many challenges:

- On the one hand, in the field of research continuing the progress in development of cognitive radars (see Section 8.1).
- On the other hand, in the fields of regulatory, industrial process and customer acceptance, legal (see Section 8.2).

8.1 RESEARCH CHALLENGES

8.1.1 Assessment and Evaluation

A fundamental research challenge is how to assess and evaluate cognitive radar algorithms.

Assessment of cognitive radar algorithms requires some characterization against which algorithms can be compared. The ontology in Horne et al., 2018 [201] provides some structure and terminology for characterizing cognitive processing algorithms according to levels or degrees of cognition. This will allow for some comparison of algorithms, but further work remains to develop tools and common terminology for describing and comparing the characteristics of cognitive radar algorithms.

Evaluation of cognitive radar algorithm performance requires quantitative metrics. System performance will still be measured in terms of standard performance metrics such as probability of target detection and false alarm, mean square error in tracking systems, and probability of correct classification in automatic target recognition systems, but cognitive systems require additional metrics that quantify the cost of using system resources, or conversely the benefit of conserving system resources, as well as information theoretic surrogates such as mutual information and Bayesian information for performing the executive processor optimization. [70] provides some strategies for developing cost functions for executive processor optimization by combining performance and measurement metrics, but this remains more of an art than a science and will continue to be a major research challenge.

8.1.2 The Research and Development Process and Experimentation

The typical/classic Research and Development (R&D) process begins with theoretical development of concepts and algorithms and demonstration and evaluation of algorithm performance via simulation. Simulations give the developer complete control over the scenarios being examined and the statistical characteristics of the data generated. This allows for comprehensive studies of performance under benign and challenging conditions. However, simulations can never completely model the characteristics of real data obtained from actual sensors in the field. The next step is usually to evaluate performance against experimentally collected data sets. The experimental data provides more realistic challenges for the algorithms and allows for different algorithms to be evaluated fairly using the same data. Experimental collections, either in a laboratory setting or in the field, can be expensive in terms of time, resources, and monetary costs as compared to simulations and can never cover all of the possible scenarios (radar system settings and target/environmental conditions) that might be encountered in practice. The final step is to test algorithm performance in real time using sensors in the laboratory in the field. Field testing of course provides the ultimate test for an algorithm but is very challenging and expensive and reserved for only the most promising technologies.

Since cognitive radar algorithms adapt the radar sensor waveforms and settings as data is being collected, there are new challenges in the R&D process. The simulation and field testing stages are the same as for standard algorithm development and are critical first and last steps. With more sophisticated and incremental simulations, such as the digital twin concept [202], new development and qualification processes, including software-in-the-loop testing as soon as possible in the development cycle, can be developed. The digital twin, since it should get the same functional performances than the real system, is also an opportunity to contribute to the explicability of cognitive radar algorithms (see Section 8.2). Evaluation on pre-collected data sets is generally no longer possible since the radar settings must be fixed during the collection, except in limited cases where the data can be "oversampled" in some manner and then downselected after the fact to emulate cognitive radar selection of parameters. For example, in Ref. [64], the pulse-Doppler Software Defined Radar (SDR) collected data at a high Pulse Repetition Frequency (PRF). The cognitive algorithm determined the number of pulses and required PRF (up to the actual PRF) and then downsampled the pulses to get the correct number of pulses at the desired PRF. A similar process was used by Oechslin et al. [143], [144], [145]. This presents a unique challenge to the cognitive radar R&D process and makes experimental testing in a laboratory setting an important component of the cognitive algorithm development process.

As of early 2015, the cognitive radar research had all been advancing concepts theoretically and examining their performance through simulation, or at best using pre-recorded data. There had been no reports of experimentally validated concepts, largely because the necessary hardware to test them had not been developed. However, this step is vital in order to establish the true performance potential of applying cognitive processing methods. In the last few years, cognitive radar testbeds have been developed at the Ohio State University (OSU) [146], Armasuisse [144], and FFI [203] and real-time experimental evaluations have been reported in Refs. [61], [146], [70], [203], [204]. Challenges in real-time experimentation involve repeatability of experiments, determining what is truth, determining metrics that can be obtained from the data and used for optimization, and timely computation (data processing and optimization).

8.2 PRACTICAL CHALLENGES

8.2.1 Requirements Definition

A cognitive radar system balances radar system performance against sensing costs to determine the next set of sensing and processing actions. Articulating the system goals in a mathematical form suitable for optimization is thus critical to the operation of a cognitive radar system. There are two approaches to cognitive optimization: task-driven and information-driven [86]. In the task-driven approach, performance Quality of Service (QoS) requirements are specified, while in the information-driven approach, an information measure is optimized.

QoS techniques have long been used in the context of radar resource management [69], [74], [75], [76], [77], [78], [79], [205]. They allow specification of multiple objectives in terms of tangible task requirements and/or mission requirements. However, this requires the system designer to be knowledgeable of the performance goals of the overall system. Furthermore, the QoS resource allocation problem is NP-hard, and requires the use of specialized algorithms to solve.

The information theoretic approach replaces task-based metrics with information theoretic measures [80], [81], [82], [83], [84]. These measures allow the value of disparate tasks to be compared directly based upon the expected information gained by performing each task. However, the final values of information theoretic measures are difficult for the end-user to understand and attribute to specific operational goals [85]. Additionally, task-based methods do outperform information theoretic based approaches at their tasks of interest [86].

A practical challenge for any cognitive radar system is determining the metric(s) to be used and the requirements for cognitive optimization with the customer and the end-user. Indeed since in some cases of cognitive radars involving algorithms such as machine learning taking into learning datasets, the performances of the radar system depend on the learning datasets and the way the cognitive radars will learn (in factory, in live trials, or in operation), new paradigm to define the requirements with the customer of the system should be studied (Quality of Service for military operation could be one option).

8.2.2 Robustness

An important factor in algorithm performance is robustness to modeling and computational errors. This topic has largely been ignored in the research to date but is beginning to be investigated [72], [206] and will be a significant challenge for future research.

8.2.3 Implementation and Regulation

In active radars, cognition requires waveforms and circuits to be reconfigurable and optimizable in real time. Initial progress has been made in the two separate fields [207] but a fully optimized solution that includes all the important aspects of radar circuitry has not yet been presented [208] even though some attempts to consider the radar as a holistic system (hardware-in-the-loop) have been presented, for instance, in Jabosky et al., 2012 [209].

The dynamic reconfiguration of the spectrum portion to be used for transmitting, as described in previous sections, is not always easily implementable. The main reason is that quite often, due to the non-linear operational regime of the high-power radar RF circuitry (particularly for vacuum tube amplifiers), there is a non-negligible spectral spreading outside the assigned radar band (spectral regrowth). This makes coexistence of communications and radar systems in close bands with narrow guard bands difficult [183]. Magnetron tubes, quite often used in legacy radar systems because they are inexpensive, have serious drawbacks in term of spectral purity. To reduce the Out-Of-Band (OOB) emissions, bandpass filters are often used, though the cost of this improvement in spectral purity means a significant loss in the effective transmitted power.

Solid-state-based amplifiers are much easier to control in terms of OOB, but unfortunately, they cannot provide the high peak power of tubes and, anyway, they represent only a small minority of current operational systems.

Of course, the frequency use and emissions by radars and other transmitting devices are all regulated. Many countries, but not all, adopt the ITU emission standard [210]. Figure 8-1 shows a typical emission mask that might be applied to radar systems.

There is a band over which the radar is designed to transmit. It is fixed in frequency and goes down -40 dB from the peak. Outside, at lower power levels, OOB emissions are permitted with, generally, a roll-off of -20 dB/decade (-40 dB/decade is under consideration). The radar transmissions should not exceed the limits imposed by the mask, but unfortunately unwanted emissions, due to nonlinearity in the transmitter and to the steep rise and fall times of the radar pulses, often occur [184].

An intermediate step toward arbitrary waveform generation is selection of waveforms or waveform parameters from a pre-specified set. Many modern radars already have this capability and a first step toward making cognitive radars a reality could be implementing cognitive processing to choose among the set of allowable waveforms [212].

In passive multisensory radar systems, the cost must be kept low, because this is one of the main reasons that justify their use, despite their poorer performance compared to active systems. Cognitive algorithms implemented on passive systems should then be easy to implement, and not be very demanding in terms of energy and memory usage. Fortunately, the rapid increase in the performance of DSPs, FPGAs and ASICs have made the signal processing more compact and low power [213].

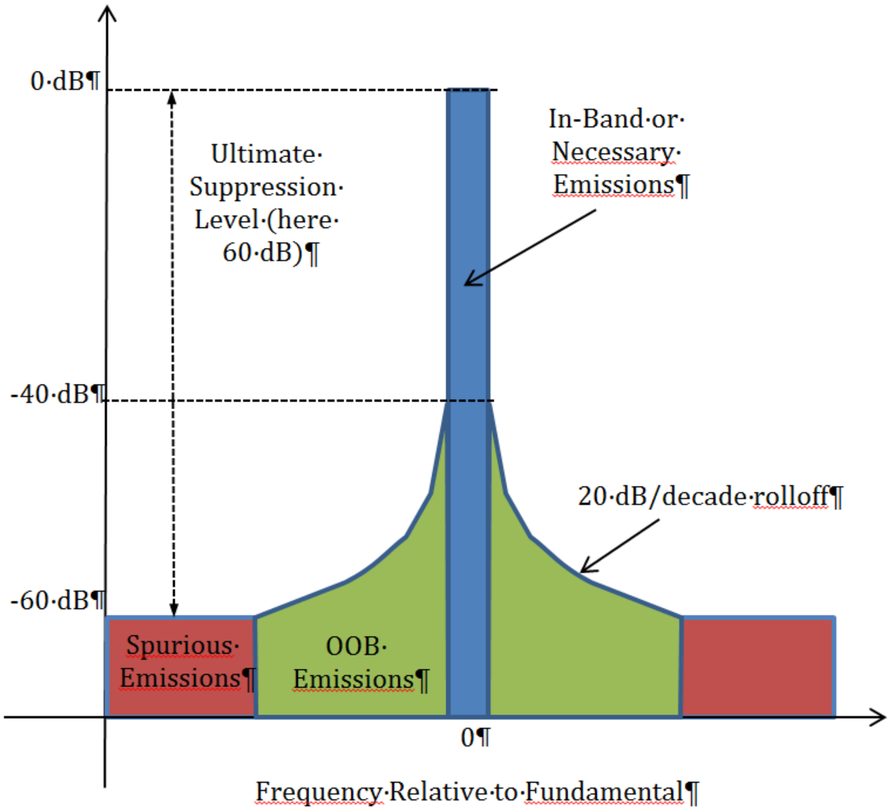


Figure 8-1: Graph of a Generic ITU Spectral Mask, Showing the Required Suppressions Relative to Power at Fundamental (dB) [211].

8.2.4 Legal Issues

Among other things, legal issues are linked to the requirement definitions that determine the responsibility of the system, especially when human safety is concerned such as for autonomous vehicles or AI applications in medicine and so far for defence systems. The confidence of the customer and end-user in the cognitive system is therefore mandatory. This confidence can help to define who, between the customer and the provider-industrial, is responsible in case of any accident due to the failure of the cognitive systems.

There are several ways to acquire this confidence, such as the digital twin of the cognitive system for a first step of comprehension of the system. But this digital twin may not be sufficient in some cases (different environment, different learning datasets, or intentionally corrupted datasets). Moreover, the customer needs to have confidence in the learning datasets as well (linked to the question of the qualification/certification of the learning datasets).

Currently, there is much research underway concerning AI explainability. This research attempts to outline some rules that can assist the legal aspect [214], [215], [216].

In the meantime, depending on the country, some rules/laws are beginning to emerge for autonomous vehicles. These rules take advantage of and return to experience gained from the use of the product prototypes. (Regional definitions of the different autonomous levels of a car may vary).

Finally, it will probably take a long time before every law, and sharing of responsibility will be determined in each country and region, especially in the context of personal safety and sometimes in the context of ethics. AI that assists people to choose their next holiday is definitely different from AI applications for medicine or defence purposes!

Chapter 9 – CONCLUSIONS AND RECOMMENDATIONS

9.1 SUMMARY AND CONCLUSIONS

Cognition has now become an established subject in modern radar systems and signal processing. Despite the level of interest, there has not been clear consensus on the exact definition, nor on the utility and benefit that cognitive processing may provide to military sensing systems. Furthermore, at the outset of this study there had been little or no experimental work to demonstrate cognitive behaviour in a practical way. This study has provided a significant step in addressing both of those issues.

This work has reviewed the different concepts and definitions in the literature and highlighted that a true cognitive system should incorporate *learning*, so that faced with a dynamically changing target scene it will do better a second time. Nevertheless, some workers argue that the term 'fully adaptive radar' is more appropriate, since 'cognitive radar' almost promises too much.

The bulk of the work of the report has been to explore the benefits (and drawbacks) of cognitive processing in a variety of experiments and simulations. The experimental work, in particular, represents some of the first of its kind, and demonstrates true cognitive behaviour. The ability to have several groups working co-operatively, sharing experimental configurations and results, has been of great benefit. However, the work has also highlighted the difficulty of experimental work on cognitive sensing, and there is much more to be done.

9.2 RECOMMENDATIONS

The experimental work of the Task Group will undoubtedly continue beyond the time limit of this Task Group, since strong links have been forged. It is recommended that a further NATO Task Group be initiated to focus on a number of key topics that were identified as important future activities during this Task Group.

The first topic is the role of machine learning techniques in cognitive radar. Although a lot of work is currently underway on machine learning for processing sensor data, the deployment of machine learning techniques in closed-loop cognitive radars and the respective military operational consequences are not well understood.

A second topic is Cognitive Radar Networks. The radars of the future are likely to be distributed, intelligent and spectrally-efficient, so the extension of cognitive techniques to distributed sensing is a natural way forward. However, the means of resource management of a distributed network of this kind still need to be fully understood and developed.

Finally, it is also recommended that a follow on activity continues to provide a platform for performing international collaborative experimental work on cognitive radar systems.

Chapter 10 – REFERENCES

[1] Fuster, J.M. 'The cognit: A network model of cortical representation', International Journal of Psychophysiology, 60(2), pp. 125-132, 2006.

[2] Braisby, N., and Gellatly, A. (eds), Cognitive Psychology, (2nd Ed.), Oxford, UK, University Press, 2012.

[3] Eysenck M.W., and Keane, M.T. Cognitive Psychology: A Student's Handbook, London, UK, Psychology Press, 2015.

[4] Duncker, K., 'On Problem Solving,' Psychological Monographs, 58(270), pp. 1-113, 1945.

[5] Lambert, D. 'A blueprint for higher-level fusion systems', Information Fusion, 10(1), pp. 6-24, 2009.

[6] McCarthy, J. What is artificial intelligence? Professor John McCarthy (Website), 2007. Retrieved from http://jmc.stanford.edu/articles/whatisai/whatisai.pdf. (7 September 2019).

[7] Minsky, M. 'Logical versus analogical or symbolic versus connectionist or neat versus scruffy', AI Magazine, 12, (1), pp. 34-51, 1991.

[8] Russel, S. and Norvig, P. Artificial Intelligence: A Modern Approach (3rd. Edition Ausg.). New Jersey, USA, Prentice Hall, 2009.

[9] McCarthy, J. 'Programs with common sense', in Proc. Symposium on Mechanisation of Thought Processes, pp. 77-84, 1958.

[10] Newell A., and Simon, H.A. 'Computer simulation of human thinking', Science, 134(3495), pp. 2011-2017, 1961.

[11] Newell, A. and Simon, H.A. Human Problem Solving, Englewood Cliffs, New Jersey, USA, Prentice-Hall, 1972.

[12] Shortliffe, E.H., and Buchanan, B.G. 'A model of inexact reasoning in medicine', Mathematical Biosciences, 23, pp. 351-379, 1975.

[13] Anderson, J. Cognitive Psychology and its Implications, W. H. Freeman, New York, 1980.

[14] Binet A., and Simon, Th. 'The development of intelligence in children', L'Annee Psych., 1916.

[15] Stern, W. The Psychological Methods of Testing Intelligence. Baltimore, USA, Warwick and York, 1912.

[16] Wechsler, D. The Measurement of Adult Intelligence, (3rd Ed.). Baltimore, USA, Williams & Wilkins, 1944.

[17] Sternberg, R.J., and Salter, W. Conceptions of intelligence, (R.J. Sternberg Ed.), Handbook of Human Intelligence. Cambridge, UK, Cambridge University Press,1982.

[18] Legg S., and Hutter, M. 'Universal intelligence: a definition of machine intelligence', Minds & Machines, 17(4), pp. 391-444, 2007.

[19] Newell, A., and Simon, H.A. 'Computer science as empirical inquiry: Symbols and search', Communications of the ACM, 19(3), pp. 113-126, 1976.

[20] Haugeland, J. Artificial Intelligence: The Very Idea. Cambridge, USA, MIT Press, 1989.

[21] Vidulich, M., Dominguez, C., Vogel, E., and McMillan, G. (1994). 'Situation awareness: papers and annotated bibliography', Technical Report, Defense Technical Information Center.

[22] Sarter, N.B., and Woods, D.D, 'How in the world did we ever get into that mode? Mode error and awareness in supervisory control', Human Factors, 37(1), pp. 5-19, 1995.

[23] Endsley, M.R. 'Design and evaluation for situation awareness enhancement', in Proc. Human Factors Society 32nd Annual Meeting, pp. 97-101, Santa Monica, USA, 1988.

[24] Wickens, C.D., and Hollands, J.G. Engineering Psychology and Human Performance. New Jersey, USA, Prentice Hall, 1999.

[25] Miller, G.A. 'The magical number seven, plus or minus two: Some limits on our capacity for processing information', Psychological Review, 63(2), pp. 81-97, 1956.

[26] Haykin, S. 'Cognitive Radar: A Way of the Future'; IEEE Signal Processing Magazine, Special Issue on Knowledge-based systems for adaptive radar, 23(1), pp. 30-40, 2006.

[27] Guerci, J.R. 'Cognitive radar: a knowledge-aided fully adaptive approach', Proc. IEEE Int. Radar Conference, pp. 1365-1370, 2010.

[28] Simons, J.A. 'The resolution of target range by echo-locating bats', Journal of the Acoustical Society of America, 54, pp. 157-173, 1973.

[29] Thomas, J.A., Moss, C.F., and Vater, M. Echolocation in Bats and Dolphins, Chicago, USA, The University of Chicago Press, 2004.

[30] Greco, M.S., and Gini, F. 'Analysis and Modeling of Echolocation Signals Emitted by Mediterranean Bottlenose Dolphins', The EURASIP Journal on Advances in Signal Processing (JASP), 2006(1), 2006.

[31] Vespe, M., Jones, G., and Baker, C.J. 'Lesson for radar: waveform diversity in echolocating mammals', IEEE Signal Processing Magazine, Vol.26, no.1, pp. 65-75, 2009.

[32] Guerci, J.R. Cognitive Radar: The Knowledge-Aided Fully Adaptive Approach. Norwood, USA, Artech House, 2010.

[33] Guerci, J.R., Guerci, R.M., Ranagaswamy, M., Bergin, J.S., and Wicks. M.C. 'Cofar: Cognitive fully adaptive radar' IEEE Radar Conference 2014, pp. 0984-0989, 2014.

[34] Haykin, S. Cognitive Dynamic System: Perception-Action Cycle, Radar and Radio, Cambridge, USA, University Press, 2012.

[35] Haykin, S. 'New generation of radar systems enabled with cognition', IEEE Int. Radar Conference, Arlington, USA, 2010.

[36] Haykin, S., Yanbo X., and Setoodeh, P. 'Cognitive radar: Step toward bridging the gap between neuroscience and engineering.' Proceedings of the IEEE 100.11: pp. 3102-3130, 2012.

[37] Martone, A.F. 'Cognitive radar demystified', Radio Science Bulletin, 350, pp. 10-22, 2014.

[38] Charlish A., and Hoffmann, F. 'Cognitive radar management', chapter in Novel Radar Techniques and Applications (R. Klemm, H. Griffiths, W. Koch, Eds.), London, UK, IET, pp. 157-193, 2017.

[39] Charlish, A., Katsilieris, F., Smith, G., and Moo, P. 'Radar resource management architecture and terminology', in Adaptive Radar Resource Management, NATO SET-223 Research Task Group Report, 2018.

[40] White, F.E., 'A model for data fusion', 1st National Symposium on Sensor Fusion, 1988.

[41] Steinberg, A.N., Bowman, C.L., and White, F.E. 'Revisions to the JDL data fusion model', AeroSense '99, pp. 430-441, 1999.

[42] Llinas, J., Bowman, C., Rogova, G., Steinberg, A., Waltz, E., and White, F. 'Revisiting the JDL Data Fusion Model II', 7th International Conference on Information Fusion, 2004.

[43] Kester, L. 'Method for Designing Networking Adaptive Interactive Hybrid Systems', Interactive Collaborative Information Systems, 281, pp. 401-421, 2010.

[44] Smits, F., Huizing, A., van Rossum W., and Hiemstra, P. 'A cognitive radar network: architecture and application to multiplatform radar management', European Radar Conference, pp. 312-315, 2008.

[45] Ender, J., and Brüggenwirth, S., 'Cognitive radar-enabling techniques for next generation radar systems'. Proc. 16th International Radar Symposium (IRS), 2015.

[46] Rasmussen, J. 'Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models', IEEE Transactions on Systems, Man and Cybernetics, 13(3), pp. 257-266, 1983.

[47] Wagner, S. 'Combination of convolutional feature extraction and support vector machines for radar ATR'. 17th International Conference on Information Fusion (FUSION), pp. 1-6, 2014.

[48] Knott, P., Stanko, S., Wilden, H., Gonzalez-Huici, M.A., and Worms, J. 'RADAR systems-technology and challenges', 18th Int Radar Symposium (IRS), Prague, pp. 1-4. 2017. doi: 10.23919/IRS.2017.
8008083

[49] Castañón, D.A. 'Approximate dynamic programming for sensor management', 36th IEEE Conference on Decision and Control, 2, pp. 1202-1207, 1997.

[50] Brüggenwirth, S., and Schulte, A. 'COSA 2-A Cognitive System Architecture with Centralized Ontology and Specific Algorithms', IEEE Int. Conf on Systems, Man, and Cybernetics (SMC), 2012.

[51] Giusti, E., Bacci, A., Stinco, P., Martorella, M., Saverino, A.L., Gini, F., Berizzi, F., and Greco, M.S. 'Cognitive multichannel ISAR imaging for maritime coastal surveillance and ground border control', 6th IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP), Cancun, Mexico, pp. 277-280, 2015. doi: 10.1109/CAMSAP.2015.7383790.

[52] Bacci, A., Martorella, M., Gray, D., and Berizzi, F. ‘Space-doppler adaptive processing for radar imaging of moving targets masked by ground clutter’, IET Radar, Sonar and Navigation, 2015.

[53] Kulpa, K., Samczyński, P., Malanowski, M., Gromek, A., Gromek, D., Gwarek, W., Salski, B., and Tański, G. ‘An advanced SAR simulator of three-dimensional structures combining geometrical optics and full-wave electromagnetic methods’, IEEE Transactions on Geoscience and Remote Sensing, 52(1), pp.776-784, 2014.

[54] Kulpa, K., Samczynski, P., Malanowski, M., Gwarek, W., Salski, B., and Tanski, G.: ‘SAR raw radar simulator combining optical geometry and full-wave electromagnetic approaches’, Proceedings of EuSAR 2012 – 9th European Conference on Synthetic Aperture Radar, Nurnberg, Germany, pp. 24-27, 2012.

[55] Gromek, D., Gromek, A., Kulpa, K., Malanowski, M., Samczynski, P., and Tanski, G. ‘SAR/InSAR raw data simulator using DTM scene definitions’, Proceedings of IRS 2012, Warszawa, Poland, pp. 153-156, 2012.

[56] Metcalf, J., Blunt, S.D., and Himed, B. ‘A machine learning approach to cognitive radar detection’, 2015 IEEE Int. Radar Conference, pp.1405-1411, 2015.

[57] Mellios, E., Kong, D., Webb, M., Doufexi, A., Hilton, G.S., Nix, A.R., and McGeehan, J.P. ‘Impact of Low-Frequency Radar Interference on Digital Terrestrial Television’, IEEE Trans. on Broadcasting, 59(1), pp. 84-95, 2012.

[58] Yucek T., and Arslan, H. ‘A survey of spectrum sensing algorithms for cognitive radio applications’, IEEE Communication Surveys & Tutorials, 11(1), pp. 116-130, 2009.

[59] Stinco, P., Greco, M., and Gini, F. ‘Spectrum sensing and sharing for cognitive radars’, IET Radar, Sonar and Navigation, 10(3), pp. 595-602, 2016.

[60] Stinco, P., Greco, M., Gini, F., and Himed, B. ‘Cognitive radars in spectrally dense environments’, IEEE Aerospace and Electronic Systems Magazine, October, 2016.

[61] Mitchell, A.E., Smith, G.E., Bell, K.L., Duly, A.J., and Rangaswamy, M. ‘Hierarchical fully adaptive radar’, IET Radar, Sonar, and Navigation, Special section on Cognitive Radar, 12(12), pp. 1371-1379, 2018.

[62] Bell, K.L., Baker, C.J., Smith, G.E., Johnson, J., and Rangaswamy, M. ‘Cognitive radar framework for target detection and tracking’, IEEE J. Sel. Top. Signal Process., 9(8), pp. 1427-1439, 2015.

[63] Bell, K.L., Baker, C.J., Smith, G.E., Johnson, J., and Rangaswamy, M. ‘Fully adaptive radar for target tracking part I: single target tracking’, 2014 IEEE Radar Conference, pp. 0303-0308.

[64] Bell, K.L., Johnson, J.T., Smith, G.E., Baker, C.J., and Rangaswamy, M. ‘Cognitive radar for target tracking using a software defined radar system’, 2015 IEEE Radar Conference, pp. 1394-1399.

[65] Fuster, J.M. Cortex and Mind: Unifying Cognition. Oxford, UK, Oxford University Press, 2010.

[66] Steinberg, A.N., Bowman, C.L., and White, F.E. ‘Revisions to the JDL data fusion model’, in Handbook of Multisensor Data Fusion, (M. Liggins II, D. Hall, and J. Llinas Eds.), pp. 65-88. Boca Raton, USA, CRC Press, 2008.

[67] Haykin, S., Xue Y., and Setoodeh, P. 'Cognitive radar: step toward bridging the gap between neuroscience and engineering', Proceedings of the IEEE 2012, 100(11), 2012.

[68] Haykin, S., Fuster, J.M., Findlay, D., and Feng, S. 'Cognitive risk control for physical systems', IEEE Access, 5, pp. 14664-14679, 2017.

[69] Charlish, A., and Hoffmann, F. 'Anticipation in cognitive radar using stochastic control,' in Proc. 2015 IEEE International Radar Conference, Arlington, USA, pp. 1692-1697, 2015.

[70] Mitchell, A.E., Smith, G.E., Bell, K.L., Duly, A.J., and Rangaswamy, M. 'Cost function design for the fully adaptive radar framework', IET Radar, Sonar, and Navigation, Special section on Cognitive Radar, 12(12), pp. 1380-1389, 2018.

[71] Mitchell, A.E., Smith, G.E., Bell, K.L., and Rangaswamy, M. 'Coordinate descent for cognitive radar adaptation', CIE Intl. Conf. Radar, Guangzhou, China, 2016.

[72] Ubeda-Medina L., and Grajal, J. 'Implementation of the fully adaptive radar framework: Practical limitations', 2017 IEEE Radar Conference, pp. 0761-0766, 2017.

[73] Ubeda-Medina L., and Grajal, J. 'Multiple target tracking in the fully adaptive radar framework', 2016 IEEE Statistical Signal Processing Workshop (SSP), pp. 1-5, 2016.

[74] Lee, C., Lehoezky, J., Rajkumar, R., and Siewiorek, D. 'On quality of service optimization with discrete QoS options', Proceedings of the Fifth IEEE Real-Time Technology and Applications Symposium, pp. 276-286, 1999.

[75] Lee, C., Lehoezky, J., Siewiorek, D., Rajkumar, R., and Hansen, J. 'A scalable solution to the multi-resource QoS problem', Proceedings 20th IEEE Real-Time Systems Symposium (Cat. No.99CB37054), pp. 315-326, 1999.

[76] Ghosh, S., Hansen, J., Rajkumar, R., and Lehoczky, J. 'Adaptive QoS optimizations for radar tracking', Proceedings of the 10th International Conference on Real-Time and Embedded Computing Systems, 2004.

[77] Nadjiasngar, R. and Charlish, A. 'Quality of service resource management for a radar network', 2015 IEEE Radar Conference, pp. 344-349, 2015.

[78] Katsilieris, F., Driessen, H., and Yarovoy, A. 'Threat-based sensor management for target tracking', IEEE Trans. Aerosp. Electron. Syst., 51(4), pp. 2772-2785, 2015.

[79] de Groot, T.H., Krasnov, O.A., and Yarovoy, A.G. 'Mission-driven resource management for reconfigurable sensing systems', IEEE Syst. J., 12(2), pp. 1531-1542, 2018.

[80] Manyika, J., and Durrant-Whyte, H.F., Data Fusion and Sensor Management: A Decentralized Information-Theoretic Approach, 1994.

[81] Kreucher, C.M., Kastella, K., and Hero, A.O., III, 'Sensor management using an active sensing approach', Signal Processing, 85(3), pp. 607-624, 2005.

[82] Kreucher, C.M., Hero, A.O., Kastella, K.D., and Morelande, M.R. 'An information-based approach to sensor management in large dynamic networks', Proc. IEEE, 95(5), pp. 978-999, 2007.

[83] Aoki, E.H., Bagchi, A., Mandal, P., and Boers, Y. 'A theoretical look at information-driven sensor management criteria', 14th Int. Conf. Inf. Fusion, 2011.

[84] Katsilieris, F., Boers, Y., and Driessen, H. ‘Optimal search: a practical interpretation of information-driven sensor management’, 5th Int. Conf. Inf. Fusion, 2012.

[85] Castañón, D.A., Mahler, R., Hintz, K.J., Reich, J., Kadar, I., Farooq, M., Kirubarajan, T., Tharmarasa, R., Sathyan, T., and Sinha, A. ‘Issues in resource management with applications to real-world problems’, Proc. SPIE Signal Processing, Sensor Fusion, and Target Recognition XV, 6235, p. 62351O, 2006.

[86] Kreucher, C.M., Hero A.O., and Kastella, K.D. ‘A comparison of task driven and information driven sensor management for target tracking’, Proceedings of the 44th IEEE Conference on Decision and Control, pp. 4004-4009, 2005.

[87] Labreuche, C., Barbaresco, F., Nguyen, D., Guenais T., and Gosselin, F. ‘Multi-criteria aggregation for adaptive multifunction Radar Resource Management performances evaluation’, 2017 18th International Radar Symposium (IRS), pp. 1-10, 2017.

[88] Aittomäki, T., and Koivunen, V. ‘Mismatched filter design and interference mitigation for MIMO radars’, IEEE Transactions on Signal Processing, 65(2), pp. 454-466, 2017.

[89] Rufang, Y., Rongbing, G., Guangfu, T., and Jie, H. ‘Range-Doppler and anti-interference performance of cognitive radar detection waveform’, 12th IEEE International Conference on Electronic Measurement Instruments (ICEMI), 2, pp. 607-612, 2015.

[90] Nieh, J.Y., and Romero, R.A. ‘Adaptive waveform for integrated detection and identification of moving extended target’, 2014 48th Asilomar Conference on Signals, Systems and Computers, pp. 1473-1478, 2014.

[91] Nieh, J.Y., and Romero, R.A. ‘Integrated range-Doppler map and extended target identification with adaptive waveform for cognitive radar’, IEEE Int. Radar Conference, pp. 1644-1649, 2015.

[92] Woodward, P.M. Probability and Information Theory with Applications to Radar. London, UK, Pergamon Press, 1953. Norwood, USA, Artech House,1980.

[93] Bell, M.R. ‘Information theory and radar waveform design’, IEEE Transactions on Information Theory, 39(5), pp. 1578-1597, 1993.

[94] Grossi, E., and Lops, M. ‘Space-time code design for MIMO detection based on Kullback-Leibler divergence’, IEEE Transactions on Information Theory, 58(6), pp. 3989-4004, 2012.

[95] Li, Y., Li, H., Sun, Y., and Zheng, N. ‘Waveform design based on J-divergence for MIMO radar detection’, 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), pp. 971-975, 2017.

[96] Naghsh, M.M., Modarres-Hashemi, M., Shahbaz Panahi, S., Soltanalian M., and Stoica, P. ‘Unified optimization framework for multi-static radar code design using information-theoretic criteria’, IEEE Transactions on Signal Processing, 61(21), pp. 5401-5416, 2013.

[97] Naghsh, M.M., Modarres-Hashemi, M., Sheikhi, A., Soltanalian M., and Stoica, P. ‘Unimodular code design for MIMO radar using Bhattacharyya distance’, IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 5282-5286, 2014.

[98] Kailath, T. ‘The divergence and Bhattacharyya distance measures in signal selection’, IEEE Transactions on Communication Technology, 15(1), pp. 52-60, 1967.

[99] Laz, E. ‘Optimal cost allocation in centralized and decentralized detection systems using Bhattacharyya distance’, IEEE Radar Conference, pp. 1170-1173, 2017.

[100] Zheng, L., Lops, M., Wang, X., and Grossi, E. ‘Joint design of overlaid communication systems and pulsed radars’, IEEE Transactions on Signal Processing, 66(1), pp.139-154, 2018.

[101] Aittomäki, T., Chepuri, S.P., and Koivunen, V. ‘Dynamic transmit power allocation for distributed MIMO radar target detection’, IEEE 10th Sensor Array and Multichannel Signal Processing Workshop (SAM), Sheffield, UK, pp. 282-286, 2018.

[102] Romero, R.A., Bae, J., and Goodman, N.A. ‘Theory and application of SNR and mutual information matched illumination waveforms’, IEEE Transactions on Aerospace and Electronic Systems, 47(2), pp. 912-927, 2011.

[103] Wang, L., Wang, H.B., and Chen, M.Y. ‘Cognitive radar waveform design for multiple targets based on information theory’, CIE International Conference on Radar, pp1-5, 2016.

[104] Romero, R., and Goodman, N.A. ‘Waveform design in signal-dependent interference and application to target recognition with multiple transmissions,’ IET Radar, Sonar, and Navigation, 3(4), pp. 328-340, 2009.

[105] Bica, M., Huang, K., Koivunen, V., and Mitra, U. ‘Mutual information based radar waveform design for joint radar and cellular communication systems’, IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Shanghai, pp. 3671-3675, 2016.

[106] Chen, C.Y., and Vaidyanathan, P.P. ‘MIMO radar waveform optimization with prior information of the extended target and clutter’, IEEE Transactions on Signal Processing, 57(9), pp. 3533-3544, 2009.

[107] Yang Y., and Blum, R. ‘MIMO radar waveform design based on mutual information and minimum mean-square error estimation’, IEEE Trans. Aerospace and Electronic Systems, 43(1), pp. 330-343, 2007.

[108] Tang, B., Tang, J., and Peng, Y. ‘MIMO radar waveform design in colored noise based on information theory’, IEEE Transactions on Signal Processing, 58(9), pp. 4684-4697, 2010.

[109] Leshem, A., Naparstek, O., and Nehorai, A. ‘Information theoretic adaptive radar waveform design for multiple extended targets’, IEEE Journal of Selected Topics in Signal Processing, 1(1), pp. 42 55, 2007.

[110] Smith, G.E., Baker, C.J., and Li, G. ‘Coupled echoic flow for cognitive radar sensing’, IEEE Radar Conference, Ottawa, Canada, pp. 1-6, 2013.

[111] Baker, C.J., Smith, G.E., and Balleri, A., et al.: ‘Biomimetic echolocation with application to radar and sonar sensing’, Proceedings of the IEEE, 102(4), pp.447-458, 2014.

[112] Goodman, N.A., Venkata, P.R., and Neifeld, M.A. ‘Adaptive waveform design and sequential hypothesis testing for target recognition with active sensors’, IEEE Journal of Selected Topics in Signal Processing, 1(1), pp.105-113, 2007.

[113] Balleri, A., Griffiths, H.D., and Baker, C.J. Biologically-Inspired Radar and Sonar: Lessons from Nature, Scitech Publishing IET, UK, 2017.

[114] Reich, G.M., Antoniou, M., and Baker, C.J. 'Frequency-dependent target localization'. IET Radar Conference, Belfast, 2017.

[115] Reich, G.M., Antoniou, M., and Baker, C.J. 'Bio-inspired techniques for target localization', in Proc. IEEE Radar Conference, Oklahoma City, 2018.

[116] Reijniers, J., and Peremans, H. 'Biomimetic sonar system performing spectrum-based localization', IEEE Transactions on Robotics, 23(6), pp.1151-1159, 2007.

[117] Thaler, L., Reich, G., and Zhang, X., et al. 'Mouth-clicks used by blind expert human echolocators – signal description and model based signal synthesis', PLoS Computational Biology, 13(8), 2017.

[118] Siemers, B.M., and Schnitzler, H.U. 'Natterer's bat (Myotis nattereri Kuhl, 1818) hawks for prey close to vegetation using echolocation signals of very broad bandwidth', Behav Ecol Sociobiol, 47(6), pp.400-412, 2000.

[119] Foote, K.G., and Simmons, J.A. 'Bat sonar and the role of frequency diversity', J. Acoust. Soc. Am., 119(5), pp.3318-3318, 2006.

[120] Ibsen, S.D., Au, W.W.L., and Nachtigall, P.E., et al. 'Functional bandwidth of an echolocating Atlantic bottlenose dolphin (Tursiops truncatus)', J Acoust Soc Am, 125(2), pp.1214-1221, 2009.

[121] Jakobsen, L., Olsen, M.N., and Surlykke, A. 'Dynamics of the echolocation beam during prey pursuit in aerial hawking bats', Proc Natl Acad Sci U S A, 112(26), pp.8118-8123, 2015.

[122] Kolarik, A.J., Cirstea, S., and Pardhan, S., et al. 'A summary of research investigating echolocation abilities of blind and sighted humans', HearRes, 310, pp.60-68, 2014.

[123] Noggle, C.A. 'Auditory Cortex'. (Goldstein, S., Naglieri, J.A. Eds.), Encyclopedia of Child Behavior and Development, Springer, US, pp. 171-172, 2011.

[124] Woodworth, R.S. 'Hearing'. In: Experimental Psychology / Robert S. Woodworth. Methuen, pp. 501-538, 1950.

[125] [126] Feddersen, W.E., Sandel, T.T., and Teas, D.C., et al. 'Localization of high-frequency tones', J. Acoust. Soc. Am., 29(9), pp.988-991, 1957.

[126] Freedman, S.J., and Fisher, H.G. 'The role of the pinna in auditory localization', (Freedman, S.J., Ed.), The Neuropsychology of Spatially Oriented Behavior, Dorsey series in Psychology. Homewood, USA, Dorsey Press, pp. 135-152, 1968.

[127] Hebrank, J., and Wright, D. 'Spectral cues used in the localization of sound sources on the median plane', J. Acoust. Soc. Am., 56(6), pp.1829-1834, 1974.

[128] Middlebrooks, J.C., and Green, D.M. 'Sound Localization by Human Listeners', Annual Review of Psychology, 42(1), pp.135-159, 1991.

[129] Wightman, F.L., and Kistler, D.J. 'Sound Localization'. In R.R. Fay, A.N. Popper, and W.A. Yost, Eds.), Human Psychophysics, Springer Handbook of Auditory Research, Springer Verlag, New York, NY. 3, pp. 155-192, 1993. Retrieved from https://doi.org/10.1007/978-1-4612-2728-1_5.

[130] Blauert, J. 'Evaluating nonidentical ear input signals'. In: Spatial hearing: the psychophysics of human sound localization, Cambridge, USA, MIT Press, pp. 137-177, 1997.

[131] Shinn Cunningham, B.G., Santarelli, S., and Kopco, N. 'Tori of confusion: Binaural localization cues for sources within reach of a listener', J. Acoust. Soc. Am., 107(3), pp.1627-1636, 2000.

[132] Kuhn, G.F. 'Model for the interaural time differences in the azimuthal plane', J. Acoust. Soc. Am., 62(1), pp.157-167, 1977.

[133] Algazi, V.R., Duda, R.O., and Thompson, D.M., et al. 'The CIPIC HRTF database'. IEEE Workshop on the Applications of Signal Processing to Audio and Acoustics, New York, USA, pp. 99-102, 2001.

[134] Moo, P., and Ding, Z. Adaptive Radar Resource Management. Cambridge, USA Academic Press, 2015.

[135] Bratley, P., Florian, M., and Robillard, P. 'Scheduling with earliest start and due date constraints', Nav. Res. Logist. Q., 18(4), pp. 511-519, 1971.

[136] Zabinsky, Z.B. 'Random search algorithms', Wiley Encyclopedia of Operations Research and Management Science, 2011. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1002/9780470400531.eorms0704.

[137] Qu, Z., Ding, Z., and Moo, P. 'A radar task scheduling method using random shifted start time with the EST algorithm', in Proc. 2019 IEEE Radar Conference, Boston, USA, 2019.

[138] Sutton, R.S., and Barto, A.G. (2018), Reinforcement learning: an introduction. Cambridge, USA, MIT Press.

[139] Bottou, L. 'Large-scale machine learning with stochastic gradient descent', Proceedings of International Conference on Computational Statistics (COMPSTAT), pp. 177-186, 2010.

[140] Qu, Z., Ding, Z., and Moo, P. 'A machine learning radar scheduling method based on the EST algorithm', in Proc. 2019 International Radar Symposium, 2019.

[141] Shaghaghi, M., Adve, R.S., and Ding, Z. 'Multifunction cognitive radar task scheduling using Monte Carlo tree search and policy networks', IET Radar, Sonar & Navigation, 12(12), pp. 1437-1447, 2018.

[142] Silver, D., Huang, A., and Maddison, C. et al., 'Mastering the game of Go with deep neural networks and tree search', Nature, 529 (7587), pp. 484-489, 2016.

[143] Oechslin, R., Aulenbacher, U., Rech, K., Hinrichsen, S., Wieland S., and Wellig, P. 'Cognitive radar parameter optimization in a congested spectrum environment', IET Radar Conference, Belfast, UK, 2017.

[144] Oechslin, R., Smith, G.E., Aulenbacher, U., Rech, K., Hinrichsen S., and Bell, K.L. 'Cognitive radar testbed development', Asilomar Conference on Signals, Systems and Computers, Monterey, USA, 2016, Retrieved from https://www.researchgate.net/publication/316739052_Cognitive_Radar_Testbed_Development.

[145] Oechslin, R., Wellig, P., Hinrichsen, S., Wieland, S., Aulenbacher, U., and Rech, K. 'Cognitive radar experiments with CODIR', 2018 IEEE Radar Conference, pp. 0218-0223, 2018.

[146] Smith, G.E., Cammenga, Z., Mitchell, A., Bell, K.L., Johnson, J.T., Rangaswamy, M., and Baker, C.J. 'Experiments with cognitive radar', IEEE Aerospace and Electronic Systems Magazine, Special issue on Waveform Diversity: Part II, Vol. 31, no. 12, pp. 34-46, 2016.

[147] Oechslin, R., Wieland, S., Hinrichsen, S., Aulenbacher, U., and Wellig, P. 'Cognitive radar performance analysis with different types of targets', IEEE Radar Conference, Boston, USA, 2019.

[148] Ravenscroft, B., and Owen, J.W., Jakabosky, S.D., Martone, A.F. and Sherbondy, K.D., 'Experimental demonstration and analysis of cognitive spectrum sensing and notching for radar,' IET Radar, Sonar & Navigation, 12(12), pp. 1466-1475, Dec 2018.

[149] Jakabosky, J., Blunt, S.D., and Himed, B. 'Waveform design and receive processing for nonrecurrent nonlinear FMCW radar', IEEE Intl. Radar Conference, Washington, DC, 11-15 May 2015.

[150] Jakabosky, J., Blunt, S.D., and Himed, B. 'Spectral-shape optimized FM noise radar for pulse agility', IEEE Radar Conference, Philadelphia, PA, 2-6 May 2016.

[151] Frost, S.W., Rigling, B. 'Sidelobe predictions for spectrally-disjoint radar waveforms', IEEE Radar Conference, Atlanta, GA, May 2012.

[152] Martone, A.F., Ranney, K.I., Sherbondy, K., Gallagher, K.A., and Blunt, S. 'Spectrum allocation for noncooperative radar coexistence', IEEE Transactions on Aerospace and Electronic Systems, Vol. 54, No.1, Feb 2018, pp. 90-105.

[153] Johnston, A. 'Improvements to a pulse compression radar matched filter', Radio and Electronic Engineer, vol. 53, no. 4, pp. 138-140, Apr 1983.

[154] Jakabosky, J., Blunt, S.D., and Martone, A. 'Incorporating hopped spectral gaps into nonrecurrent nonlinear FMCW radar emissions', IEEE International Workshop Computational Advances in Multi-Sensor Adaptive Processing, Cancun, Mexico, Dec. 2015.

[155] Jakabosky, J., Ravenscroft, B., Blunt, S.D., and Martone, A. 'Gapped spectrum shaping for tandem-hopped radar/communications and cognitive sensing', IEEE Radar Conference, Philadelphia, PA, May 2016.

[156] Blunt, S.D., Mokole, E.L., 'An overview of radar waveform diversity, IEEE AESS Systems Magazine, vol. 31, no. 11, pp. 2-42, Nov 2016.

[157] Blunt, S.D., Cook, M., Jakabosky, J., de Graaf, J., and Perrins, E. 'Polyphase-coded FM (PCFM) radar waveforms, part I: implementation', IEEE Trans. Aerospace & Electronic Systems, vol. 50, no. 3, pp. 2218-2229, July 2014.

[158] Higgins, T., Webster, T., and Shackelford, A.K. 'Mitigating interference via spatial and spectral nulling', IET Radar, Sonar & Navigation, vol.8, no.2, pp.84-93, Feb 2014.

[159] Mohr, C.A., Blunt, S.D. 'Analytical spectrum representation for physical waveform optimization requiring extreme fidelity', IEEE Radar Conference, Boston, MA, 22-26 Apr 2019.

[160] Ravenscroft, B., Owen, J.W., Blunt, S.D., Martone, A.F. and Sherbondy, K.D. 'Optimal mismatched filtering to address clutter spread from intra-CPI variation of spectral notches', IEEE Radar Conference, Boston, MA, 22-26 Apr 2019.

[161] Owen, J.W., Ravenscroft, B., and Blunt, S.D. 'Devoid clutter capture and filling (DeCCaF) to compensate for intra-CPI spectral notch variation', submitted to International Radar Conference, Toulon, France, Sept. 2019.

[162] Grossi, E., Lops, M., Venturino, L., Zappone, A. 'Opportunistic Radar in IEEE 802.11ad Networks', IEEE Transactions on Signal Processing, Vol. 66 , No. 9, pp. 2441-2454, 2018.

[163] Chiriyath, A.R., Paul, B., and Bliss, D.W. 'Radar-communications convergence: coexistence, cooperation, and co-Design', IEEE Transactions on Cognitive Communications and Networking, 3(1), pp. 1-12, 2017.

[164] Hassanien, A., Amin, M.G., Zhang, Y.D., and Ahmad, F. 'Signaling strategies for dual-function radar communications: Sn overview', IEEE AES Magazine, vol.31, no.10, pp. 36-45, 2016.

[165] Blunt, S.D., Cook, M.R., and Stiles, J., 'Embedding information into radar emissions via waveform implementation', Proc. Int. Waveform Diversity and Design Conf., Niagara Falls, Canada, Aug. 2010, pp. 195-199.

[166] Ahmed, A., Zhang, Y.D., and Himed, B. 'Multi-user dual-function radar-communications exploiting sidelobe control and waveform diversity', IEEE Radar Conference 2018, pp. 0698-0702.

[167] Alaya-Feki, A.B.H., Jemaa, S.B., Sayrac, B., Houze, P., and Moulines, E. 'Informed spectrum usage in cognitive radio networks: Interference cartography', Proc. PIMRC Conf., Cannes, France, pp. 1-5, 2008.

[168] Kim S.-J., and Giannakis, G.B. 'Cognitive radio spectrum prediction using dictionary learning', Proc. IEEE Global Commun. Conf., Atlanta, USA, pp. 3206-3211, 2013.

[169] Bazerque, J.A., Mateos, G., and Giannakis, G.B. 'Group-lasso on splines for spectrum cartography', IEEE Trans. Signal Process., 59(10), pp. 4648-4663, 2011.

[170] Yilmaz, H.B., Tugcu, T., Alagöz, F., and Bayhan, S. 'Radio environment map as enabler for practical cognitive radio networks', IEEE Communications Magazine, Vol. 51, Issue 12, pp 162-169, 2013.

[171] Romero, D., López-Valcarce, S.J.K., and Giannakis, G.B. 'Spectrum cartography using quantized observations', IEEE Int. Conf. Acoust. Speech and Signal Process., pp. 3252-3256, 2015.

[172] Melvasalo, M., Lunden, J., and Koivunen, V. 'Spectrum maps for cognition and co-existence of communication and radar systems', 2016 Conference Record of the 50th Asilomar Conference on Signals, Systems and Computers, 2016.

[173] Melvasalo, M., and Koivunen, V. 'Using spectrum maps for surveillance avoiding path planning', 2018 IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2018.

[174] Paul, B., Chiriyath, A.R., and Bliss, D.W. 'Survey of RF communications and sensing convergence research', IEEE Access, 5, pp. 252-270, 2017.

[175] Huang, K.W., Bica, M., Mitra, U., and Koivunen, V. 'Radar waveform design in spectrum sharing environment: coexistence and cognition', 2015 IEEE Radar Conference, pp.1698-1703, 2015.

[176] Bica, M. Radar-Communications Systems Coexistence and Agile Multicarrier Radars, Doctoral Thesis, Department of Signal Processing and Acoustics, School of Electrical Engineering, Aalto University, Espoo, Finland, 2018.

[177] Geng, Z., Deng, H., and Himed, B. 'Adaptive radar beamforming for interference mitigation in radar-wireless spectrum sharing', IEEE Signal Processing Letters, 22(5), pp. 484-488, 2015.

[178] Bica, M., Huang, K., Mitra U., and Koivunen, V. 'Opportunistic radar waveform design in joint radar and cellular communication cystems', 2015 IEEE Global Communications Conference (GLOBECOM), San Diego, USA, pp. 1-7..

[179] Sen S., and Nehorai, A. 'Adaptive design of OFDM radar signal with improved wideband ambiguity function', IEEE Trans. Signal Process., 58(2), pp. 928-933, 2010.

[180] Levanon N., and Mozeson, E. Radar Signals, New York, USA, Wiley, pp. 327-372, 2004.

[181] Cui, Y., Koivunen, V., Jing, X. 'Interference alignment based spectrum sharing for MIMO radar and communication systems', 2018 IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2018.

[182] Wang, X., Hassanien, A., and Amin, A.G. 'Dual-function MIMO radar communications system design via sparse array optimization', IEEE Trans. Aerospace and Electronic Systems, 55(3), pp. 1213-1226, 2019.

[183] Mahal, J.A., Khawar, A., Abdelhadi, A., and Clancy, T.C. 'Spectral coexistence of MIMO radar and MIMO cellular system', IEEE Trans. Aerospace and Electronic Systems, 53(2), pp. 655-668, 2017.

[184] Griffiths, H.D., Cohen, L., Watts, S., Mokole, E., Baker, C., Wicks, M., and Blunt, S. 'Radar spectrum engineering and management: technical and regulatory issues', Proceedings of the IEEE, 103(1), pp. 85-102, 2015.

[185] Datla, D., Rajbanshi, R., Wyglinski, A., and Minden, G. 'An adaptive spectrum sensing architecture for dynamic spectrum access networks,' IEEE Trans. Wireless Comm., 8(8), pp. 4211-4219, 2009.

[186] Reich, G., Antoniou, M., and Baker, C.J. 'Biologically-inspired wideband target localization,' IET Radar, Sonar & Navigation, 12(12), pp. 1410-1418, 2018.

[187] Farley, B., McGrath, J., and Erdmann, C. 'An all-programmable 16-nm RFSoC for digital-RF communications,' IEEE Micro, 38(2), pp. 61-71, 2018.

[188] Olsson III, R.H., Bunch, K., Gordon, C., and Zhou, N. 'Creating a universal radio frequency front-end for elemental digital beam formed phased arrays,' in Proc. 2016 IEEE Intl. Symp. on Phased Array Syst. and Tech., Boston, USA, pp. 1-4, 2016.

[189] Epstein, B., Olsson, R.H., and Bunch, K. 'Arrays at commercial timescales: addressing development and upgrade costs of phased arrays,' in Proc. 2018 IEEE Radar Conf., Oklahoma City, USA, pp. 327-332, 2018.

[190] Pillai, S.U., Oh, H.S., Youla, D.C., and Guerci, J.R. 'Optimal transmit-receiver design in the presence of signal-dependent interference and channel noise,' IEEE Trans. Info Theory,' 46(2), pp. 577-584, 2000.

[191] Dunn, Z., Yeary, M., Fulton, C., and Goodman, N.A. 'Wideband digital predistortion of solid-state radar amplifiers,' IEEE Trans. Aerospace and Electronic Syst., 52(5), pp. 2452-2466, 2016.

[192] Hasan, M., and Saeedi, S., et al., 'Design methodology of N-path filters with adjustable frequency, bandwidth, and filter shape,' IEEE Trans. Microwave Theory and Techniques, 66(6), pp. 2775-2790, 2018.

[193] Qin, P., Wei, F., and Guo, Y. 'A wideband-to-narrowband tunable antenna using a reconfigurable filter,' IEEE Trans. Antennas and Propagation, 63(5), pp. 2282-2285, 2015.

[194] Huff, G.H., Feng, J., Zhang, S., and Bernhard, J.T. 'A novel radiation pattern and frequency reconfigurable single turn square spiral microstap antenna,' IEEE Microwave and Wireless Components Letters,' 13(2), pp. 57-59, 2003.

[195] Wagner, S., Barth, K., and Bruggenwirth, S. 'A deep learning SAR ATR system using regularization and prioritized classes,' in Proc. 2017 IEEE Radar Conference, Seattle, USA, pp. 772-777, 2017.

[196] Rabideau, D.J., and Parker, P. 'Ubiquitous MIMO multifunction digital array radar,' in Proc. Thirty-Seventh Asilomar Conference on Signals, Systems and Computers, Monterey, USA, pp. 1057-1064, 2003.

[197] Fulton, C., and Yeary, M., et al., 'Digital phased arrays: challenges and opportunities,' Proc. of the IEEE, 104(3), pp. 487-503, 2016.

[198] Talisa, S.H., and O'Haver, K.W., et al., 'Benefits of digital phased array radar,' Proc. of the IEEE, 104(3), pp. 530-543, 2016.

[199] Palmer, R.D., and Fulton, C.J., et al., 'The 'Horus' radar – an all-digital polarimetric phased array radar for multi-mission surveillance,' in Proc. 35th Conf. on Environmental Information Processing Technologies, 2019.

[200] Fagan, R., Robey, F.C., and Miller, L. 'Phased array radar cost reduction through the use of commercial RF systems on a chip,' in Proc. 2018 IEEE Radar Conf., Oklahoma City, USA, pp. 935-939, 2018.

[201] Horne, C., Ritchie, M., and Griffiths, H. 'Proposed ontology for cognitive radar', IET Radar, Sonar, and Navigation, Special section on Cognitive Radar, 12(12), pp.1363-1370, 2018.

[202] Nouaille, J. 'Digital twins applied for embedded electromagnetic sensors development', ITEC 2018, 2018.

[203] Christiansen, J.M., Smith, G.E., and Olsen, K.E. 'USRP based cognitive radar testbed', 2017 IEEE Radar Conference, pp. 1115-1118, 2017.

[204] Christiansen, J.M., Olsen, K.E., and Smith, G.E. 'Fully adaptive radar for track update control', 2018 IEEE Radar Conference, pp. 0400-0404, 2018.

[205] Charlish, A., and Katsilieris, F. 'Array radar resource management', chapter in Novel Radar Techniques and Applications (R. Klemm, H. Griffiths, W. Koch, Eds.), IET, pp. 135-172, 2017.

[206] Ubeda-Medina, L., Garcia-Fernandez, A.F., and Grajal, J. 'Robust sensor parameter selection in fully adaptive radar using a sigma-point Gaussian approximation', 2018 IEEE Radar Conference, pp. 0263-0268, 2018.

[207] Baylis, C., Dunleavy, L., Lardizabal, S., Marks II, R.J., and Rodriguez, A. 'Efficient optimization using experimental queries: A peak-search algorithm for efficient load-pull measurement', J. Adv. Comput. Intell. Infor., 15(1), pp. 13-20, 2011.

[208] Baylis, C., Fellows, M., Cohen, L., and Marks II, R.J. 'Solving the spectrum crisis', IEEE Microwave Magazine, pp. 94-107, 2014.

[209] Jakabosky, J., Blunt, S.D., Cook, M.R., Stiles, J., and Seguin, S.A. 'Transmitter-in-the-loop optimization of physical radar emission', 2012 IEEE Radar Conference, Atlanta, GA, USA, May 2012.

[210] International Telecommunication Union (2012), Radio regulations. (Online). Retrieved from http://www.itu.int/pub/R-REG-RR-2012.

[211] Greco, M.S., Gini, F., Stinco P., and Bell, K. 'Cognitive radars: on the road to reality: progress thus far and possibilities for the future', IEEE Signal Processing Magazine, 35(4), pp. 112-125, 2018.

[212] Blunt S.D., and Mokole, E.L. 'An overview of radar waveform diversity', IEEE Aerospace and Electronic Systems Magazine, 31(11), pp. 2-42, 2016.

[213] Inggs, M. 'Passive Coherent Location as Cognitive Radar', IEEE AES Magazine, pp. 12-17, 2010.

[214] Dam, H., Tran, T., and Ghose, A. 'Explainable Software Analytics' ICSE'18 NIER, Gothenburg, Sweden, 2018.

[215] Doshi-Velez, A.F., and Kim, B. 'Towards a rigorous science of interpretable machine learning', 2017.

[216] Molnar, C. Interpretable Machine Learning' A Guide for Making Black Box Models Explainable, Retrieved from https://christophm.github.io/interpretable-ml-book/index.html. (22 February 2019).

Annex A – LIST OF MEETINGS

First Meeting	16 – 17 February 2015	CSO Headquarters, Neuilly-sur-Seine, FR
Second Meeting	21 – 22 September 2015	NRL, Washington DC, USA
Third Meeting	29 Feb – 01 March 2016	Australian High Commission, London, UK
Fourth Meeting	9 – 10 November 2016	Naval Postgraduate School, Monterey, CA, USA
Fifth Meeting	6 – 7 March 2017	Tec^Edge, Dayton, OH, USA
Sixth Meeting	19 – 20 October 2017	Fraunhofer FKIE, Wachtberg, Germany
Seventh Meeting	22 April 2018	Cox Convention Center, Oklahoma City, OK, USA
Eighth Meeting	21 – 22 January 2019	CSO Headquarters, Neuilly-sur-Seine, FR

Annex B – BIBLIOGRAPHY OF WORK/OUTPUTS OF SET-227

The work of the Task Group and its participants, and of the SET-227 Task Group, has resulted in a substantial number of publications, including Special Sessions and Tutorials at international conferences and a Special Issue in an international journal. The following provides a listing of these outputs at the time of writing of this report:

Books and Book Chapters

1) Charlish, A., and Katsilieris, F., 'Array radar resource management', chapter in Novel Radar Techniques and Applications (R. Klemm et al. eds.), IET, 2017, pp. 135-172.

2) Charlish, A., and Hoffmann, F. 'Cognitive radar management', chapter in Novel Radar Techniques and Applications (R. Klemm et al. eds.), IET, 2017, pp. 157-193.

Journal

1) Stinco, P., Greco, M., Gini, F., and Himed, B., "Cognitive radars in spectrally dense environments," IEEE Aerospace and Electronic Systems Magazine, October 2016.

2) Smith, G.E., Cammenga, Z., Mitchell, A., Bell, K.L., Johnson, J.T., Rangaswamy, M., and Baker, C.J., "Experiments with cognitive radar," IEEE Aerospace and Electronic Systems Magazine, special issue on Waveform Diversity: Part II, vol. 31, no. 12, pp. 34-46, Dec. 2016.

3) Aittomäki, T., and Koivunen, V., "Mismatched filter design and interference mitigation for MIMO radars," IEEE Transactions on Signal Processing 65 (2), pp. 454-466, 2017.

4) Greco, M.S., Gini, F., Stinco, P., and Bell, K., "Cognitive radars: on the road to reality: progress thus far and possibilities for the future," IEEE Signal Processing Magazine, vol.35, no.4, pp. 112-125, July 2018.

5) Horne, C., Ritchie, M., and Griffiths, H., "Proposed ontology for cognitive radar," IET Radar, Sonar, and Navigation, vol. 12, no. 12, pp. 1363-1370, December 2018.

6) Mitchell, A.E., Smith, G.E., Bell, K.L., Duly, A.J., and Rangaswamy, M., "Hierarchical fully adaptive radar," IET Radar, Sonar, and Navigation, special section on Cognitive Radar, vol.12, no.12, pp. 1371-1379, December 2018.

7) Mitchell, A.E., Smith, G.E., Bell, K.L., Duly, A.J., and Rangaswamy, M., "Cost function design for the fully adaptive radar framework," IET Radar, Sonar, and Navigation, special section on Cognitive Radar, vol. 12, no. 12, pp. 1380-1389, December 2018.

8) Palamà, R., Griffiths, H.D. and Watson, F., "Joint dynamic spectrum access and target-matched illumination for cognitive radar," IET Radar, Sonar and Navigation, vol.13, no.5, pp. 750-759, May 2019.

9) Patel, J., Fioranelli, F., Ritchie, M.R. and Griffiths, H.D., "Fusion of deep representations in multistatic radar networks to counteract the presence of synthetic jamming," IEEE Sensors Journal, vol.19, no. 15, pp. 6362-6370, August 2019.

Conference/Workshop

1) Horne, C., Ritchie, M., Griffiths, H.D., Hoffmann, F. and Charlish, A., "Experimental validation of cognitive radar anticipation using stochastic control," 50th Asilomar Conference on Signals, Systems and Computers, 6 – 9 November 2016.

2) Griffiths, H.D., Charlish, A. and Goodman, N., "Challenge problems in cognitive radar," 50th Asilomar Conference on Signals, Systems and Computers, 6 – 9 November 2016.

3) T. Aittomäki, S.P. Chepuri and V. Koivunen, "Dynamic transmit power allocation for distributed MIMO radar target detection," IEEE 10th Sensor Array and Multichannel Signal Processing Workshop (SAM), Sheffield, 2018, pp. 282-28.

4) J.M. Christiansen, G.E. Smith and K.E. Olsen, "USRP based cognitive radar testbed," 2017 IEEE Radar Conference, pp. 1115-1118.

5) Horne, C.P., Brown, J., Smith, G.E., Mitchell, A.E. and Griffiths, H.D., "Experimental spectral coexistence investigation for cognitive radar," IET Int. Radar Conference RADAR 2017, Belfast, 23 – 26 October 2017.

6) J.M. Christiansen, K.E. Olsen and G.E. Smith, "Fully adaptive radar for track update control," 2018 IEEE Radar Conference, Oklahoma City OK, pp. 0400-0404, 23 – 27 April 2018.

7) Jones, A., Horne, C., Griffiths, H.D Smith, G., Mitchell, A. and John-Baptiste, P., "Experimentation of an adaptive and autonomous RF signalling strategy for detection," IEEE Radar Conference 2018, pp. 1213-1218, Oklahoma City OK, 23 – 27 April 2018.

8) Oechslin, R., Wellig, P., Hinrichsen, S., Wieland, S., Aulenbacher, U., and Rech, K., "Cognitive radar experiments with CODIR," 2018 IEEE Radar Conference, pp. 0218-0223.

9) Oechslin, R., Wellig, P., Hinrichsen, S., Aulenbacher, U., and Wellig, P., "Cognitive radar performance analysis with different types of targets," IEEE Radar Conference, Boston, April 2019.

10) Palamà, R., Griffiths, H.D. and Watson, F., "A radar architecture for joint dynamic spectrum access and target-matched illumination," IEEE Radar Conference 2017, Seattle WA, pp. 1472-1477, 8 – 12 May 2017

11) Reich, G.M., Antoniou, M., and Baker, C.J., "Frequency-dependent target localization," IET Radar Conference, Belfast, 2017.

12) Reich, G.M., Antoniou, M., and Baker, C.J., "Bio-inspired techniques for target localization," IEEE Radar Conference, Oklahoma City, 23 – 27 April 2018.

Journal Special Issue

1) IET Radar, Sonar & Navigation special section on "Cognitive Radar," vol.12, no.12, December 2018.

Special Conference Session

1) Special Session on Cognitive Radar: 50th Asilomar Conference on Signals, Systems and Computers, Asilomar CA, 6 – 9 November 2016.

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14. Abstract

For NATO's military and peacekeeping operations radar is used in virtually all applications, including air defence, weapon locating, surveillance, reconnaissance and target acquisition. Radar systems are able to function during day and night, have relative immunity to weather, and can even provide over the horizon coverage. They can provide high-resolution imagery, detect, localize and track targets at all ranges. The emerging theme of cognitive radar sensing has roots in mammalian cognition. It embraces both the "perception-action cycle" and the more explicit generation and exploitation of memories. Applying the ideas of cognition to radar has the potential to usher in a new era of sensing, not just improving the performance of existing radar systems but opening up whole new capability areas. The objectives of this Task Group have been to develop and conduct experiments and theoretical investigations to illustrate the benefits and challenges of enabling cognition-based capabilities in radar systems. Several of the participating groups have conducted experiments on cognitive, and the co-operation afforded by the task group has allowed ideas, experiences and results to be shared. At the outset of this study there had been little or no experimental work to demonstrate cognitive behaviour in a practical way. The work has been able to demonstrate true cognitive behaviour in a radar sensor. However, the work has also highlighted the difficulty of experimental work on cognitive sensing, and there is much more to be done. The experimental work of the task group will undoubtedly continue beyond the time limit of this Task Group, since strong links have been forged. It is recommended that a further NATO Task Group be initiated on the subject of Cognitive Radar Networks.

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