Fusing Hard & Soft Information

Cornerstone of Information Processing and Management

NATO LECTURE SERIES STO IST-155

ADVANCED ALGORITHMS FOR EFFECTIVELY FUSING HARD AND SOFT INFORMATION

La Spezia, ITA, September, 26-27, 2016

Delft, NLD, September 29-30, 2016

Linköping, SWE, October 3-4, 2016

Porton Down, GBR, October, 6-7, 2016

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Head of Sensor Data Fusion

Fraunhofer FKIE

Prior to any technical realization or scientific reflection,

Data Fusion / Computational Sensorics / Observational Informatics

is an omnipresent phenomenon.

All creatures "fuse" mutually complementary sense organs with prior information / communications: prerequisites for orientation, action, protection.

This is quite naturally "hard" and "soft" fusion.

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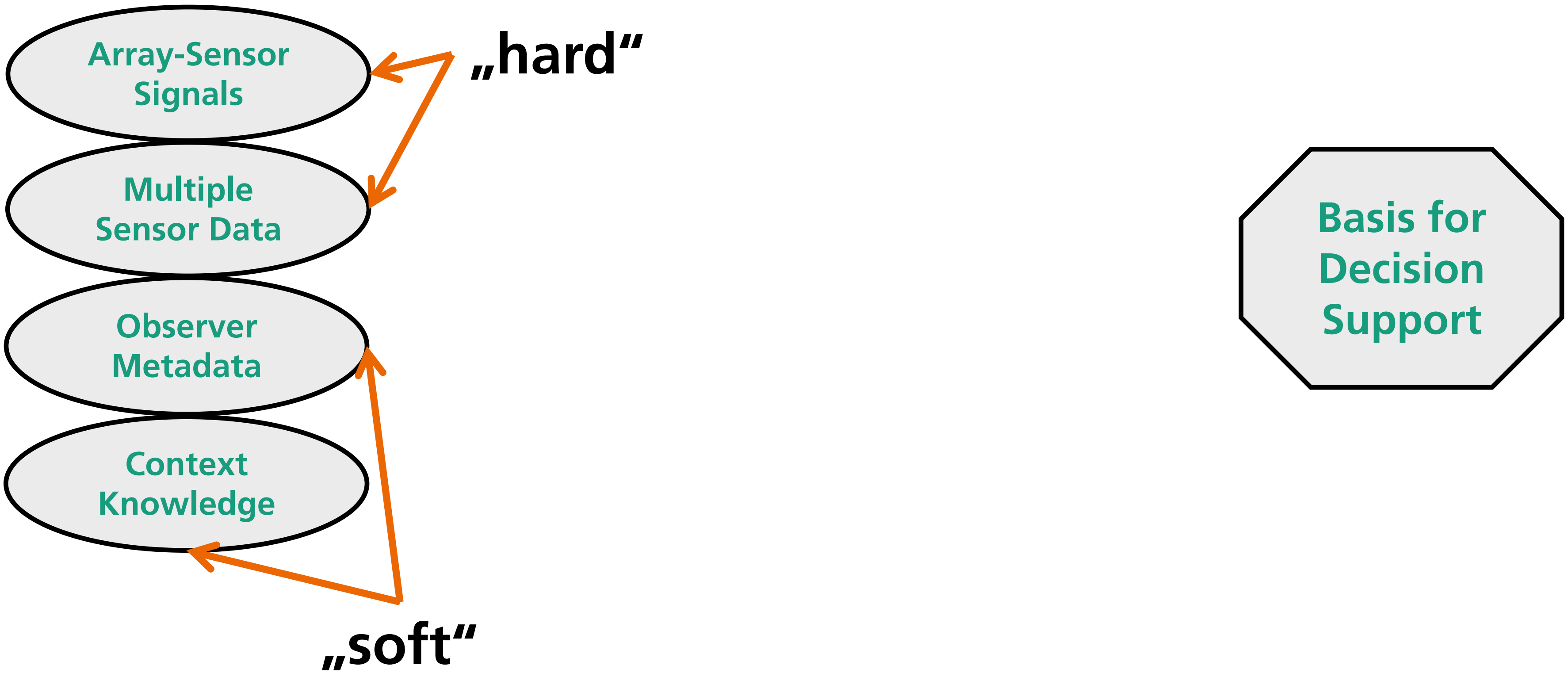
Branch of engineering providing *cognitive assistance*:

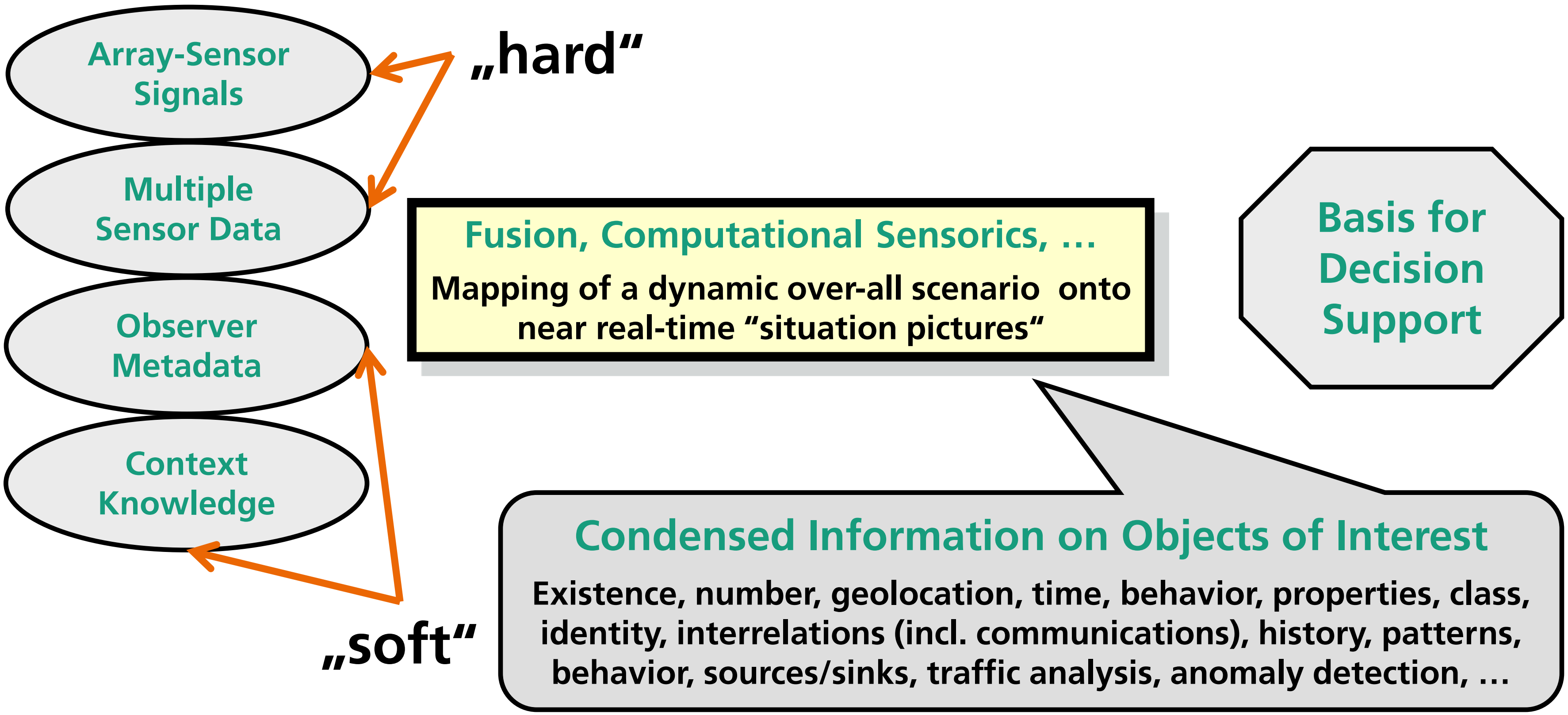
1. **Understand, partially automate, enhance.**
2. **Integrate new sources and platforms.**
   - networking, mobility: new dimensions of apprehension
   - Data base systems with vast context information
   - Interaction with humans: exploit natural intelligence
3. **Informational basis for manned/unmanned teaming**

Observational Informatics: Mission Statement



Data to be fused: imprecise, incomplete, ambiguous, unresolved, false, deceptive, hard-to-be-formalized, contradictory, ...

Observational Informatics: Mission Statement



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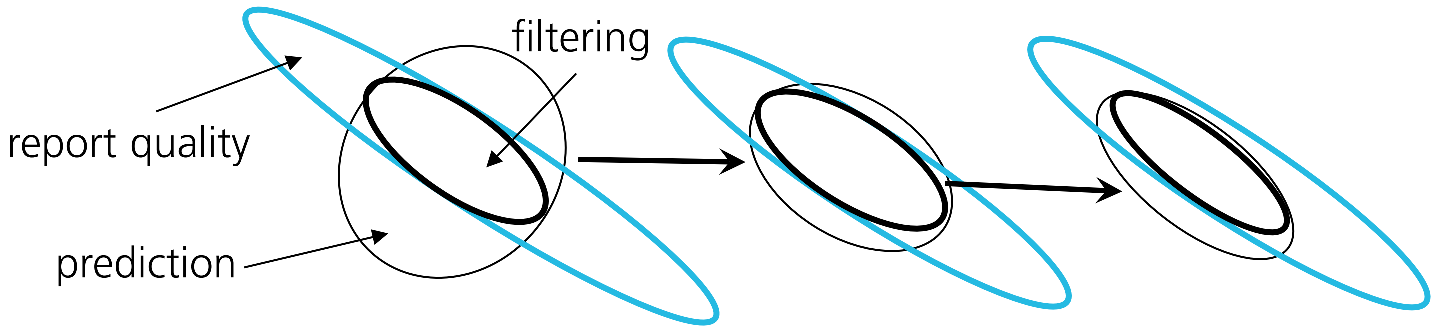
The Four Columns of Sensor Data Fusion

- Statistical Estimation
  - Object states (typically: non-linear filtering problems)
- Combinatorial Optimization
  - Which measurements belong to which objects?
- Optimal Decision Making
  - Track initiation, cancelling, classification, anomaly detection
- Resources Management
  - Optimal use of sensor modes, platforms, links, …

Many fusion systems make use of these distinctions. Innovative approaches develop a unified methodology. Room for “soft” data!

Target Tracking and Report Data Fusion

- Tracking: report data fusion along time (using an object evolution model)



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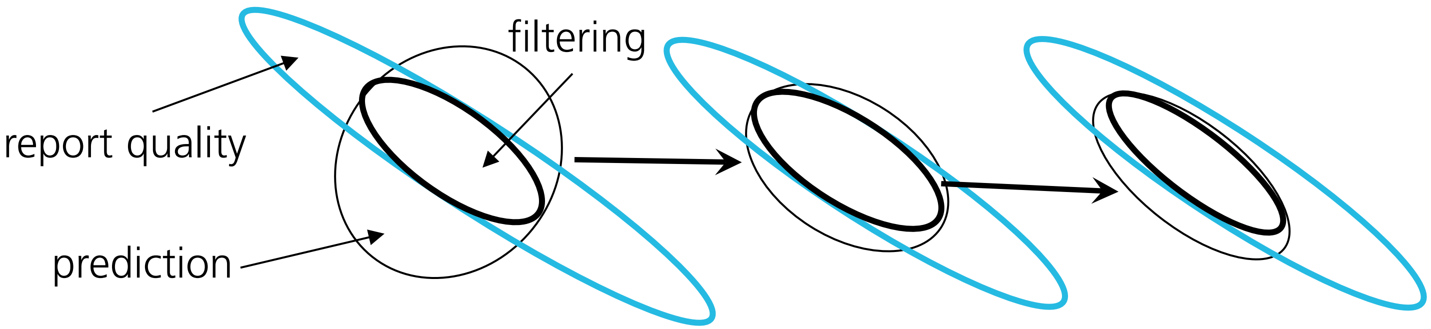
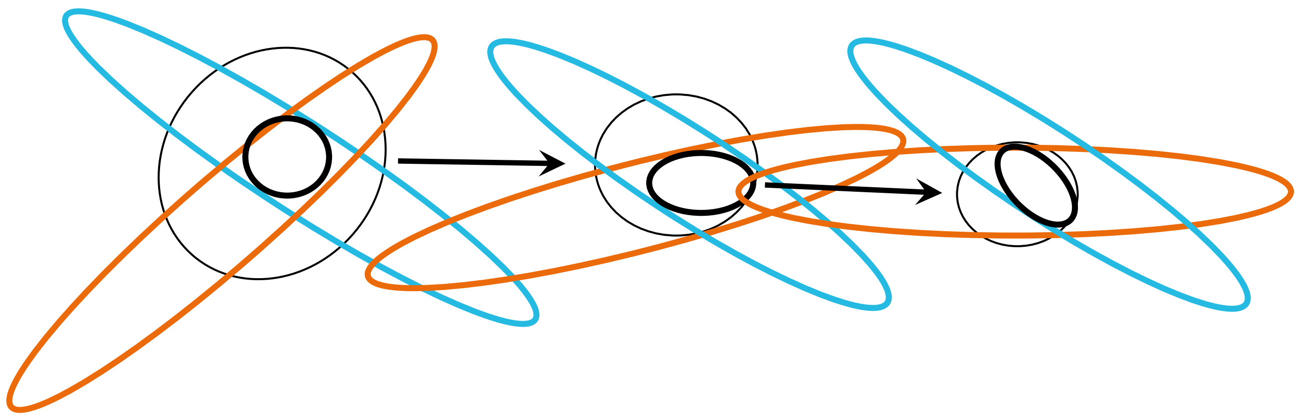


- Fusion of mutually complementary multiple report data along time



→ **Key role of the Bayesian Paradigm**

Why is Data Association so important?

- The tracking and fusion task has to solve two problems:
  1. Data Association (find reports belonging to the same target)
  2. State Estimation (typically a non-linear estimation/filtering problem)

- Many trackers and fusers make explicitly use of these distinctions:
  - Probabilistic Data Association Filters (PDAF)
  - various versions of Multiple Hypothesis Tracking (MHT)

- Exceptions: Label-free methods, Probabilistic Hypothesis Density (PHD) filtering, iFiltering (based on Poisson Point Processes PPP), …

  Both problems are solved in a unified manner, no explicit enumeration of data association hypotheses (→ Willett, Coraluppi).

The two dimensions of the Data Fusion Spiral

Increasingly complex phenomena

Individual objects
Collective phenomena
Overall mission - *and I*

Existence: Is there anything at all? Quantitative: How is it behaving? Qualitative: What is it? Intention: Why is it behaving – is it a threat, e.g.?

Increasing depth of understanding phenomena

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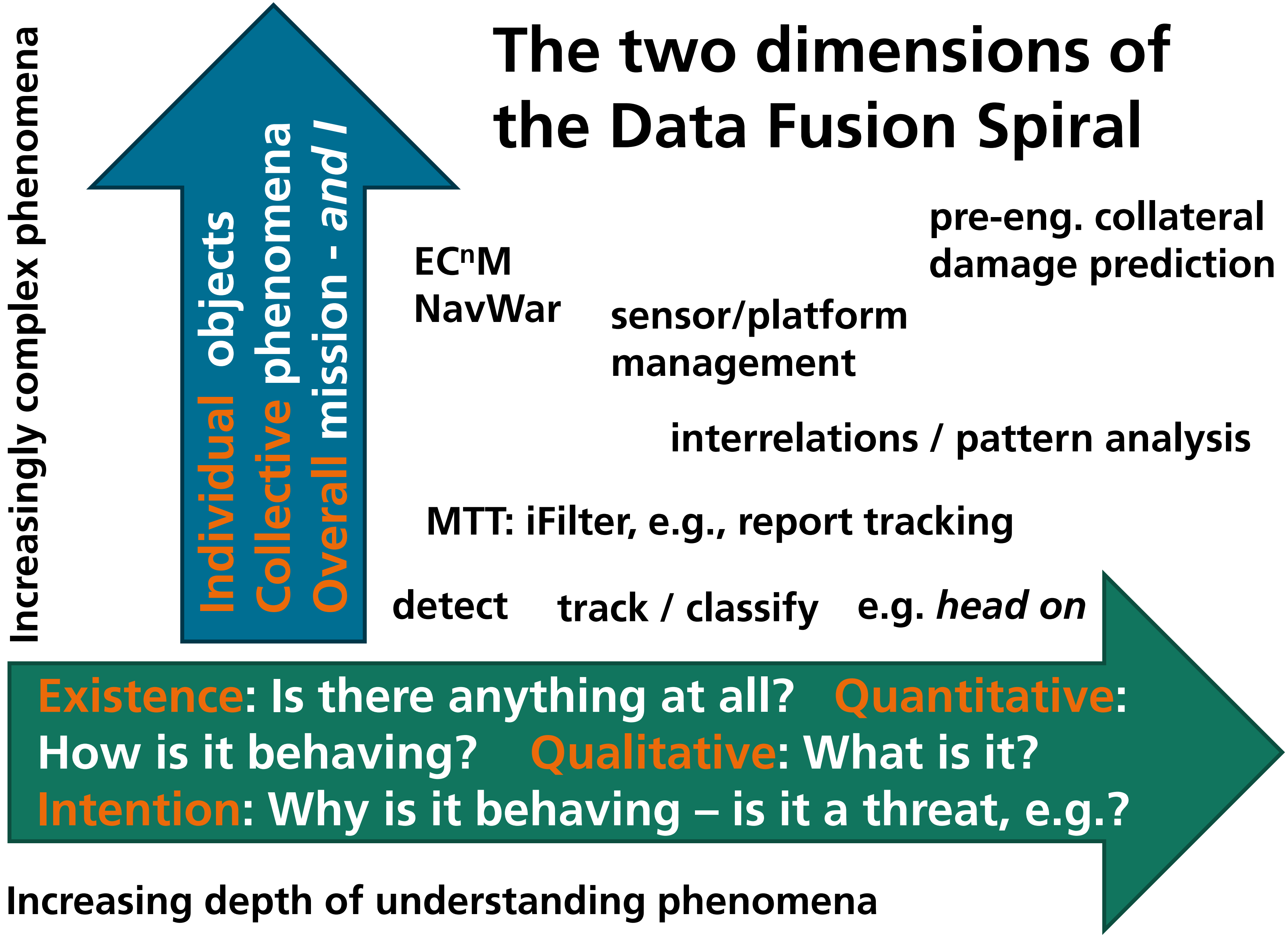
The two dimensions of the Data Fusion Spiral



Some preliminary distinctions and relations

Hard Data
physical sensors
focus on algorithms

← “hard” when formalized
→ often imperfect, false …

Soft Data
language encoded
Focus on HMI, linguistics

Report Data
close to evolution time
measurements
observer reports

← processing prerequisite
→ extract, check validity

Context Data
stationary, slowly changing
sensor/target/env. models
taxonomies, ontologies

Content Data
measurements, tracks
Context information
HumINT, ontologies

← processing prerequisite
→ content of metadata

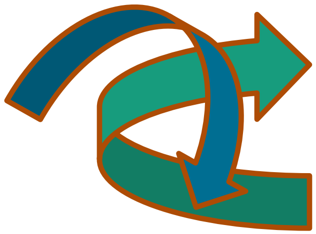
Metadata
data on content data / comms
space-time stamps, addresses,
sources, formats, context

Raw Data
to be interpreted
physical signals
spoken/written

← input for next level
→ extraction of information

Processed Data
interpretable data
measurements, target tracks
formatted observer reports

Low-level Data
signals, spoken/written text
meas., metadata, reports
classified tracks, interrelations
vignette/situation pictures



Data Fusion Spiral

High-level Data
meas., metadata, reports
classified tracks, interrelations
vignette/situation pictures
patterns, intent, anomalies

What is the methodological essence of *Multiple Source Object Tracking*?

Learn classified tracks of time-varying objects from uncertain data!

Which object properties are of interest?

Define an *object state* at varying time instants.

Which information is to be fused?

Time series of report data, context information

How to describe imprecise information?

E.g. functions of the state: pdfs, PHDs, intensities

What does "learning" from reports mean?

Iteratively calculate these functions (Bayes!)

What is required for the learning process?

Source and evolution models, data association

How to initiate/terminate object tracks?

Sequential decision making (implicitly, explicitly)

“hard” data		**“soft” data**
- physical sensors - to be interpreted - focus on algorithms	⟷	- observers, context - directly understandable - focus on HMI, linguistics

→ **Evolution of two different research communities / mentalities**

“hard” data
- physical sensors
- to be interpreted
- focus on algorithms

↔

“soft” data
- observers, context
- directly understandable
- focus on HMI, linguistics

→ Evolution of two different research communities / mentalities

- **vast amounts of hard and soft data to be exploited**
- **enormous potential gain by fusing hard & soft data**

Beware: situational awareness, understanding, only by human beings!

At least partial automation: cognitive assistance, “computational” ISR

Personal opinion: There is no “AI” in a philosophically reflected sense.

Very general prerequisites of algorithmic processing:

Formal representation of the data

- Qualitatively
  - Which object / phenomenon?
  - Interrelation between objects
  - Strength of human reports
- Quantitatively
  - Which properties are reported?
  - Data on details, aspects
  - Strength of physical sensors

Reliability measures for the data

- Validity
  - Is it a plausible report at all?
- Accuracy
  - How good is the message?

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On this level of abstraction:

no fundamental difference bet-ween "hard" and "soft" data.

Reliability measures for the data

- Validity
  - Is it a valid report? (→ Willett)
- Accuracy
  - How good is the message?

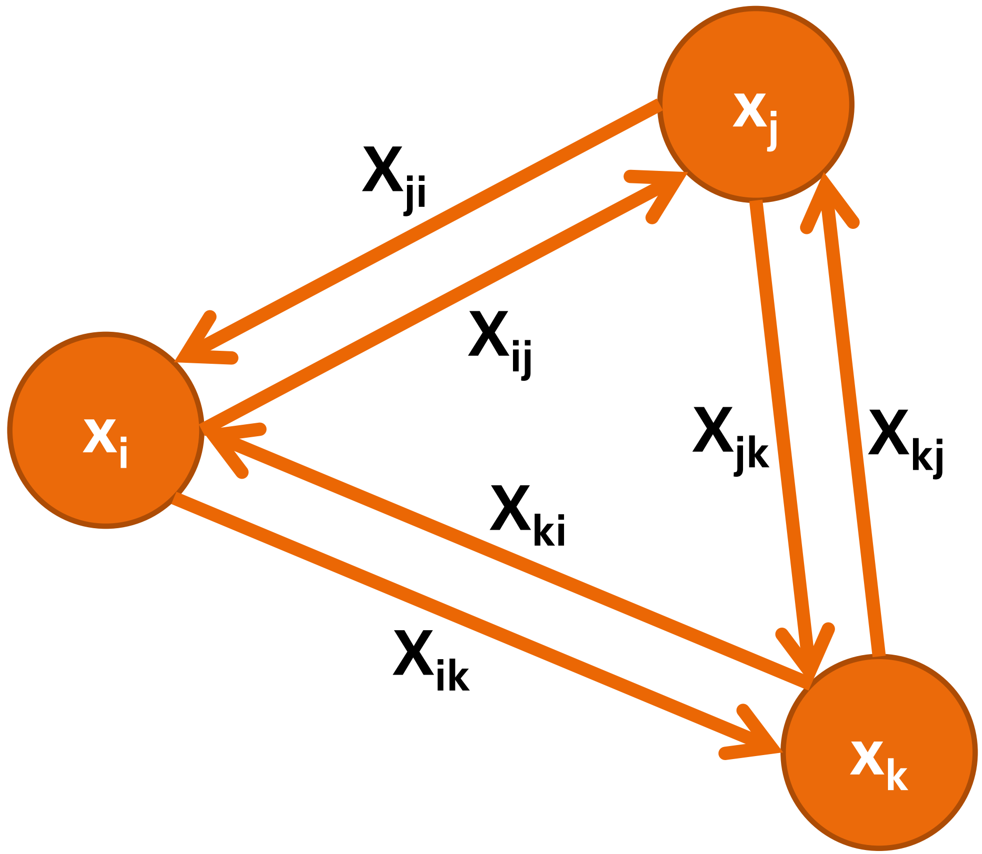
Context information is crucial for "hard" and "soft" fusion equally!

Characterization of Object Interrelations:

Estimate and track adjacency matrices!

- **Multiple object tracking: estimate from kinematic sensor or observer reports Z at each time state vectors of all relevant objects: $p(x| Z)$ (*x*: joint state).**
- **Of interest: interrelations between objects currently under track. E. g.: reachability between two objects (communications, help/support), known to each other.**

Graphical Description



Adjacency matrices formally describe multiple object interrelations.

Characterization of Object Interrelations:

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- **Of interest: interrelations between objects currently under track. E. g.: reachability between two objects (communications, help/support), known to each other.**
- **Interrelations are mathematically described by the adjacency matrix *X* of a graph: nodes represent the objects under track, matrix elements: pair interrelations.**
- **Because of uncertain attributive / kinematic observer reports (*z, Z*), adjacency matrices are random variables, characterized by *matrix variate* probability densities.**

Characterization of Object Interrelations:

Estimate and track adjacency matrices!

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- Interrelations are mathematically described by the adjacency matrix X of a graph: nodes represent the objects under track, matrix elements: pair interrelations.
- Because of uncertain attributive / kinematic observer reports (z, Z), adjacency matrices are random variables, characterized by *matrix variate* probability densities.
- The state to be estimated thus consists of the joint state x representing all objects involved and the adjacency matrix X. With accumulated reports z, Z: the available knowledge on x, X contained n: $p(x, X|\, z, Z) \sim p(z|\, X)\, p(X|\, x, Z)\, p(x|\, Z)$.
- With suitable families of matrix variate densities and likelihood fctns, the Bayes formalism is applicable for iteratively calculating the joint density $p(x, X|\, z, Z)$.

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Examples for context data (representation, reliability)

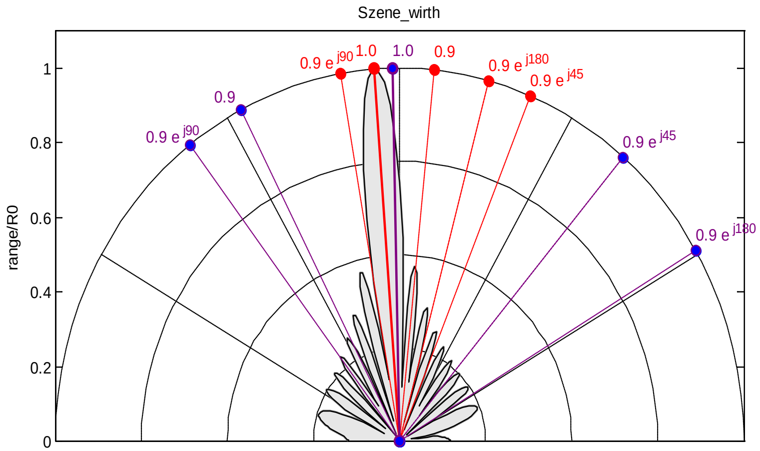
Sensor context: *What and how do sensors see?* Likelihood functions.

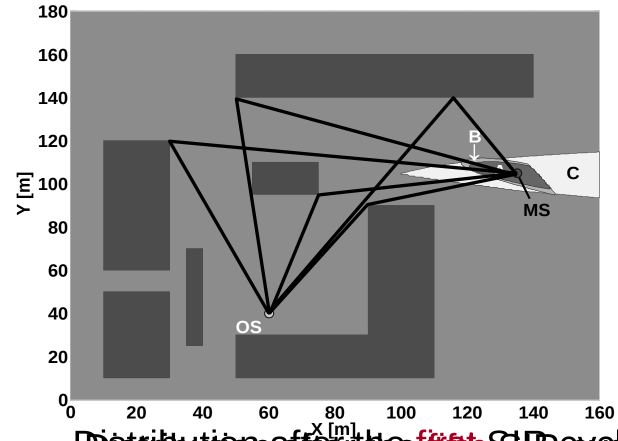
Observer context: *Why not likelihood functions for observer reports?*

Geographical context: roads, constraints, visibility, signal propagation

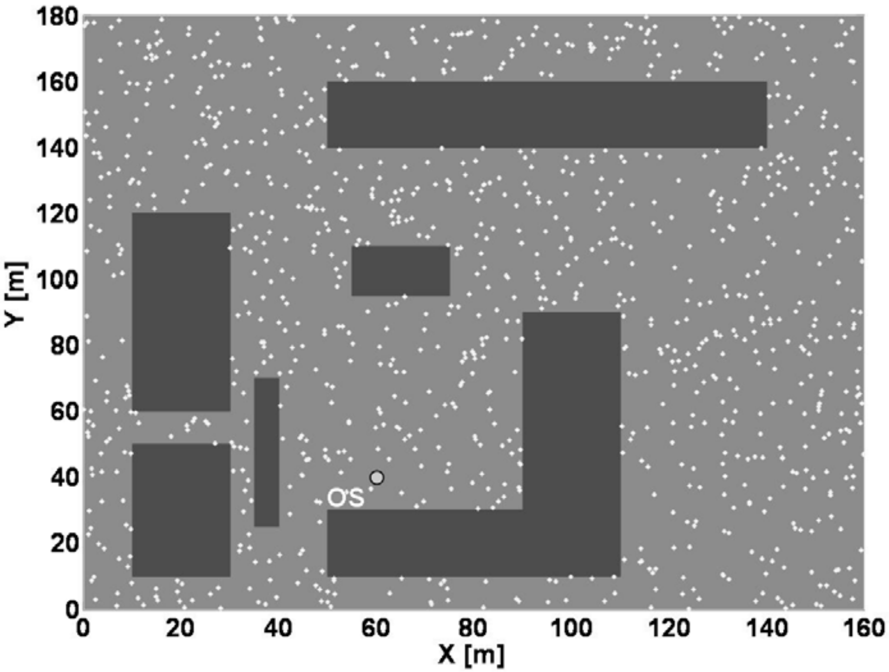
→ algorithmically calculated likelihood fctns (e.g. ray tracer)

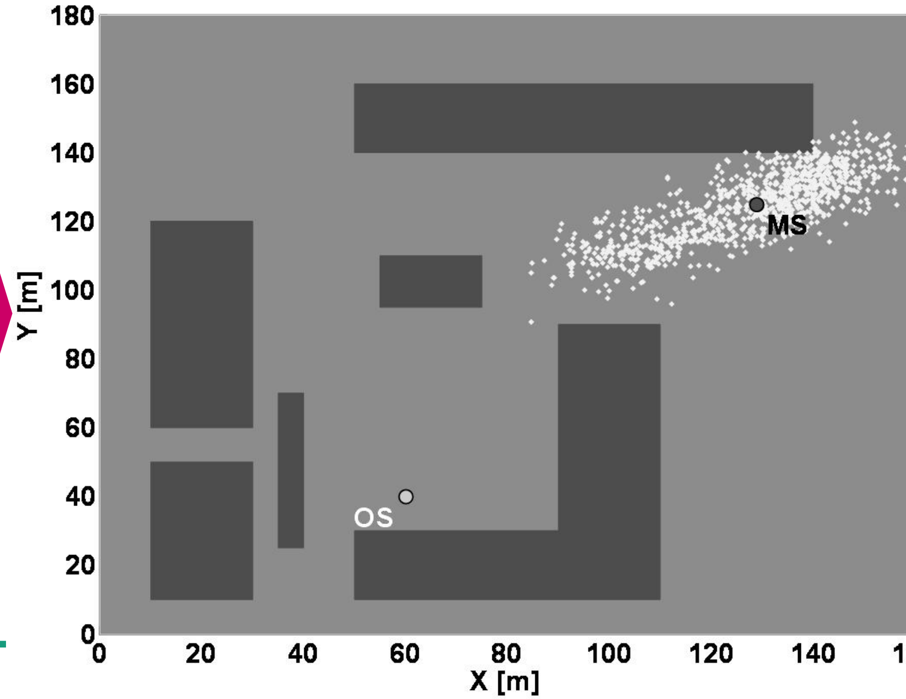
Propagation context for urban emitter localization

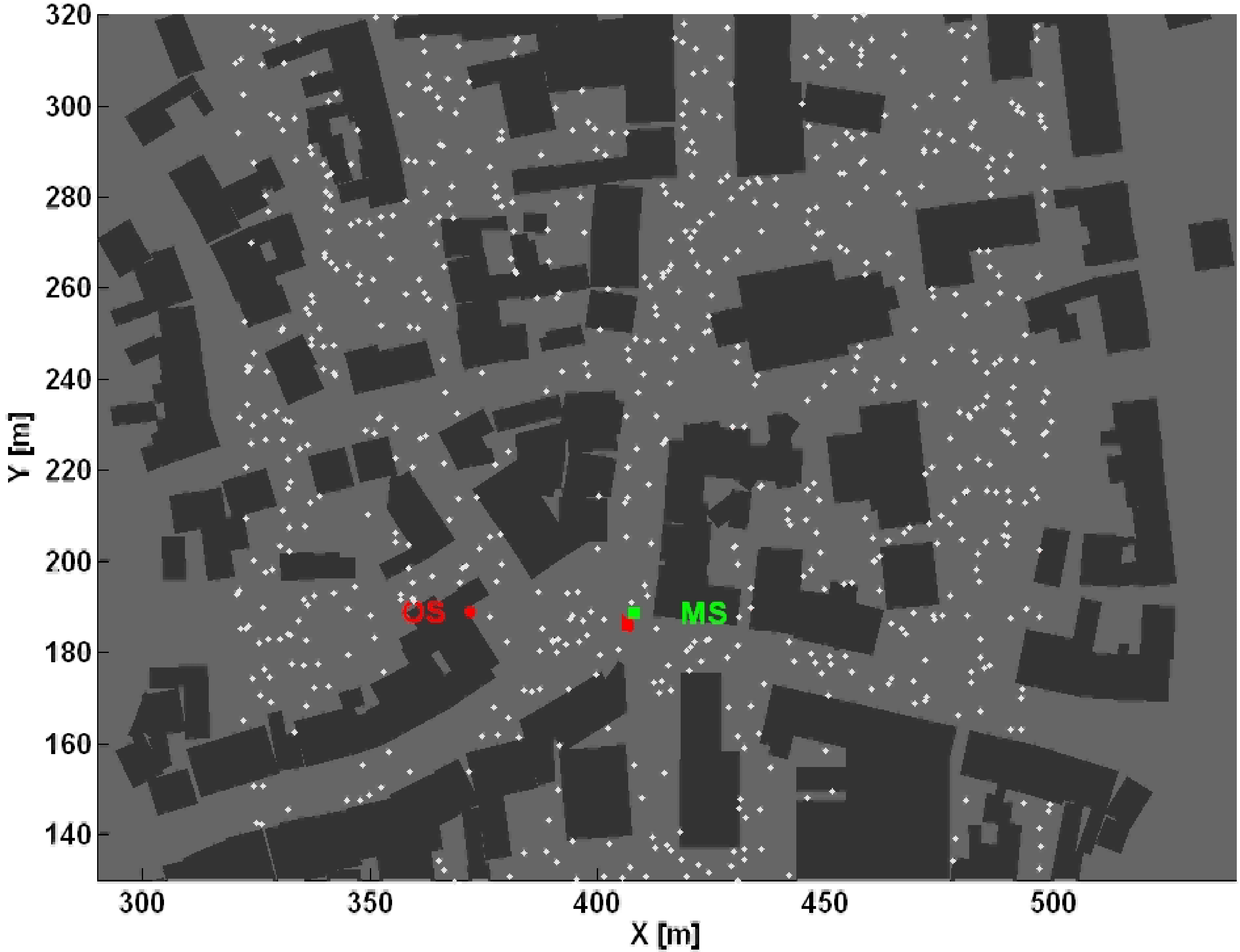




Distribution after the first SIR cycle
Distribution after the fifth SIR cycle







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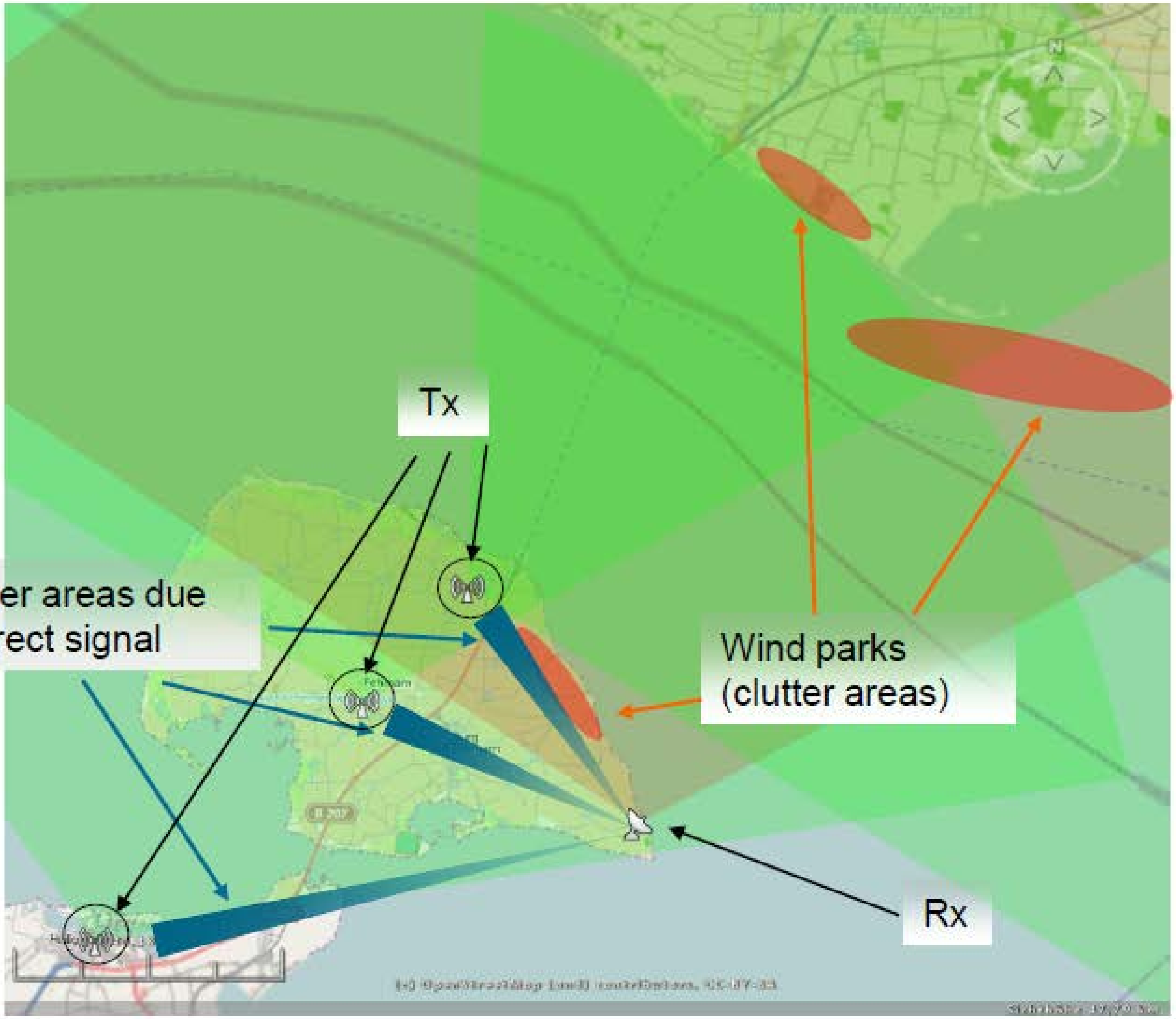
Knowledge Based Adaptive Processing

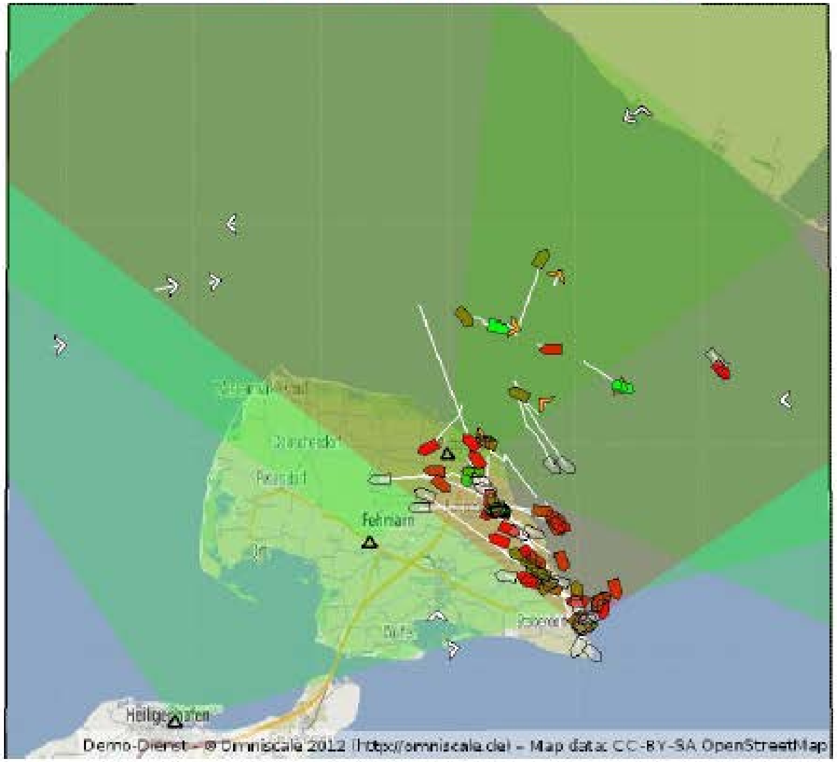
Clutter Mapping



Knowledge Based Adaptive Processing
Clutter Mapping

Perception
Working Memory
Reasoning (Inference)

Without Clutter Mapping



With Clutter Mapping

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Knowledge context: *Which features can tell what about objects / phenomena* → taxonomy-based likelihood fcts (→ Snidaro).

Planning context: often detailed information: motion constraints.

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Planning context: often detailed information: motion constraints.

Sometimes context information can be extracted from sensor / report data, e.g. road map generation from ground moving target tracks.

Validity of context information can be tested by processing sensor / report data assuming its validity / non-validity: anomaly detection

A reasonable distinction: “hard” & “soft”?

- **Close-to-object-evolution data** (short time-scale)
  - real-time sensor measurements (really “hard”?)
  - human observer reports (really “soft”?)
- **Slowly-changing context data** (long time-scale)
  - environmental context, typically determined in operation
  - partially known context, often given by statistical models
  - language-encoded context, background information

A reasonable distinction: “hard” & “soft”?

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Apparently, there is “hard” and “soft” context information.

Often, the categories of context information are not isolated from each other. A sensor model, for example, combines physical and partially known context for describing an imprecise measurement with environmental context, e.g. when a clutter background has to be estimated online.

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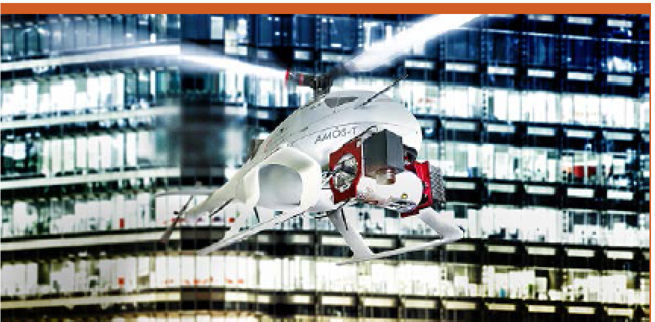

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Please respect latest enrolment dates (no fees):
NATO Nations: September 9, 2016
Non-NATO Nations: September 2, 2016

This Lecture Series is open to citizens from NATO and Partnership for Peace Nations

NATO OTAN S&T organization

organized by
Information Systems Technology Panel

Thursday, October 6, 2016

08:30 STO overview and introduction (W. Koch)

09:00 Hard & soft fusion – cornerstone of information processing / management (W. Koch)

10:15 Coffee Break

10:45 Distributed detection and decision fusion (P. Willett)

12:00 Lunch Break

13:00 Hard & soft fusion in defence and security (W. Koch)

14:15 Coffee Break

14:45 Issues and approaches for data fusion (P. Willett)

16:00 Break

16:15 Uncertainty in natural language data (K. Rein)

Friday, October 7, 2016

09:00 Uncertainty in natural language data (K. Rein)

10:15 Coffee Break

10:45 Context-enhanced information fusion (L. Snidaro)

12:00 Lunch Break

13:00 Fundamentals of multiple-hypothesis tracking (S. Coraluppi)

14:15 Coffee Break

14:45 Recent advances in multiple-hypothesis and graph-based tracking (S. Coraluppi)

16:00 Break

16:15 Context-enhanced information fusion: applications (L. Snidaro)

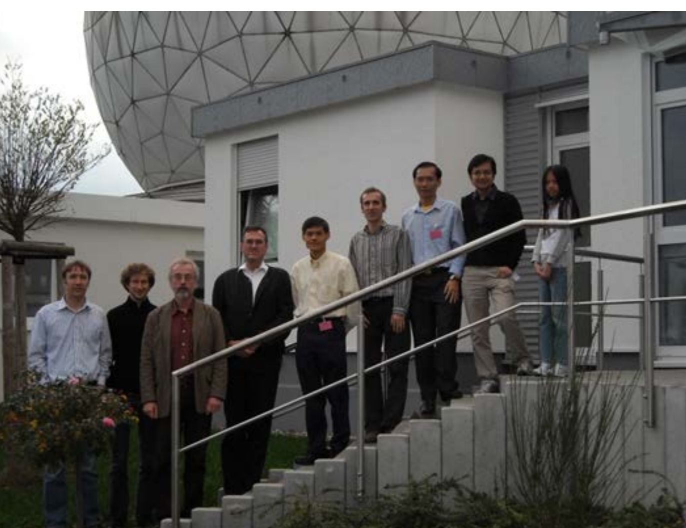
Hard & Soft Fusion Stimulus: Co-operation with SGP

Integrated GMTI Radar and Report Tracking for Ground Surveillance

Aim: Perform joint R&D on Ground Surveillance by developing a scheme to combine GMTI tracks from FKIE and H/I report tracks from DSO for better appreciation of ground situation picture.

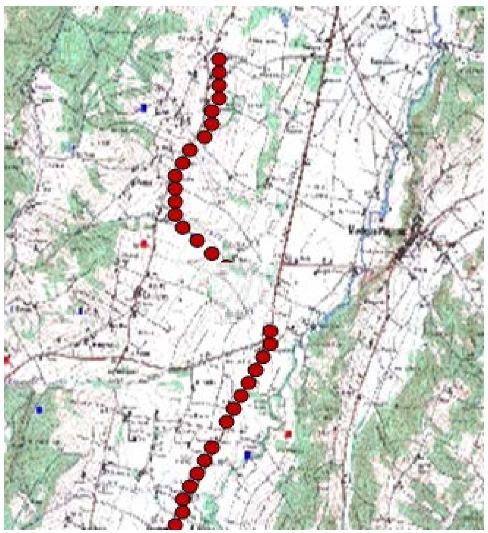
Contents: Development of a data fusion architecture, software development and integration, evaluation with realistic ground scenario

Work 2009/10: 3 months research visit at Fraunhofer FKIE; Germany
Lead: Chan Ho Keong (DSO), Martin Ulmke (FKIE)



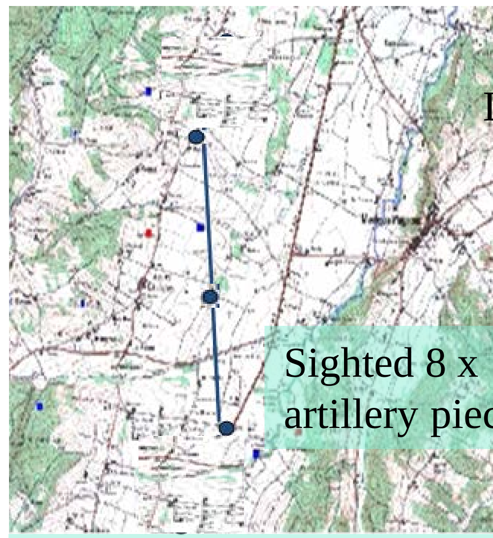
Results:
DSO-FKIE research report
paper at FUSION 2010, Edinburgh, UK
H. K. Chan, H. B. Lee, X. Xiao, M. Ulmke: *Integrated GMTI Radar and Report Tracking for Ground Surveillance*

Perform joint R&D on Ground Surveillance by develop a scheme to combine FKIE GMTI tracker with DSO report tracker for better appreciation of ground situation picture



GMTI
- Regular and fast update
- Good location estimate

+



Sighted 8 x artillery pieces

SALUTE Report
- Irregular and low update
- Equipment types & qty

Location/Time to correlate

=

A timely and more complete situation picture to assist Intel analyst in decision making.

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Conclusions

- improved track quality by providing location updates
- improved target classification for the GMTI tracks
- improved track continuity by segment-to-segment association, e.g. unit in tactical movement

Implementation MUCH easier

if a unifying language existed!

→ Snidaro, Rein

FUSION: Mathematical-Algorithmical Core of NEC

Network Enabled Capabilities (NEC)

situational awareness: timely, comprehensive, accurate

supply/retrieve information according to particular roles

exploit all available heterogeneous information sources

Some perhaps provocative statements:

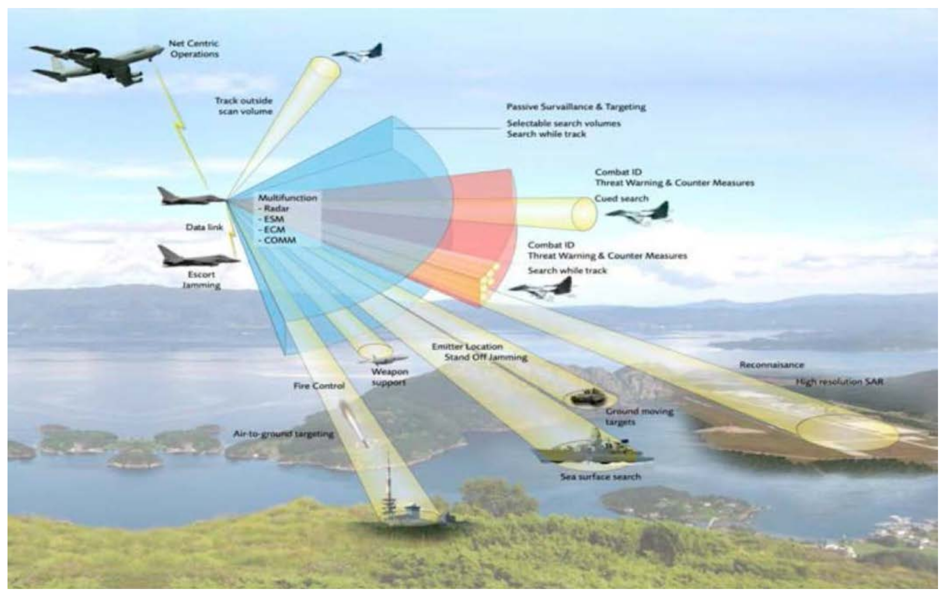
1. **FUSION technology aims at mathematically formulated algorithms from which cognitive assistance systems can be created.**
2. **What cannot be represented *on principle* mathematically / algorithmically cannot be transformed in a technical assistance system.**
3. **We fundamentally have to deal with hybrid systems combining the strengths of mathematical and characteristically human reasoning.**

Cognitive Assistance Systems versus Autonomously Operating Systems

- **Human decision makers must always be in control of the situation: only human being are able to be responsible of actions.**
- **Cognitive Assistance Systems provide capabilities and options for actions even in complex and challenging Situations.**

Example:

Massive need for support cognitive assistance systems whenever multifunctional multiple sensors on multiple platforms are to be used.



AIRBUS DEFENCE & SPACE

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Cognitive Assistance Systems versus Autonomously Operating Systems

Factors driving the technological development

- sensor, platform, weapon, IT & communications technology
- military / civilian logistics, demographic / social trands
- fertilizing: automotive, manufacturing, production, medical, …

Using demanding technologies without over-burdening the acting and deciding humans!

Aspects of Cognitive Assistance from a Military Perspective

Faster, more simply/precisely/reliably/comprehen-sively, with longer endurance / less risk …

- **command & control, targeting, protect own / others**
- **planning, realization, ethical responsibility.**

Enhancement of "natural" human capabilities:

- **decision maker's perception by *sensor assistance***
- **situational awareness by *cognitive* assistance**
- **action, presence by *physical* assistance.**

human decision makers

C5JISR in complex missions:
Command, Control, Communications, Computer, Cyber, Joint Intelligence, Surveillance, Reconnaissance

→ **common, role-oriented situation pictures**

Prerequisite

to lead, to protect, to act

C5JISR based on:

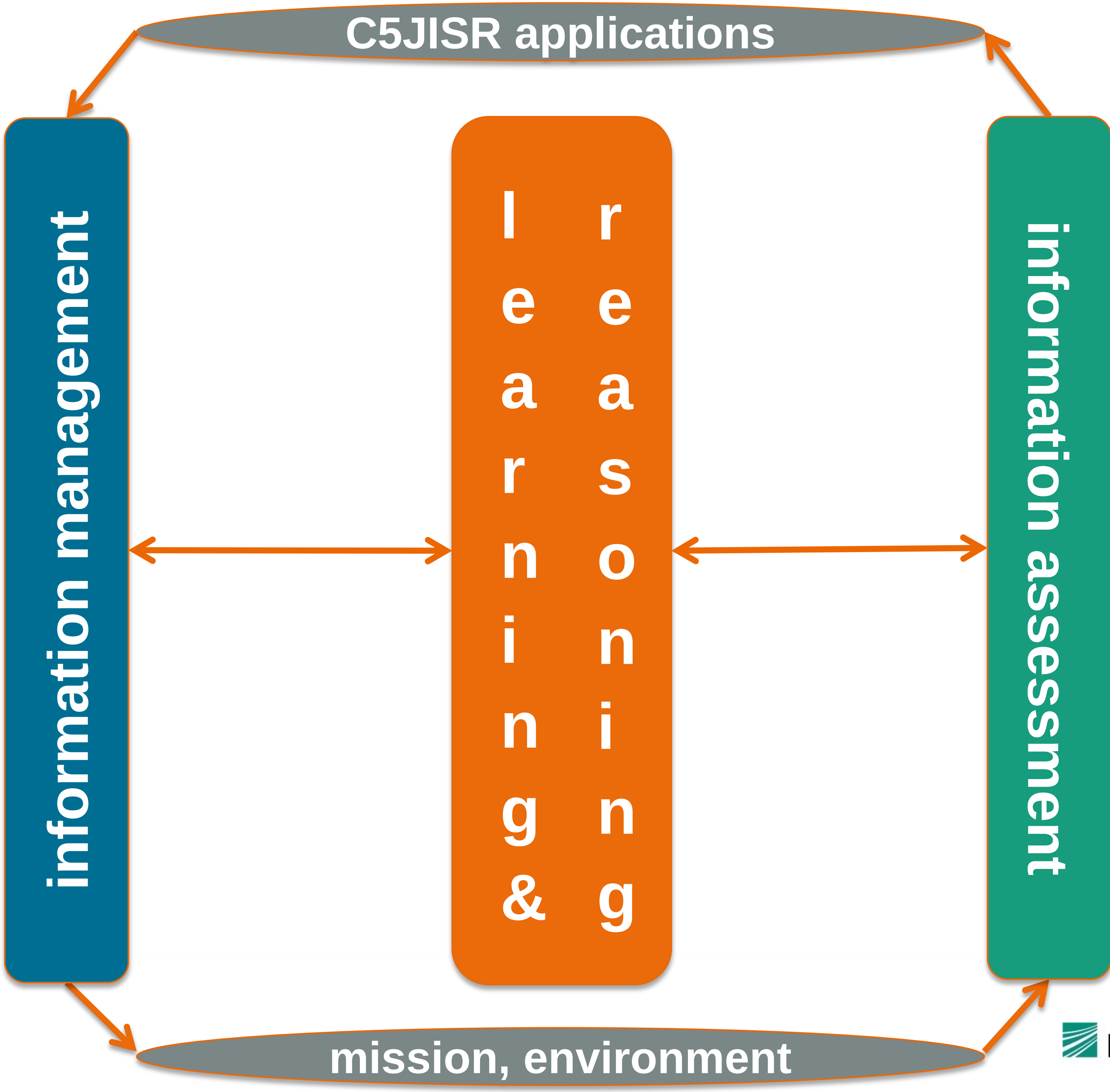
multifunctional sensors
mobile sensor platforms
comprehensive networking

Key role:

***system-secure* multiple sensor / platform / effector network (cyber, e.g.: Willett)**

observe protect act

mission, environment



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Information Assessment

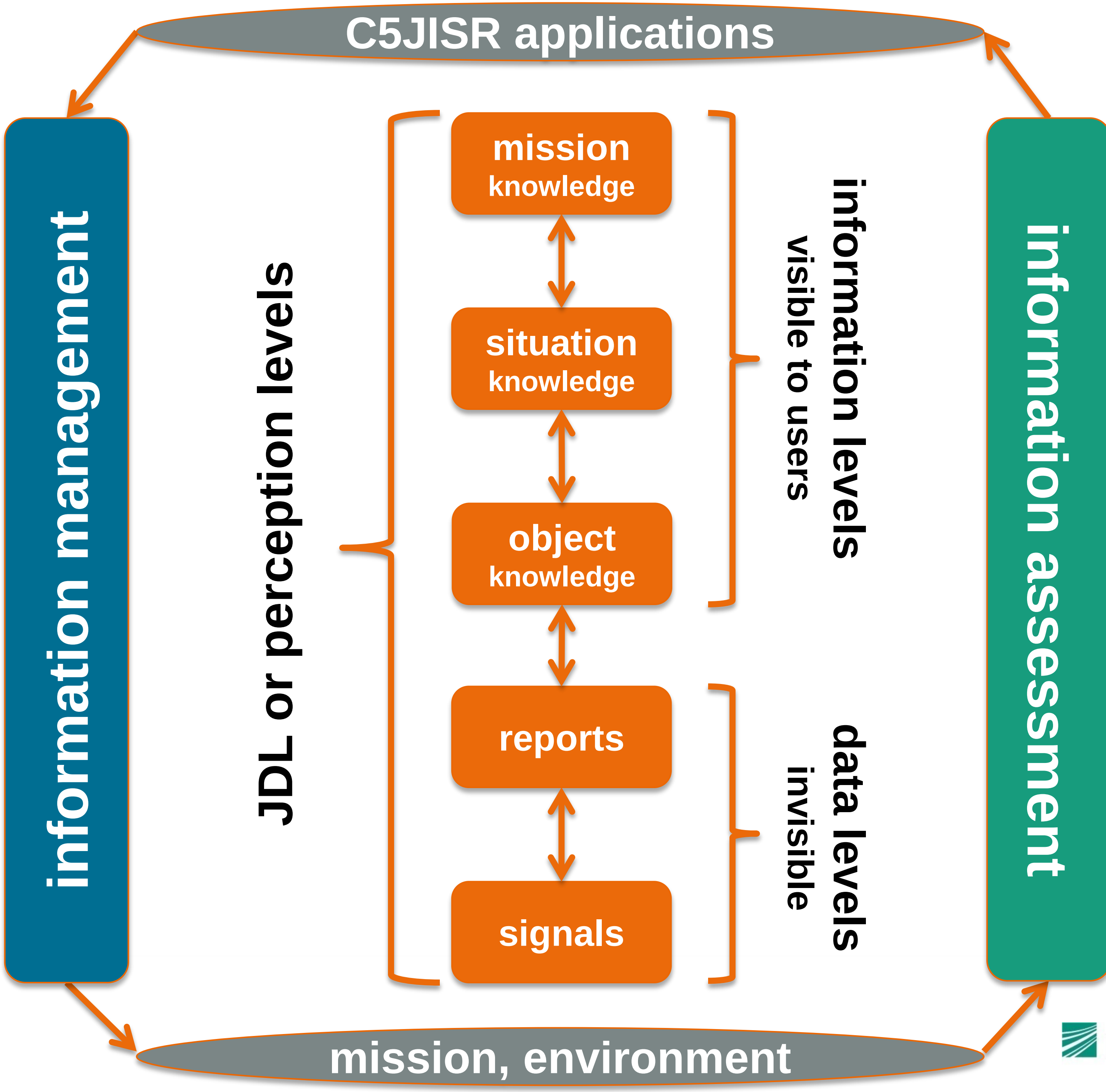
- information extraction from reported data
- computer linguistics, statistics, combinatorics
- starting point: signals / HUMINT → higher levels

Learning & Reasoning

- adaptively learn elements of the observed environment
- situation: What belongs where when how to what?
- predict effect of potential data acquisition decision

Information Management:

- control of sensor data / report collection: decisions
- statistical decision theory, mathematical game theory
- goal-oriented: mission → signals, report requests



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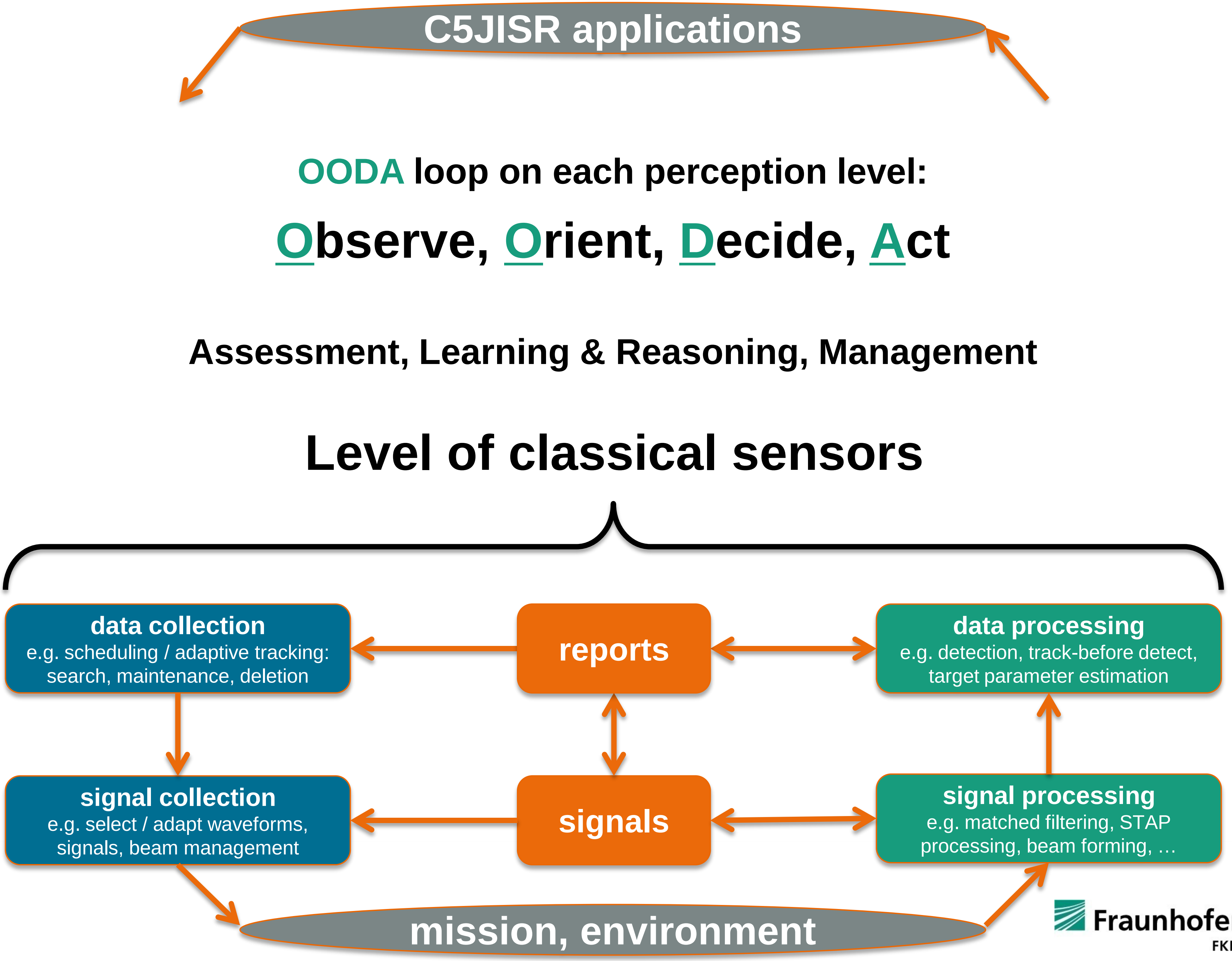
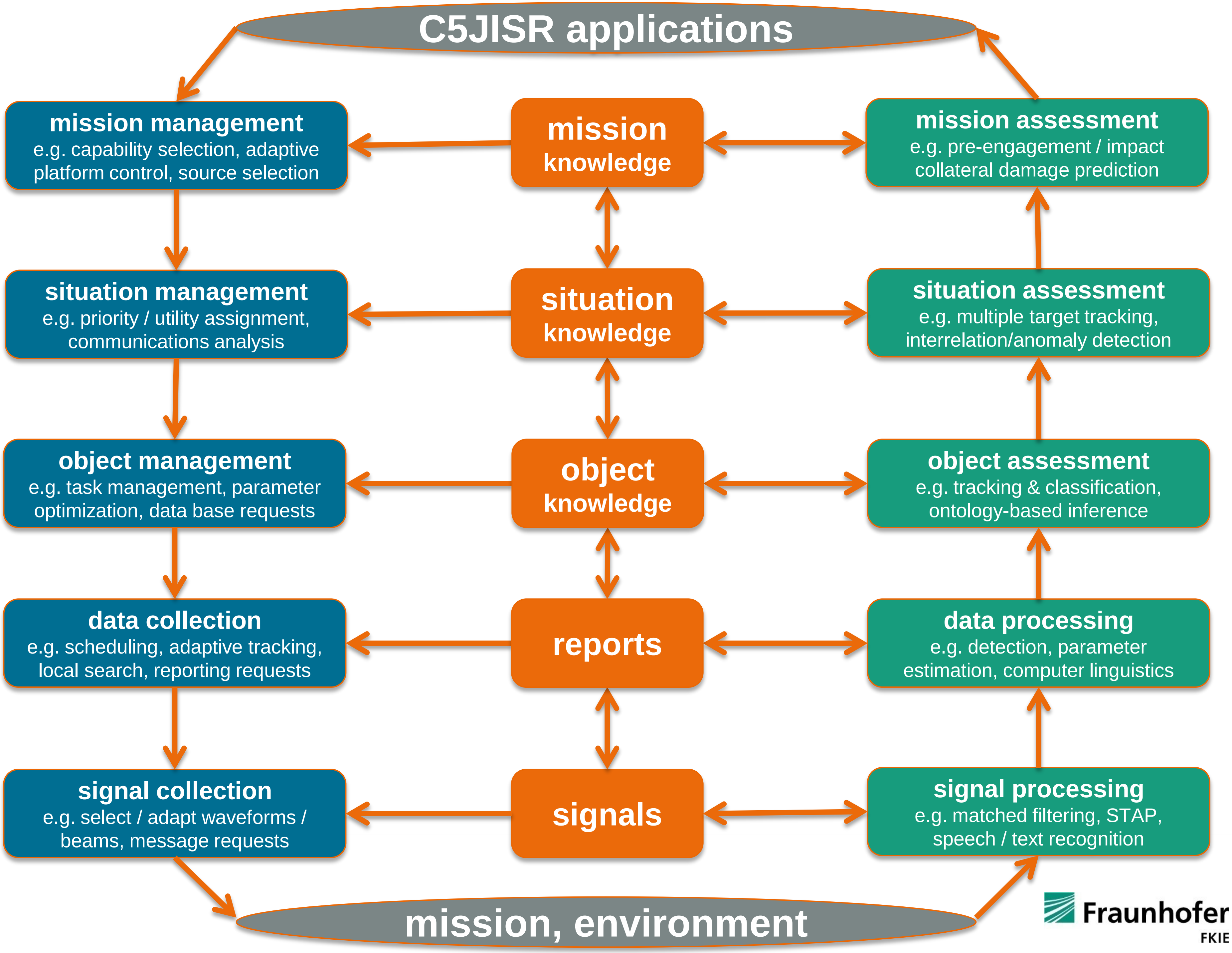

C5JISR applications
OODA loop on each perception level:
Observe, Orient, Decide, Act
Assessment, Learning & Reasoning, Management
Level of classical sensors
data collection
e.g. scheduling / adaptive tracking: search, maintenance, deletion
reports
data processing
e.g. detection, track-before detect, target parameter estimation
signal collection
e.g. select / adapt waveforms, signals, beam management
signals
signal processing
e.g. matched filtering, STAP processing, beam forming, …
mission, environment
Fraunhofer
FKIE



C5JISR applications
mission management
e.g. capability selection, adaptive platform control, source selection
mission knowledge
mission assessment
e.g. pre-engagement / impact collateral damage prediction
situation management
e.g. priority / utility assignment, communications analysis
situation knowledge
situation assessment
e.g. multiple target tracking, interrelation/anomaly detection
object management
e.g. task management, parameter optimization, data base requests
object knowledge
object assessment
e.g. tracking & classification, ontology-based inference
data collection
e.g. scheduling, adaptive tracking, local search, reporting requests
reports
data processing
e.g. detection, parameter estimation, computer linguistics
signal collection
e.g. select / adapt waveforms / beams, message requests
signals
signal processing
e.g. matched filtering, STAP, speech / text recognition
mission, environment
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Mission Aspects: RF Sensor Platform
Support optimized (multiple) UAS Trajectories

mission adapted platform trajectories:

control beyond human capabilities

online sequential decision making

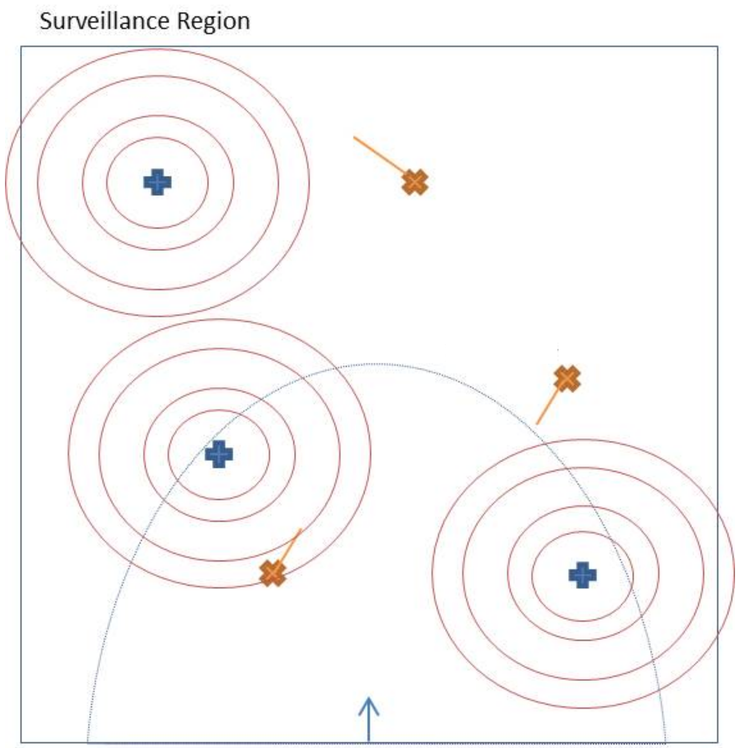
non-myopic

platform / sensor management

powerful methods: POMDPs

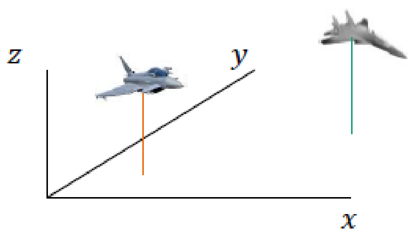
Partially Observable Markov Decision Processes

Blue	Static emitters
Orange	Moving emitters
Dashed line	Sensor platform field of view
Pink rings	Distance contours to threat



airborne sensor platform

Partially Observable Markov Decision Processes
Sequential Decision Making

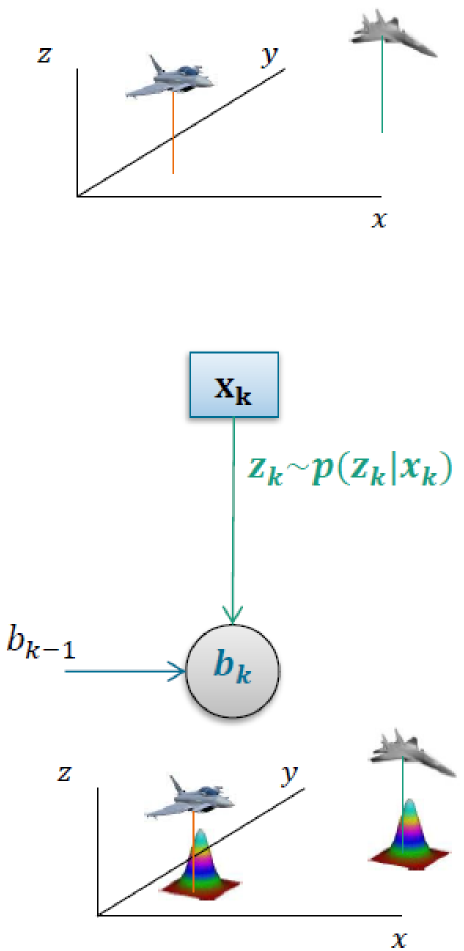


$\mathbf{x}_k$

System State:

- Parameters of system at time k
- For example:
  Target and platform kinematic parameters

Partially Observable Markov Decision Processes
Sequential Decision Making



Measurements

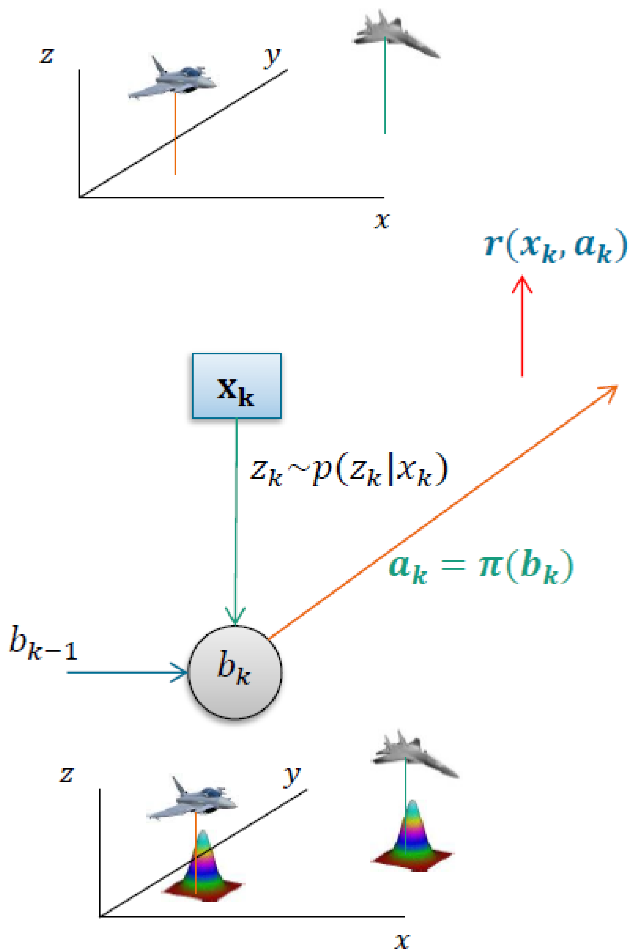
- True system state is only **partially observable** through noisy measurements z_k

Belief:

- Noisy measurements generate a **belief** of the system state
- Belief is a probability distribution on the state space

Partially Observable Markov Decision Processes

Sequential Decision Making



Action

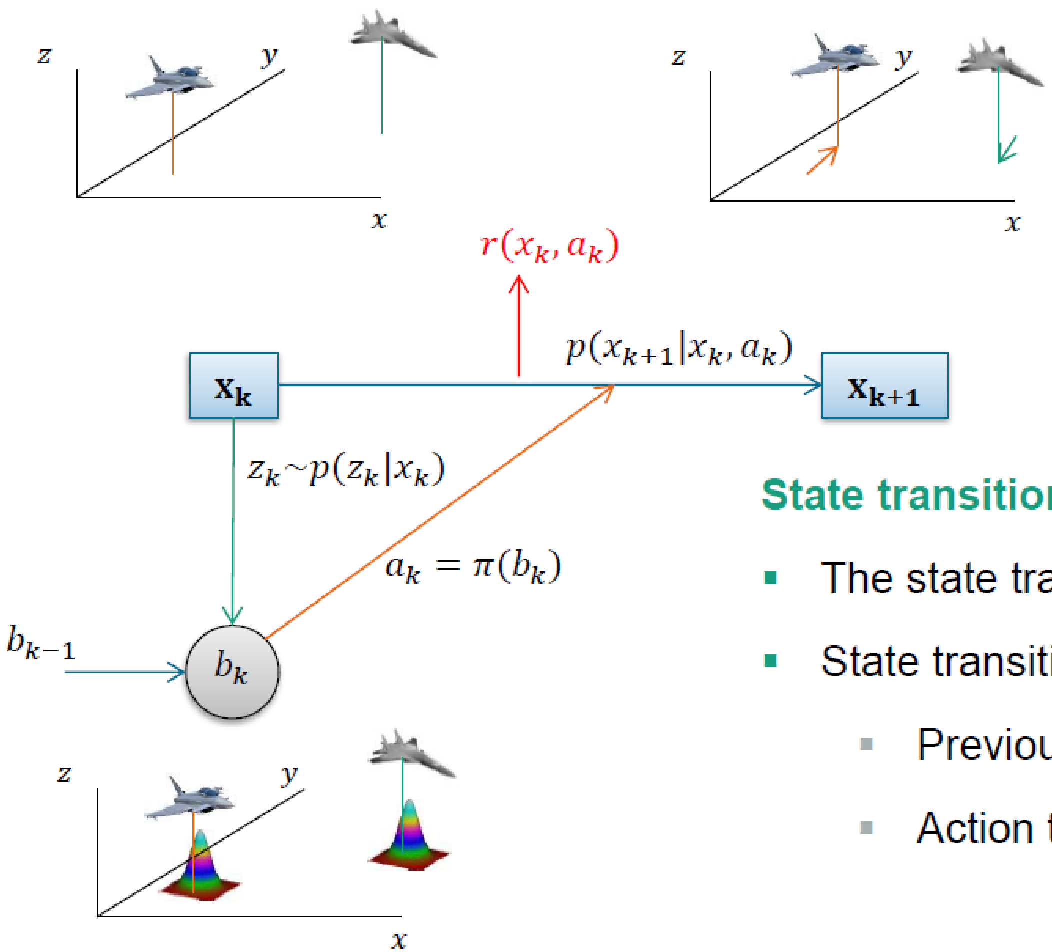
- Action is taken based on current belief b_k
- Policy π maps belief into action to take

Reward

- Reward is received based on:
  - System state x_k
  - Action taken a_k

Partially Observable Markov Decision Processes

Sequential Decision Making

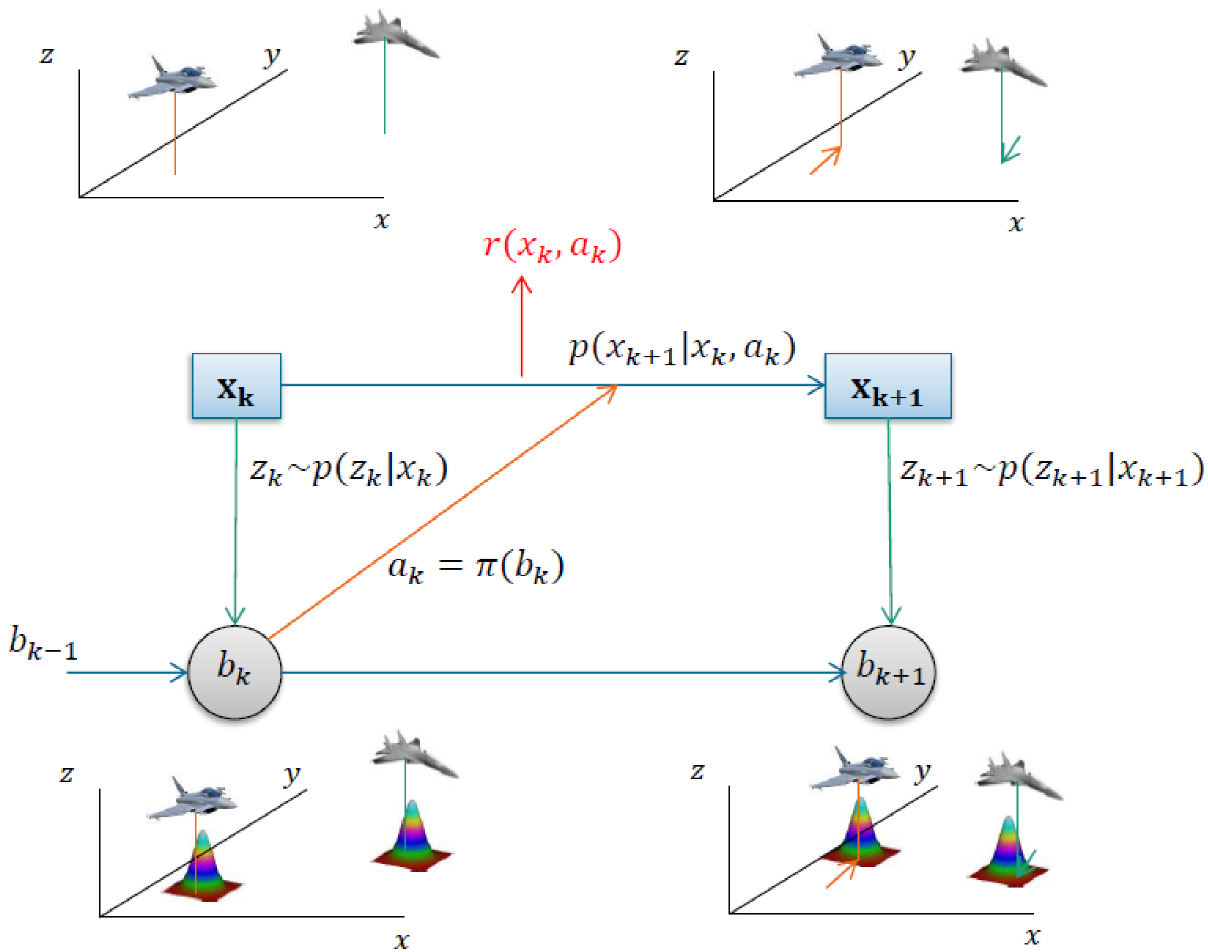


State transition

- The state transitions to new state for time $k+1$
- State transition depends:
  - Previous state x_k
  - Action taken a_k

Partially Observable Markov Decision Processes

Sequential Decision Making

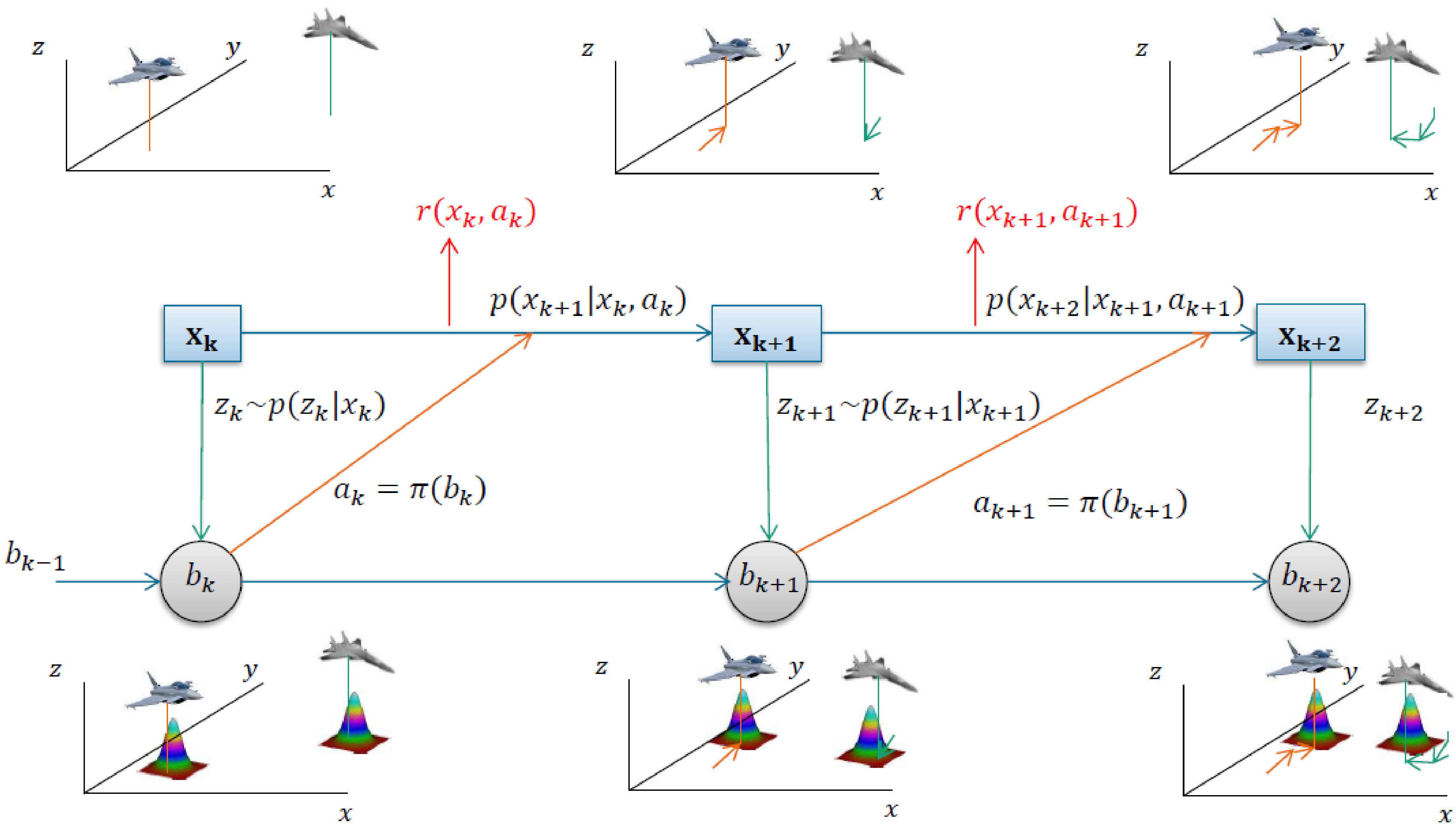


Process repeats:

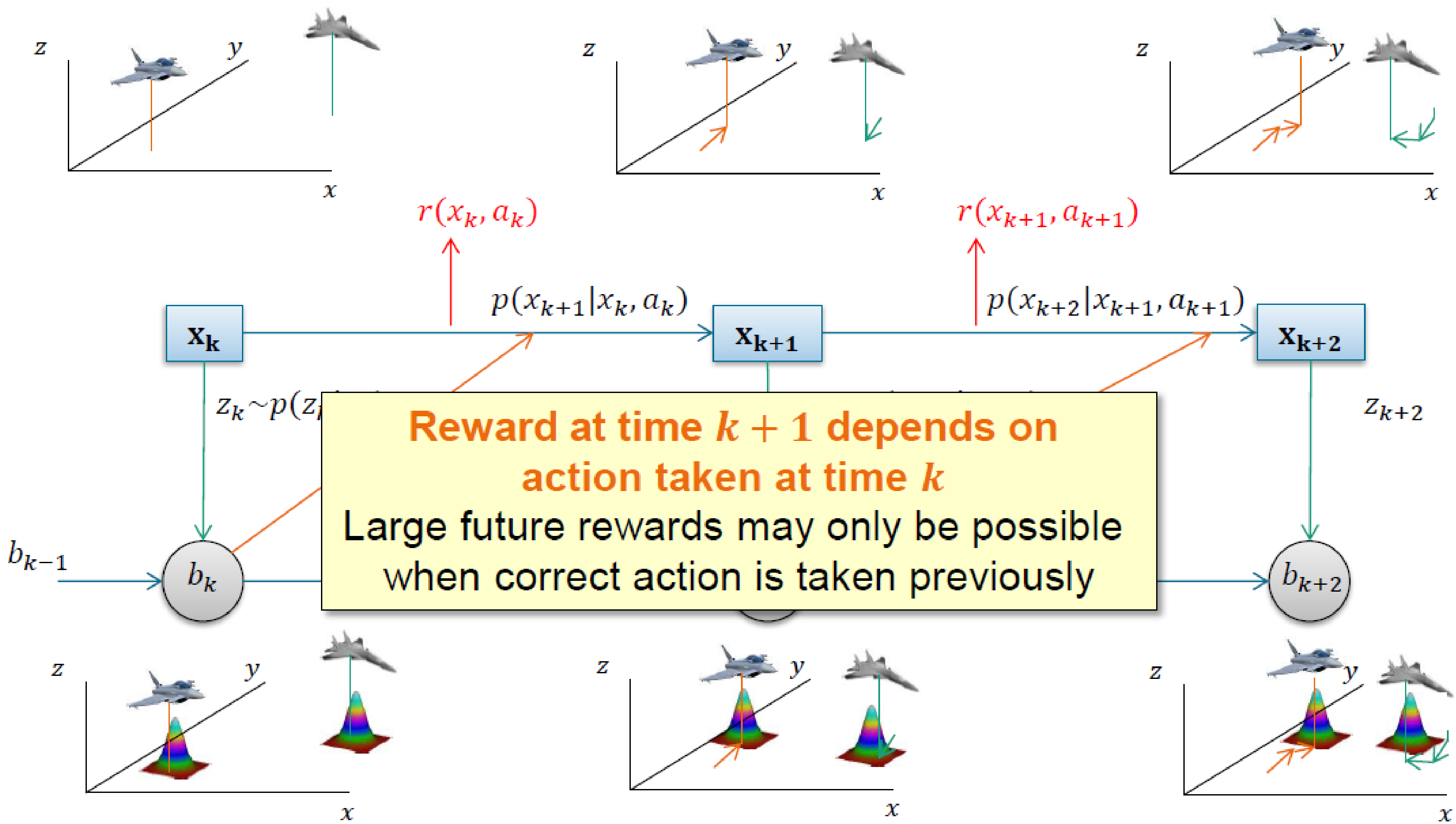
- New measurement
- Belief state update

Partially Observable Markov Decision Processes

Sequential Decision Making



Partially Observable Markov Decision Processes
Sequential Decision Making



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Partially Observable Markov Decision Processes
Problem Components

A POMDP consists of:

		Example
Action Space:	Possible actions that can be taken $a_k \in A$	*Waveform, measurement time, platform motion*
State Space:	Set of possible system states $x_k \in X$	*Kinematics of targets and platform*
State Transition Probability:	Probability of the system transitioning between states $p(x_{k+1} \mid x_k, a_k)$	*Model of platform and target motion*
Observation Space:	Range of possible measurements that can be observed $z_k \in Z$	*Radar measurements*
Observation Likelihood Function:	Likelihood of a measurement given a system state $z_k \sim p(z_k \mid x_k)$	*Radar measurement model*
Reward Function:	The reward of taking an action from the current state $r(x_k, a_k)$	*Sensing objective e.g. localization performance*

POMDP Approximate Solutions
Methods

Offline

- Computes possible policies before deployment *(Belief -> Action)*
- Point based value iteration
  Approximate value function by performing value iteration on set of belief points

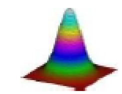
Online

- Action is found based on current system belief state
- Involves the approximation of the Q-value:
  - Pruning
    Branches can be ignored depending on bounds on future reward
  - Rollout
    Approximates future actions with a base policy
  - Value approximation
    Direct approximation of value of a belief state
  - Reward substitution
    If reward is hard to compute, it can be substituted with an approximation

Cognitive Processes
POMDP

Memory History of actions and measurements $d_k = \{z_0, a_o, \dots, z_{k-1}, a_{k-1}\}$

Perception Belief is conditioned on memory incorporates: $b_k = p(x_k | d_k)$



- Target motion model

Know

Lear

Actio

POMDPs may cover information assessment / management for all information levels (i.e. object, scenario, mission).

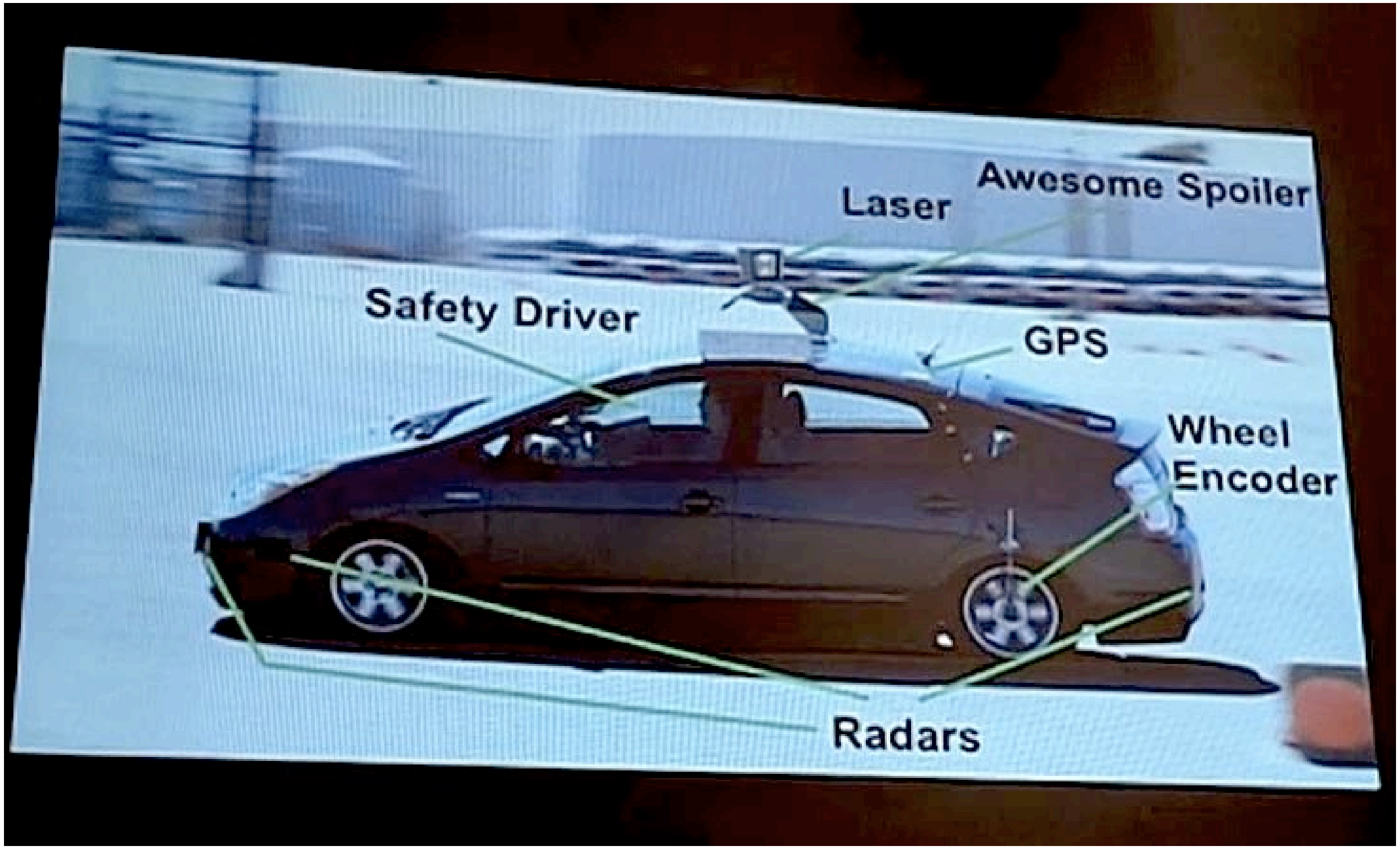
Extendable to formalizable "soft" data?

Anticipation **Action selection based on expected future system evolution**

Adaptive	**Anticipative**
Time horizon $H = 1$	Time horizon $H \gg 1$
$Q_{H-t}(b_t, a) = R(b_t, a)$	$Q_{H-t}(b_t, a) = R(b_t, a) + E[V^*_{H-t-1}(b_{t+1}) \| b_t, a]$
Adapts to current belief	**Anticipates future rewards**

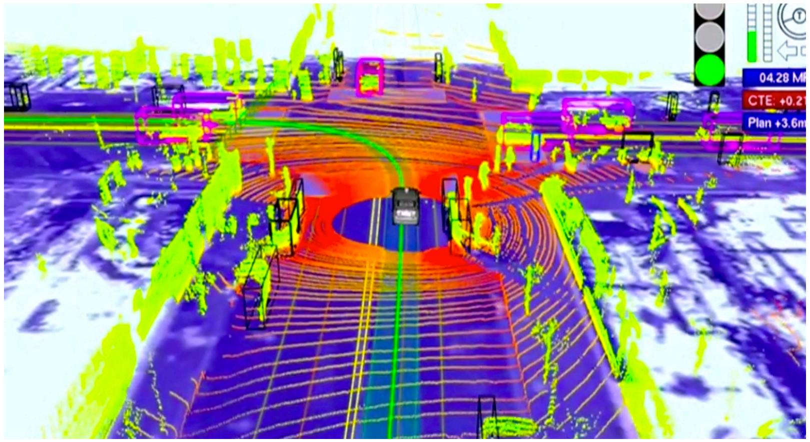
Civilian example (dual use): autonomous cars

World View of the Google-Car



Civilian example (dual use): autonomous cars

World View of the Google-Car



Automation of perception, decision making, action:

Solve complex and varying tasks in a challenging environment.

Highway

- Stay on lanes
- Avoid collisions
- Drive to destination

City traffic

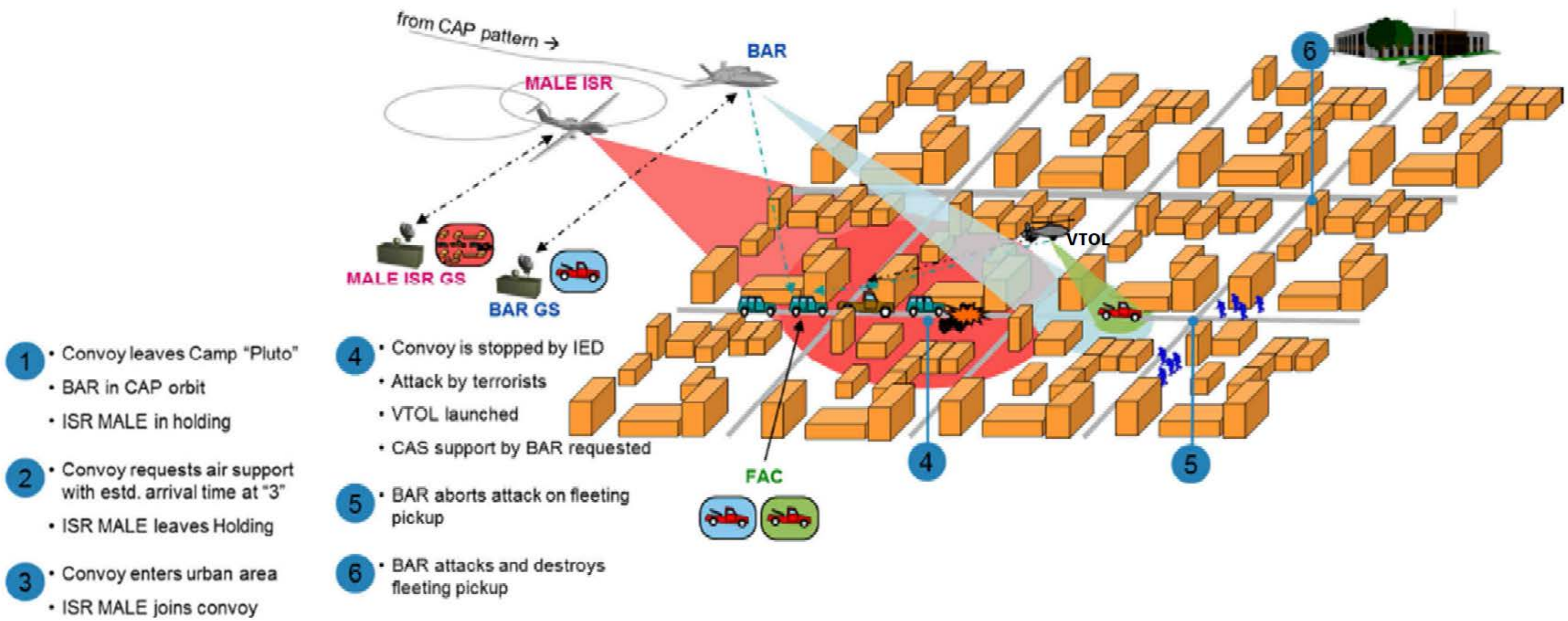
- Keep traffic rules.
- No collisions with pedestrians at all

How to reconfigure the overall system CAR adaptively for operation in dynamically changing traffic situations?

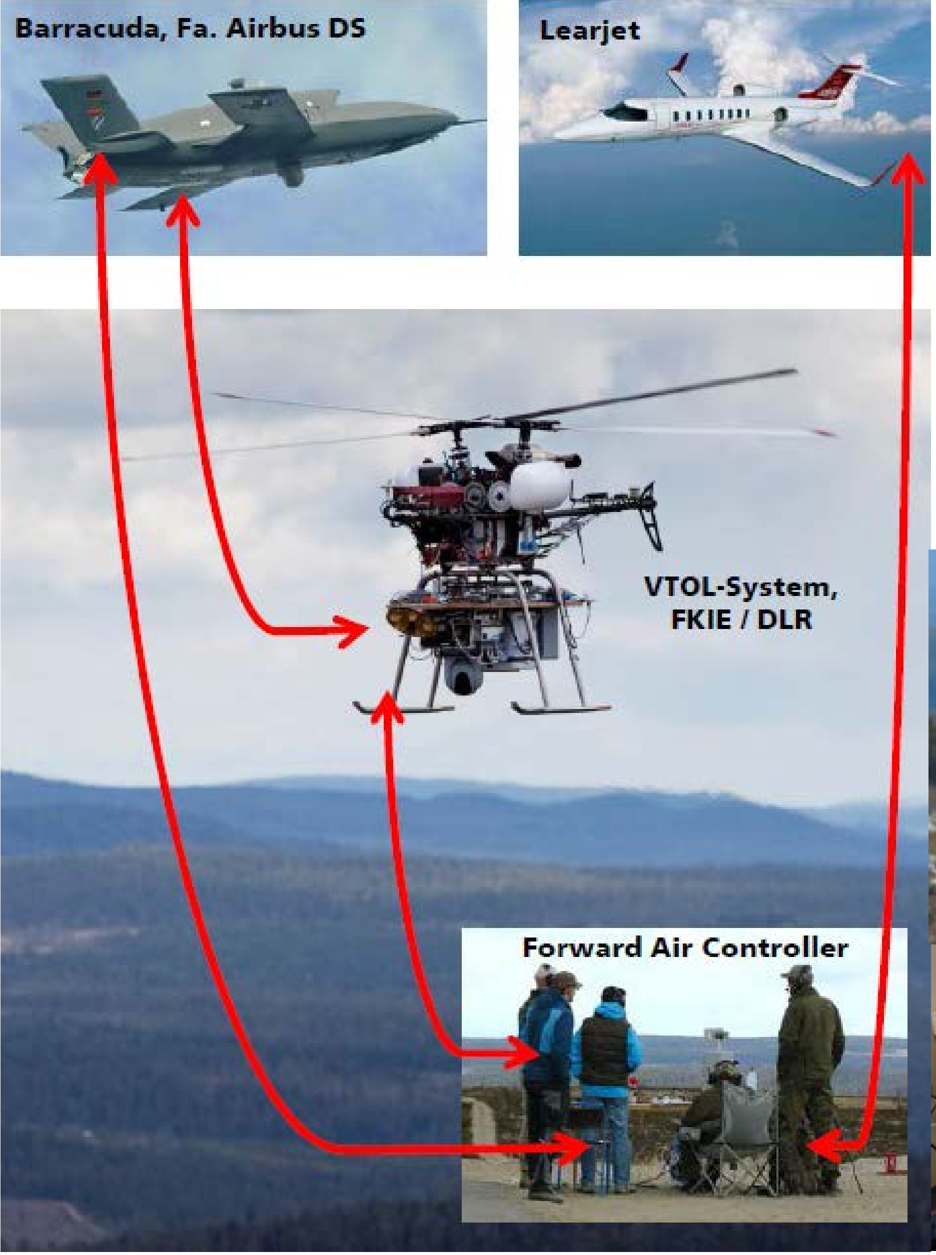
http://spectrum.ieee.org/automaton/robotics/artificial-intelligence/how-google-self-driving-car-works

Example: Convoy under attack - Urban Close Air Support

→ directly related to ongoing political discussions in Germany



Vidsel Campaign: VTOL Sensor Payload Ground Control Station



ELS Display

GCS Payload DL Antenna System

Video Display

Gefördert durch

Bundesministerium der Verteidigung

AIN II.6

AIRBUS DEFENCE & SPACE

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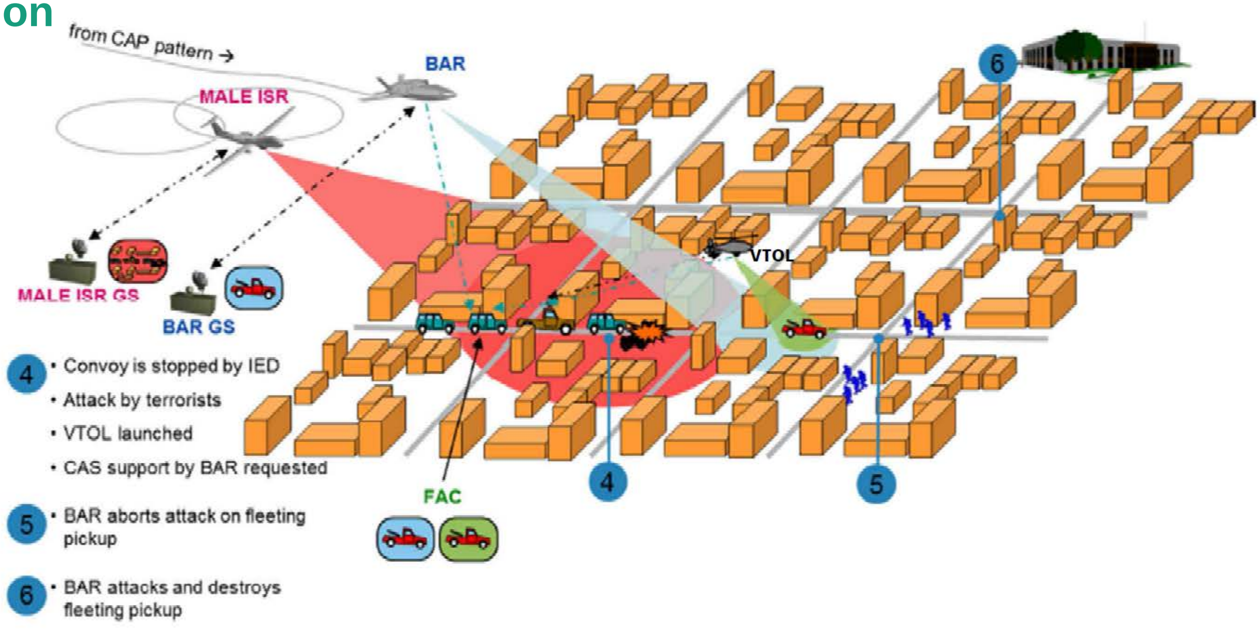
Urban Close Air Support: Hard *hard&soft fusion* problem!

Rules of Engagement (RoE) = *ius in bello:* scenario-specific framework for actions

- **Discrimination: engagement only when seamlessly observed without gaps**
- **Proportionality: Choose weapons that adequately correspond to threat**
  - **Challenging in urban environments: lacking line of sight**
  - **UAS copter: signal and image collection, context data**
  - ***Pre-engagement collateral damage prediction***
- **Responsibility: decisions made only by *Forward Air Controller* – Situation picture**
- **Future systems: *RoE Compliance by Design***
- **Mission Documentation**
  - **Transparency**
  - **Legal conformity**

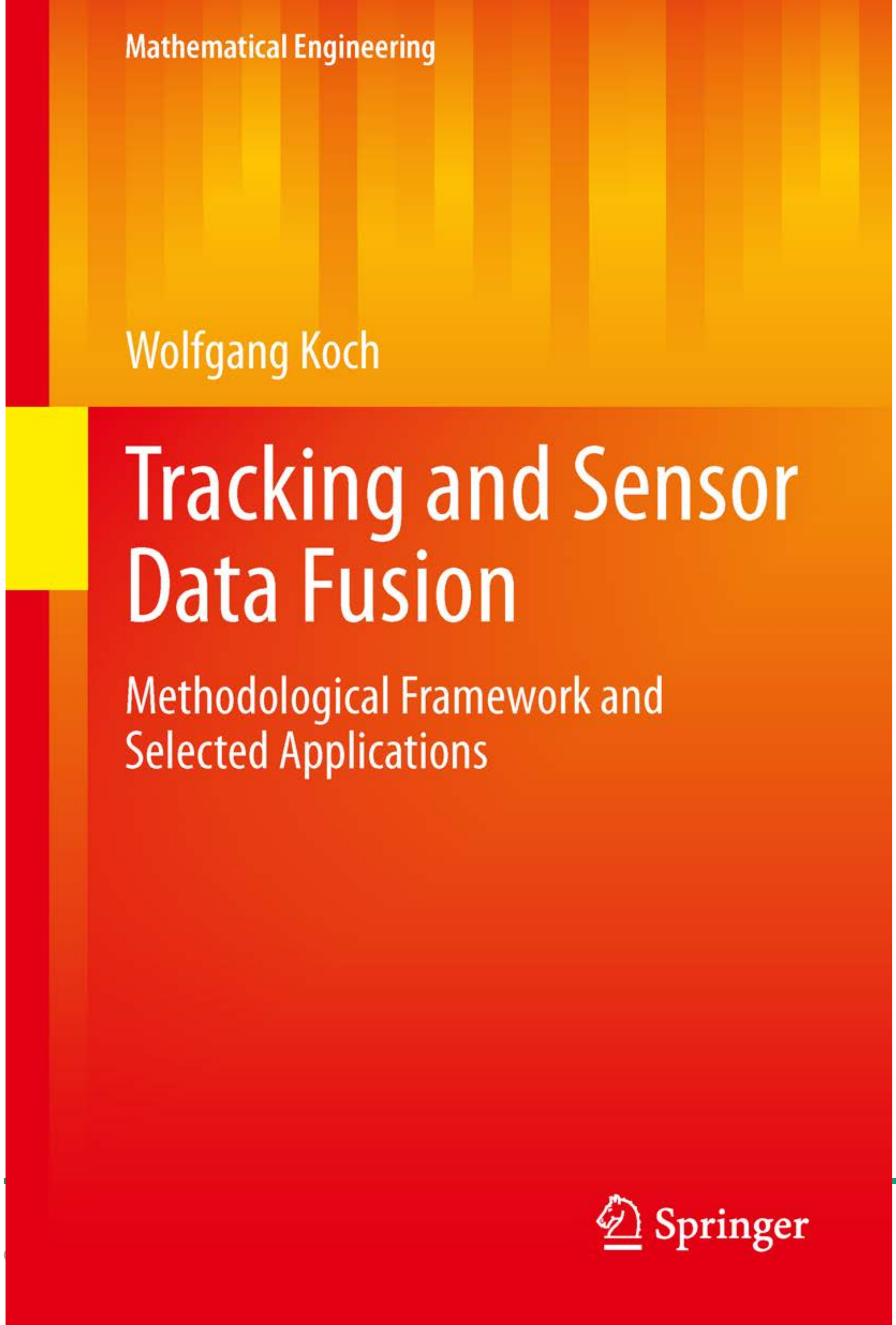


Fusion of “Hard” and “Soft” Data.

An interdisciplinary “universal technology“?

Ars generalis ultima of Raimundus Lullus?

Sensor and object models:	physics, chemistry, HF technology
Environmental modeling:	physics, geodesy, oceanography, …
Estimation / association:	stochastics, statistics, combinatorics
Processing of textual data:	linguistics, cognitive psychology
Data base management:	data base technology, data mining
Communications problems:	network technology, comms
Navigation, resource management:	control theory, game theory
Assistance for decision support:	human factors, ergonomics
Socio-cultural impact, ethics	philosophy, psychology, law



Many topics of previous work at Fraunkofer FKIE, Dept. *Sensor Data and Information Fusion.*

Appeared in 2014.

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