Attention in Cognitive Radar Using Effective Resources Management

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ABSTRACT

Attention is the cognitive process that controls which data is collected and processed to a higher level of awareness. The attention of cognitive radar should be focussed on mission objectives to facilitate problem solving and goal orientated behaviour. This paper describes how quality of service optimisation can be used to manage the radar resources of electronically steered phased array radar with respect to mission objectives. A quality of service management problem formulation is given, followed by optimality conditions as well as algorithms that are designed to satisfy the optimality conditions. In simulated examples, it is shown how quality of service optimisation can be used to manage the radar resources and hence attention between conflicting search and tracking tasks.

1.0 INTRODUCTION

Attention is a key cognitive process that selects the data upon which higher level awareness is based. For cognitive radar, the process of attention can be enabled using radar resources management (RRM) techniques. RRM addresses the two key problems of deciding how to allocate finite radar resource between numerous radar tasks, as well as deciding how to optimise the selection of control parameters for each individual radar task. Conventional radar resource management approaches optimise individual radar task control parameter selection using rules and heuristics, which are tuned by the system designer. This 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 focussed on mission objectives. One approach for achieving effective RRM is to use mission orientated quality of service (QoS) optimisation techniques. These QoS techniques applied to multifunction radar with an electronically steered phased array antenna is the focus of this paper.

2.0 QUALITY OF SERVICE RADAR RESOURCE MANAGEMENT

The majority of radar task management approaches select task control parameters considering each task in isolation. Therefore, the balance of the resource allocation between tasks is not considered and an effective attention process emerges instead of being directly controlled. Quality-of-service (QoS) management methods [1] enable task control parameters to be selected for multiple tasks, by considering the trade-off between each task's utility contribution and resource usage. The task utility contribution is determined by a mapping from a task relevant quality measure into utility, and represents the satisfaction associated with the task quality level. This utility function as well as a task importance weighting can be defined depending on the current situation and the mission objectives. The task utility contribution ultimately determines whether a radar task is preferred or ignored.

With respect to the architecture presented in the accompanying paper, this paper focuses on object management. This involves the selection of radar task control parameters for persistent radar tasks such as searching and tracking. The other components which are assumed to be present but not discussed in this paper are shown in Fig. 2-1. Once control parameters are selected, a scheduler orders the job requests from the multiple tasks to form a timeline which can be executed by a phased array antenna. The resulting signal data is processed to generate measurements, which are used to update the object level perception of the current situation. As the focus is on object level management, scheduling, priority assignment, utility definition, signal and data processing are beyond the scope of this paper.

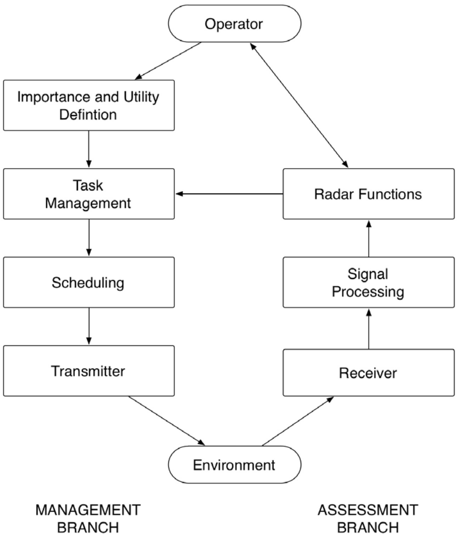

Figure 2-1: Assumed System Architecture.
(This paper focusses on object level management. It is assumed that scheduling, priority assignment, utility definition, signal and measurement data processing are performed.)

The control parameters that are selected represent the current resource management plan for a time horizon extending into the future. The resource allocation problem is dynamic, in that the number of tasks, the environmental parameters for each task and the maximum resource available can vary over time. Therefore, it is necessary to iteratively solve the resource management problem for all time instances, by applying receding horizon control as illustrated in Fig 2-2. When applying receding horizon control, a resource allocation is sought for each of the sequential resource allocation frames, however, the allocation is based on a non-myopic quality model that extends over multiple allocation frames in the future.

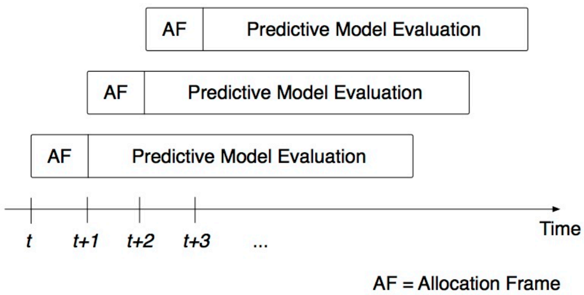

Figure 2-2: Receding Horizon Control.
(A solution to the resource management problem is found sequentially in time, based on a performance model that extends over a time horizon in the future.)

2.1 Problem Formulation

RRM involves selecting control parameters for radar tasks, such that the resource is optimally allocated between tasks and optimally utilised by each task. Examples of the control parameters are the task dwell duration, the task revisit interval time or the transmitted waveform for a track update or search beam position. The control parameters for task T_k are denoted υ_k.

To solve the QoS resource management problem, it is required to select parameters for all the tasks, to give the set of selections $\upsilon = \{\upsilon_1, \upsilon_2, \dots, \upsilon_K\}$. As each control parameter for each task uses a certain amount of resource, a resource allocation is also generated. The parameter selection υ_k is itself a set of parameters with a number of dimensions which depends on the task, i.e. $\upsilon_k = \{\upsilon_k^1, \upsilon_k^2, \dots, \upsilon_k^{M_k}\}$ where M_k is the number of control parameter dimensions for task T_k. Let $\upsilon_k \in \Upsilon_k$ denote the control parameter space for task T_k and $\upsilon \in \Upsilon$ denote the control parameter space for all tasks.

The influence of the environment can be modelled through uncontrollable environmental parameters which impact on the resource loading and the quality achieved by each radar task. Examples of the environmental parameters for a tracking task are the target range, target bearing or parameters of the target model. The environmental parameters for task T_k are denoted $e_k \in E_k$. In practice these environmental parameters are not known and must be estimated from the received measurements.

The operational parameters selected for each radar task impact on the resource loading of the radar task. A task resource function is also required, which maps the task control parameters and environmental parameters into resource space:

$$g_k : \Upsilon_k \times E_k \mapsto R_k \tag{1}$$

Where R_k is the resource space in the interval $[0,1]$ for a task. Each task achieves a quality of service level based on the control parameter selected and the resource allocated. The expected quality level over the considered time horizon is represented by a quality function, which maps task control parameters and environmental parameters into quality space:

$$q_k : \Upsilon_k \times E_k \mapsto Q_k \tag{2}$$

Each task can use a different quality measure, which is relevant to the task being performed. This formulation is easy to extend if a task has multiple quality dimensions, for example by taking a weighting sum [2].

To formulate an objective function for the resource allocation problem, a mapping between K task specific quality measures to a scalar valued mission effectiveness is sought. This mapping is based on the mission specific task requirements. A task requirement is comprised of a task utility function, which describes the satisfaction associated with an achieved task quality, and a task weighting, which describes the mission relevance of the task relative to other tasks. The utility of task T_k can be calculated through the task utility function:

$$u_k : \mathrm{Q}_k \mapsto U \tag{3}$$

where U is the task utility space defined on the real numbers in the interval $[0,1]$. Models for the quality and utility functions are discussed in Sec. 4.0. The importance weighting of task T_k is denoted ω_k and:

$$\sum_{k=1}^{K} \omega_k = 1 \tag{4}$$

The mission effectiveness can then be found as a weighted sum across the individual task utilities:

$$u(\upsilon) = \sum_{k=1}^{K} \omega_k \cdot u_k(q_k(\upsilon_k, e_k)) \tag{5}$$

This mission effectiveness represents the ability of the radar system to meet the mission specific task quality requirements.

Based on these functions the resource, quality and utility of control parameter selections can be evaluated. The evaluation of control parameters can then be visualised in resource utility space, as illustrated in Fig. 2-3. Each line in Fig. 2-3 represents the variation in a single control parameter dimension, while the other dimension is kept static.

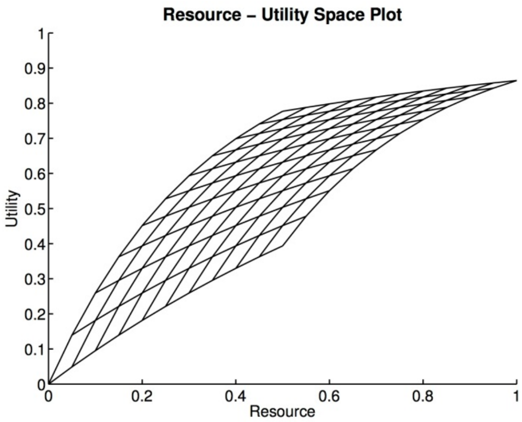

Figure 2-3: Example Resource-Utility Space.

Based on the resource and quality functions, and the utility function from the resource allocation problem, a constrained optimisation problem can be formulated for the RRM problem:

$$\textbf{maximise}_{\upsilon} \qquad u(\upsilon) = \sum_{k=1}^{K} \omega_k \cdot u_k(q_k(\upsilon_k, e_k)) \tag{6}$$

$$\textbf{subject to} \qquad g(\upsilon) \leq 0 \tag{7}$$

$$\text{where} \qquad g(\upsilon) = \left(\sum_{k=1}^{K} g_k(\upsilon_k, e_k) \right) - \hat{r} \tag{8}$$

2.2 Optimality Conditions

Consider, that the objective function $u(\upsilon)$ is a concave differentiable function and the resource function $g(\upsilon)$ is a convex differentiable function and that $\upsilon^* = \{\upsilon_1^*, \upsilon_2^*, \ldots, \upsilon_K^*\}$ is a globally optimal parameter selection set. Then, the Karush-Kuhn-Tucker (KKT) conditions [3] are a set of sufficient conditions for the optimal parameter selection set υ^*. The KKT conditions for the radar resource management problem are:

$$\text{Stationarity:} \qquad -\nabla u(\upsilon^*) + \mu \nabla g(\upsilon^*) = 0 \tag{9}$$

$$\text{Primal Feasibility:} \qquad g(\upsilon^*) \leq 0 \tag{10}$$

$$\text{Dual Feasibility:} \qquad \mu \geq 0 \tag{11}$$

$$\text{Complementary Slackness:} \qquad \mu g(\upsilon^*) = 0 \tag{12}$$

where μ is a KKT multiplier. Note that as the problem involves a maximisation, the objective function $u(\upsilon)$ must be concave for the KKT conditions to be sufficient instead of just necessary.

Eq. (9) has an important interpretation, due to the independence of the radar tasks. First note that υ_k^* is itself a vector given by $\upsilon_k^* = (\upsilon_k^{1*}, \upsilon_k^{2*}, \dots, \upsilon_k^{M_k*})$, namely the set of optimal parameters for radar task T_k. Therefore we write the gradient components in Eq. (9) as:

$$\frac{\partial u(\upsilon^*)}{\partial \upsilon_k^*} = \begin{pmatrix} \dfrac{\partial\, u(\upsilon^*)}{\partial\, \upsilon_k^{1*}} \\ \dfrac{\partial\, u(\upsilon^*)}{\partial\, \upsilon_k^{2*}} \\ \dfrac{\partial\, u(\upsilon^*)}{\partial\, \upsilon_k^{M_k*}} \end{pmatrix} \tag{13}$$

Due to the independence of the radar tasks, $u(\upsilon)$ in Eq. (5) is a sum of independent components and so:

$$\frac{\partial\, u(\upsilon^*)}{\partial\, \upsilon_k^{l*}} = \frac{\partial\, u_k(q_k(\upsilon_k, e_k))}{\partial\, \upsilon_k^{l*}} \qquad \forall l \in \{1,2, \dots, M_k\} \tag{14}$$

Likewise from Eq. (8) $g(\nu)$ is a sum of independent components and so:

$$\frac{\partial\, g(\upsilon^*)}{\partial\, \upsilon_k^{l*}} = \frac{\partial\, g_k(\upsilon_k, e_k)}{\partial\, \upsilon_k^{l*}} \qquad \forall l \in \{1,2, \dots, M_k\} \tag{15}$$

Therefore the stationarity condition in Eq. (9) indicates that:

$$\mu = \frac{\partial_l\, u_k(q_k(\upsilon_k, e_k))}{\partial_l\, g_k(\upsilon_k, e_k)} \qquad \begin{matrix} \forall k \in \{1,2, \dots, K\} \\ \forall l \in \{1,2, \dots, M_k\} \end{matrix} \tag{16}$$

where ∂_l denotes the partial derivative with respect to υ_k^{l*}. This set of conditions implies that the stationarity condition is satisfied when the gradients of resource over utility in all dimensions and for all tasks are equal to a common value, which is the KKT multiplier μ. The optimal solution is found when the stationarity condition is satisfied (Eq. (9)) and Eq. (16)) and the solution is primal feasible (Eq. (10)) and dual feasible (Eq. (11)) and either all the resource has been allocated or there would be no utility increase from further resource allocation (Eq. (12)).

3.0 QOS MANAGEMENT ALGORITHMS

If the resource, quality and utility functions are closed form expressions, then the KKT conditions can be solved analytically. However, it is often the case that these models do not have a closed-form, and instead require numerical evaluation. In the previous subsection it was assumed that the resource, quality and utility functions are defined on a continuous space. However, the control parameters may in fact be discrete, or it may be desirable to discretise the control parameters due to the need to perform numerical evaluations. In the discrete case, it is unlikely that the gradients in Eq. (16) can be equal, instead the optimum is found when they are as close to equal as possible. This section presents two algorithms that find discrete parameters selections based on the optimality conditions given in the previous section: the quality of service resource allocation method (Q-RAM) and the continuous double auction parameter selection (CDAPS) algorithm.

Once control parameters are selected by the resource management algorithm, these selected control parameters are used to schedule radar dwells for each task. Therefore, it is assumed that a scheduler at the measurement level below has access to the control parameters at every resource management frame. The scheduler may not be able to perfectly resolve radar dwell conflicts and therefore the actual behaviour may deviate from the desired control parameters. However, as the quality of service management ensures that the resource allocated is matched to the resource available, the scheduler is never overloaded and therefore the deviation should be small. It is also assumed that the mission level above provides the utility function and importance weighting for each task, with respect to the current mission.

3.1 Quality of Service Resource Allocation Method

Q-RAM is a numerical method for satisfying the Karush-Kuhn-Tucker conditions for discrete parameter selections. The algorithm starts with no resource allocated to any task, and then allocates resource increments to tasks in order of the highest marginal utility. Consequently, when the resource runs out, the marginal utilities will be as close to equal as possible, thus satisfying the KKT conditions.

Q-RAM [4] generates a solution through the following steps:

- Evaluate the resource and utility values for all possible control parameter selections for all tasks.
- Apply a convex hull operation [5] to extract the parameter selections that lie on the concave majorant [6] for each task.
- Calculate the marginal utility between the parameter selections on the concave majorant for each task. The marginal utility is the difference in utility over the difference in resource.
- Order parameter selections on the concave majorants for all tasks in a single list with descending order with respect to marginal utility.
- Iteratively allocate resource to the parameter selection with the highest marginal utility until no resource remains.
- Resource allocation frame is complete.

The algorithm achieves a near-optimal solution, as the optimal parameter selections may not lie on the concave majorant as identified by the sub-optimal stopping conditions in [7]. However, large deviations from the optimal can be avoided when a reasonable number of control parameters are used and the performance model is well behaved.

The original Q-RAM algorithm proposed Graham's scan as the convex hull extraction procedure, which requires all parameter selections to be evaluated. However, assuming monotonic resource and utility functions in the parameter dimensions, then traversal methods can be applied [8], [9] which do not require all parameter selections to be evaluated. This can greatly reduce the number of parameter selections that are evaluated, which is especially valuable if the performance model has non-trivial computation.

3.2 Continuous Double Auction Parameter Selection

The CDAPS algorithm [10]–[13] is an alternative algorithm for solving the RRM problem. CDAPS utilises a continuous double auction mechanism [14] which settles on a market equilibrium that satisfies the KKT conditions.

In the CDAPS algorithm each radar task is represented by a task agent, who competes with other task agents for the finite radar resource. The competition takes place in a CDA, which has the following protocol:

- Each agent can hold an amount of resource at any time r_k which may be used for its task.
- The total resource held by all agents may not exceed the resource available.
- Each agent announces offers to trade comprising of bids to buy more resource or asks to sell resource.
- At any time a set of currently active bids and asks from any agent exists.
- Bids are matched to ask such that the resource trade results in a net increase in utility.

Each agent calculates its bids and asks based on the utility and resource evaluation of control parameters adjacent to the currently active control parameter. As illustrated in Fig. 3-1, the announced bid price p_b^k for agent T_k is the possible increase in utility over the increase in resource:

$$p_b^k = \frac{\Delta u_b}{\Delta r_b} \tag{17}$$

and the announced ask price p_a^k is the possible decrease in utility over the decrease in resource:

$$p_a^k = \frac{\Delta u_a}{\Delta r_a} \tag{18}$$

As each trade results in a utility increase, the market settles on an equilibrium that maximises utility. As shown in [13] this equilibrium satisfies the KKT conditions.

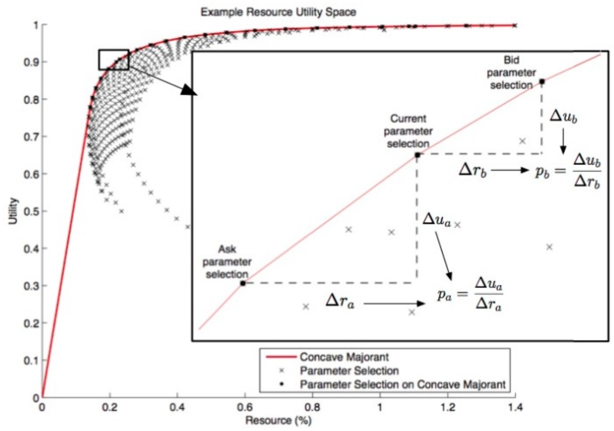

Figure 3-1: Bid and Asks in CDAPS.
(Bid and ask evaluation process in continuous double auction parameter selection algorithm.)

The key benefit of CDAPS in comparison to Q-RAM, is that the solution from the previous time step can be adapted to the current time step, without a complete re-computation of the resource allocation. Consequently, the number of parameter selections that are evaluated per second is significantly reduced. This is useful when the performance model used to calculate the resource, quality and utility has a non-trivial computational cost.

4.0 PERFORMANCE MODELS

Quality of service management relies on performance models that relate the control parameters to the quality that can be achieved. A performance model can be a forwards model, which calculates the quality a task can achieve given a set of control parameters. Alternatively, a model can be a backwards model, which calculates the control parameters that are required to achieve a specified quality. Forwards models are generally easier to define and consequently the problem formulation and algorithms in the previous subsections assumed forwards models. However, using backwards models can result in a simpler implementation, as it is not necessary to search over a large number of control parameters for suitable quality values. Practically, a high fidelity model can be used as a basis for curve fitting or a look-up table in order to reduce online computation.

A forwards model predictively evaluates the expected resource and quality for a candidate parameter selection, over a future time horizon but based on the current state of the task. A performance model for active tracking was given in an application of Q-RAM to radar tracking [8], however, the model was not claimed to be accurate. This subsection describes alternative performance models that can be used for the search and tracking functions.

4.1 Active Tracking Models

Active tracking is the process of maintaining tracks on targets using measurements from a series of dwells which are dedicated to each target. Control parameters for waveform and revisit interval selection must be performed such that the quality requirement of the tracking task is met. Additionally, the selection of control parameters must consider the beam positioning loss that results from the mismatch between the target's true and estimated position. This beam positioning loss increases as the track estimation error increases and therefore limits the revisit time between track updates.

4.1.1 Van Keuk and Blackman Model

Van Keuk and Blackman [15] describe models that can be used for active tracking. In the model the task control parameters are the track revisit interval and the received signal to noise ratio, which implies the coherent dwell length. The quality of the task is the track sharpness, which is the track angular estimation error in units of the radar 3dB beamwidth. Van Keuk and Blackman give a backwards model that enables the track revisit interval control parameter to be selected:

$$t_r = 0.4\left(\frac{R\sigma\sqrt{\Theta}}{\Sigma}\right)^{0.4}\frac{U^{2.4}}{1+\frac{1}{2}U^2} \tag{19}$$

where σ is the measurement error standard deviation, R is the target range and Θ and Σ are the Singer model parameters. U is the variance reduction ratio, which the ratio of the track to measurement angular error [16]. It is also recommended to select the coherent dwell length to give a received $16-19$dB signal to noise ratio, based on the estimated target radar cross section.

The equations from the Van Keuk and Blackman model can also be used as a forwards model [13], so that the steady state expected track sharpness can be calculated based on a specified track revisit interval and the coherent dwell length. The track sharpness v_0 can be calculated by finding the root of the function:

$$1+\left(\frac{\beta}{2}+2\right)v_0^2-\alpha\beta v_0^2=0 \tag{20}$$

where:

$$\alpha = \frac{0.4}{t_r}\left(\frac{R_t \theta_B \sqrt{\Theta}}{\Sigma}\right)^{0.4} \tag{21}$$

and $\beta = SN_0 - \ln P_f$. This can be done numerically, for example using the Newton-Raphson method [17].

The van Keuk and Blackman model is useful as it is a computationally light forwards and backwards model. However, the model is empirical and not easily extendable. For example, it is fixed to the use of a Singer target model and the quality is fixed as the track sharpness. However, other tracking quality measures or target models would likely be of interest, which limits the applicability.

4.1.2 Covariance Analysis

Alternatively, a forwards model for target tracking can be produced using covariance analysis. Covariance analysis predictively evaluates the track estimation error standard deviation over a future time horizon based on the track at the current time. In this case the control parameters can be the revisit interval, dwell time and waveform. The track quality can be derived from the predicted track, for example the filter predicted RMSE. A covariance analysis approach is described in [18] for a radar network, however, the process is also the same for a single radar.

To summarise the covariance analysis procedure, the track from the current time can be evaluated over multiple prediction and expected measurement updates stages based on the specified control parameters. The prediction can be based on the tracking filter that is used for tracking. As the evaluation is predictive, no measurements are available for the performance evaluation. Therefore an expected measurement update process is performed as described in [18]. The use of covariance analysis involves more computation than the Van Keuk and Blackman model, however, it can be used for any tracker, any target model, and any task quality model that is derived from the track state.

4.2 Search Models

A search volume can be served by a number of beam positions. It is then possible to control the time between revisits as well as the transmitted waveform and hence dwell time in each beam position. As the objective of search is to detect previous undetected targets, control parameters should be selected to detect targets as early as possible. Therefore a suitable performance criterion is the cumulative detection range.

4.2.1 Cumulative Detection Range

The cumulative probability of detection is the probability that a target is detected at least once from a certain number of dwells on a target [19]. The cumulative detection range is the range at which the cumulative detection probability over multiple dwells on a target exceeds a specified probability, e.g. 0.9. In order to calculate the cumulative detection probability or range, the target trajectory and radar cross section should be known. As this is not known, an expected of the worst case can be taken, such as assuming an inbound trajectory with radial velocity v_r.

The cumulative probability of detection after n dwells for a target appearing at range r_{pu} is then:

$$P_C(r \mid r_{pu}) = 1 - \prod_{i=1}^{n} 1 - P_D(r_{pu} - v_r \cdot ri \cdot i - \Delta) \tag{22}$$

where Δ is a uniform distributed random variable, between 0 and $v_r \cdot ri$, which is the time between the targets appearance and the first scheduled dwell. $P_D(r)$ is the probability of detection at range r.

A simple method to calculate the 90% cumulative detection range is to successively increase n until the cumulative probability of detection is greater than 90% and then averaging over the possible arrival time Δ between the scans [11]. If more information is known about the environment then the search can be better modelled. For example, targets may pop-up at specific ranges instead of following inbound trajectories from great range. This could be due to for example targets breaking the horizon, airports, shadowing from terrain, or the beam position intersecting the ground plane for an airborne platform [20].

5.0 RESOURCE MANAGEMENT EXAMPLES

This section describes simulated examples of applying quality of service radar resource management to enable the process of attention. The first example considers only tracking tasks and the second example considers both searching and tracking tasks.

5.1 Active Tracking Management

Quality of service management can be applied to control multiple targets that are actively tracked [13]. Following the problem formulation in Sec. 2.1 the resource manager must select the set of operational parameters $\upsilon_t = \{\upsilon_1, \upsilon_2, \ldots, \upsilon_K\}$ at each measurement instance $t \in T_s$ where $\upsilon_k = \{\tau_c, t_r\}$ are the operational parameters for tracking task T_k, τ_c is the coherent dwell time and t_r is the revisit interval time. The operational parameters selected are time-varying, to respond to changes in the environmental parameters. For each tracking task, the coherent dwell duration can be chosen in the range $[0.1, 0.2, \ldots, 10]$ms and the revisit interval time can be chosen in the range $[0.1, 0.2, \ldots, 3.5]$s.

In the simulation, 200 targets require active tracking. Full details of the simulation setup and methods can be found in [13]. The environmental parameters $e_k = \{R_t, \theta_t, \rho, \Theta, \Sigma\}$ for tracking task T_k are the target range R_t, bearing θ_t as well as the radar cross section ρ and Singer manoeuvre model parameters Θ and Σ. The initial Cartesian coordinates of each target is uniformly distributed within the radar field of view, which is between $[10, 120]$km in range and $[-45, 45]^0$ in bearing. The Cartesian positions of the targets evolve over the simulation time according to a randomly generated Singer trajectory. In the simulations Q-RAM and CDAPS are compared against two rule based methods (RBPS1 and RBPS2). Q-RAM and CDAPS use an exponential utility function with a sensitivity parameter η that can be varied based on the mission requirements.

Fig. 5-1 plots the number of targets that were chosen to be maintained for each of the four methods, over a range of resource constraints. It can be seen that Q-RAM and CDAPS with $\eta = 0.012$ maintain the greatest number of targets, with RBPS2 maintaining a similar number due to its rule specification. The number of targets maintained using Q-RAM and CDAPS depends on the tracking sensitivity parameter in the utility function, which can be mission specific.

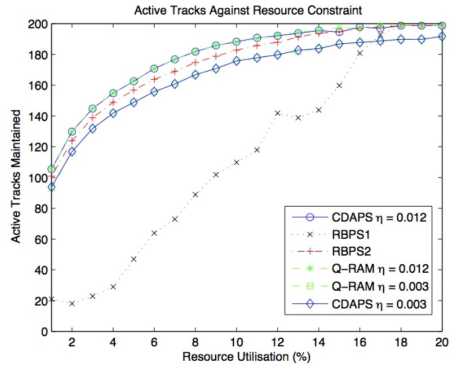

Figure 5-1: Number of Active Tracks Maintained.

The average angular estimation error for the four methods is plotted in Fig. 5-2 against varying resource constraints. It can be seen in Fig. 5-2 that RBPS1 and RBPS2 maintains an angular accuracy that emerges from the rule specification. Q-RAM and CDAPS control the angular accuracy quality depending on the utility function specification.

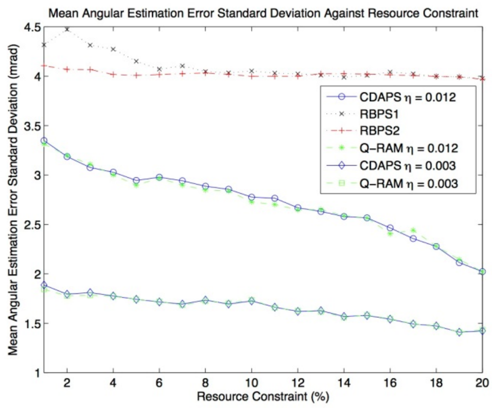

Figure 5-2: Average angular estimation error standard deviation against varying resource constraints.

Ultimately the best performance depends on what is actually required, that is, to track more targets or to achieve a better estimation error. However, the utility function describes what is required and can therefore be used as an indicator of the overall performance. The total utility for varying resource constraints is shown in Fig. 5-3 for the four methods. In the figure, it can be seen that CDAPS and Q-RAM significantly outperform the rule based approaches in terms of utility. This is to be expected, as CDAPS and Q-RAM achieve a near-optimal maximisation of utility.

This result verifies that CDAPS and Q-RAM produce the same near-optimal solution, with equal performance. Both methods have a total utility which significantly improves upon the conventional rule based methods. This performance improvement is attributable to CDAPS and Q-RAM optimising the complete multiple task parameter selection problem, whereas the rule based methods apply rules to each task separately. The trade-off between the number of targets and the tracking accuracy can be changed by redefining what is required from the task via the utility function. However, by producing the near-optimum parameter selection set, CDAPS and Q-RAM must always perform equal to or better than the locally optimised rules in terms of the total utility of the resource allocation.

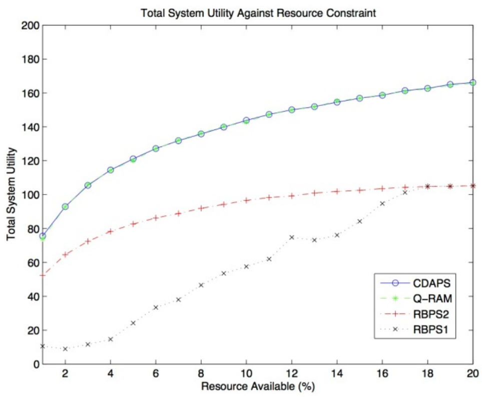

Figure 5-3: Total utility against varying resource constraints.

5.2 Search and Track Management

Quality of service management can also be used to control radar tasks for differing radar functions, such as search and track. The following simulated scenario considers an airborne platform which must search, detect and track two incoming targets. This scenario is illustrated in Fig. 5-4. In the scenario, the platform and targets are all at an altitude of 1km.

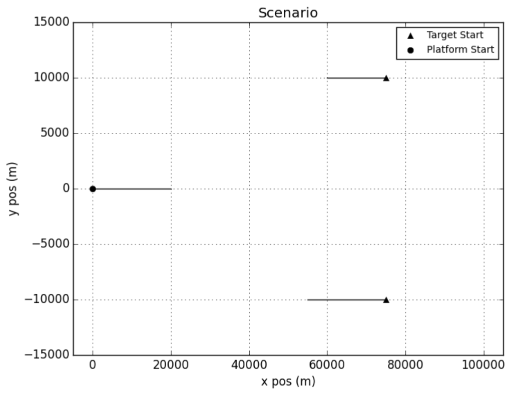

Figure 5-4: Simulation Scenario.

In the following results a rule based method is compared to the quality of service approach described in this paper. For the rule based method, a uniform search strategy is applied, that transmits uniform energy in each search beam position with a search frame time of $2 - 4$s depending on the resource available for search. Once a target is detected in the search and confirmed, it is tracked using adaptive tracking [15], [21], [22] with track sharpness set at 0.12. The quality of service method uses the covariance analysis model described in Sec. 4.1.2 for target tracking and the cumulative detection range model described in Sec. 4.2.1 for search. The utility function for target tracking is specified as a linear function between the best necessary and worst possible track sharpness values of 0.15 and 0.2 respectively. The utility function for search is designed for long range target acquisition, as it is desired to acquire targets between 40km and 100km. These bounds on the utility function define the acceptable tasks utilities with respect to the mission.

Fig. 5-5 plots the first measurement and track acquisition ranges for the rule based and QoS method. It can be seen that both the first measurement and track acquisition ranges are significantly increased when using the QoS method. This is due to the optimisation of the revisit interval and dwell length for every beam position in the search. Firstly, beam positions that intersect with the ground plane at short range select short dwell lengths, which save resource. Secondly, beam positions that do not intersect the ground plane have a long dwell and a long revisit interval, which is suited to maximising the cumulative detection range. These parameters are selected based on the mission objective which is long range detection. A short range search can easily be implemented by adjusting the bounds on the utility function, in which case shorter beam position revisit intervals and dwell times would be preferred.

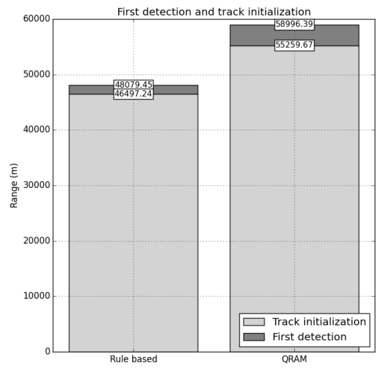

Figure 5-5: First Measurement and Track Acquisition Ranges.

Figure 5-6 plots the track completeness for the simulation. The track completeness is the number of targets that are tracked over the total number of targets in the defined surveillance region. It can be seen that the QoS management approach enables a completer picture to be presented to the operator. This is primarily due to the optimisation of the control parameters of every search beam position to be suited to long range search.

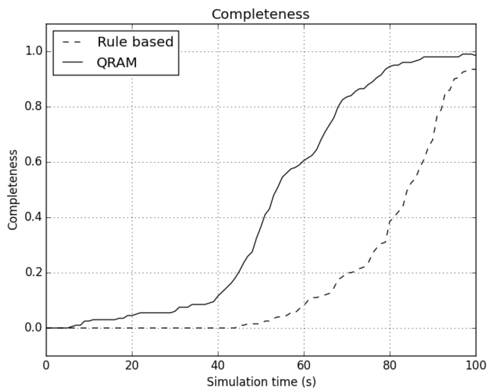

Figure 5-6: Track Completeness.

Figure 5-7 plots the average track sharpness over the simulation time for the rule based method as well as the QoS method with two differing utility functions. The utility functions specify that the best and worst required track sharpness is between $0.15 - 0.2$ and $0.1 - 0.15$ respectively. It can be seen that the achieved track quality (track sharpness) can be control and varied based on these mission specific utility specifications.

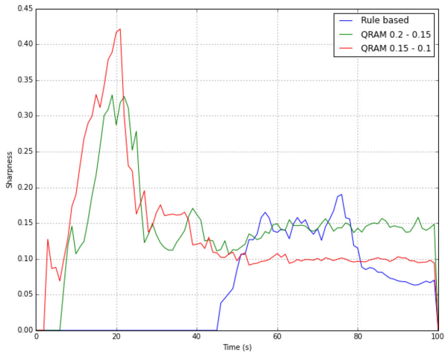

Figure 5-7: Track Angular Estimation Error.

6.0 SUMMARY

This paper described how the cognitive process of attention can be generated by using quality of service optimisation techniques to enable effective radar resources management that is focused on mission objectives. Quality of service resource management aims to maximise the global utility production of all radar tasks by balancing each task's utility production and resource usage. As utility is defined as the satisfaction associated with a level of task quality, it can be related to mission objectives. Optimality conditions can be derived by applying the KKT conditions, and these optimality conditions are the basis for algorithms that solve the quality of service radar resource management problem. In the paper it was shown that these algorithms can be used to control many tasks from different radar functions, such that the control is orientated towards mission objectives. Hence the processes of problem solving, goal orientated behaviour and attention can be generated.

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