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A literature survey of radar resource management algorithms

Zhen Ding

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Principal Author

Original signed by Zhen Ding

Zhen Ding

Defence Scientist

Approved by

Original signed by Doreen Dyck

Doreen Dyck

Head/Radar Systems Section

Approved for release by

Original signed by Pierre Lavoie

Pierre Lavoie

Chief Scientist, Head/Document Review Panel

Abstract

DRDC Ottawa has launched an applied research project (ARP) called “Advanced Concepts for Naval Multi-function Radar (MFR)”. Two major science and technology topics are identified for this project. The first major topic is the radar detection and tracking of small targets in littoral environments. The second major topic is the investigation of the adaptive radar resource management (RRM) problem. This report presents a survey of the second topic based on existing open literature. The surveyed algorithms are grouped into five categories: artificial intelligence algorithms, dynamic programming algorithms, quality of service (QoS) resource allocation management (Q-RAM) algorithms, waveform-aided algorithms and adaptive update rate algorithms. The first three categories are adaptive radar scheduling algorithms and the remaining two categories are resource-aided algorithms. The US Navy’s phased array radar benchmark problems and solutions are also reviewed. Comments are provided for each category of the RRM algorithms, which lead to recommendations for future study.

Résumé

RDDC Ottawa a lancé un projet de recherche appliquée (PRA) intitulé « Concepts avancés pour radar multifonction (MFR) naval ». Ce projet comporte deux thèmes majeurs de science et technologie : l’étude du problème de gestion des ressources radar (RRM) adaptative ainsi que la détection et la poursuite radar de petites cibles dans des environnements littoraux. Le présent rapport comprend une étude documentaire du deuxième thème selon les sources publiées. Les algorithmes étudiés sont groupés selon cinq catégories : les algorithmes d’intelligence artificielle, les algorithmes de programmation dynamique, les algorithmes d’affectation des ressources fondés sur la qualité de service (Q-RAM), les algorithmes fondés sur les formes d’onde et les algorithmes à fréquence de mise à jour variable. Les algorithmes des trois premières catégories sont des algorithmes adaptatifs d’ordonnancement radar, tandis que ceux des deux autres catégories sont des algorithmes fondés sur les ressources. Les problèmes de référence pour les radars à balayage électronique de la Marine américaine et leurs solutions sont également étudiés. Des commentaires sur chaque catégorie d’algorithmes de RRM sont fournis, et ces commentaires mènent à des recommandations sur les recherches futures.

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Executive summary

A literature survey of radar resource management algorithms

Zhen Ding; DRDC Ottawa TM 2008-334; Defence R&D Canada – Ottawa; March 2009.

Introduction or background: DRDC Ottawa has launched an applied research project (ARP) called "Advanced Concepts for Naval Multi-function Radar". Two major science and technology topics are identified for this project. The first major topic is the radar detection and tracking of small targets in littoral environments. The second major topic is the investigation of the adaptive radar resource management (RRM) problem for the naval MFR.

Results: This report presents a survey of the second topic based on existing open literature. The surveyed algorithms are grouped into five categories: artificial intelligence algorithms, dynamic programming algorithms, quality of service (QoS) resource allocation management (Q-RAM) algorithms, waveform-aided algorithms and adaptive update rate algorithms. The first three categories are adaptive radar scheduling algorithms and the remaining two categories are resource-aided algorithms. The US Navy's phased array radar benchmark problems and solutions are also reviewed. Comments are provided for each category of the RRM algorithms, which lead to recommendations for future study.

Significance: The technical survey reviewed possible solutions to the RRM problem. Some identified algorithms have been used to upgrade DRDC's multi-function radar test-bed, and to support the study of adaptive radar control. Future research topics have been recommended to fulfill the ARP objectives.

Future plans: The following topics are recommended for future study:

- Study of adaptive classification algorithm for RRM;
- Comparison of the fuzzy logic, neural network and entropy algorithms;
- Application of fuzzy logic for task scheduling;
- Evaluation of the dynamic programming and Q-RAM algorithms with realistic RRM problems;
- Investigation of the waveform diversity benefits for RRM;
- Study of the motion noise models for adaptive update rate tracking;
- The Benchmark 3 problem should be studied and future solutions should be tested and compared against the existing solution. Also, additional sensors should be considered to enhance the RRM performance. Other measures of performance (MOP) such as task occupancy and timeliness should be included.

Sommaire

A literature survey of radar resource management algorithms

Zhen Ding; DRDC Ottawa TM 2008-334; R & D pour la défense Canada – Ottawa; Mars 2009.

Introduction : RDDC Ottawa a lancé un projet de recherche appliquée (PRA) intitulé « Concepts avancés pour radar multifonction (MFR) naval ». Ce projet comporte deux thèmes majeurs de science et technologie : l'étude du problème de gestion des ressources radar (RRM) adaptative ainsi que la détection et la poursuite radar de petites cibles dans des environnements littoraux.

Résultats : Le présent rapport comprend une étude documentaire du deuxième thème selon les sources publiées. Les algorithmes étudiés sont classés selon cinq catégories : les algorithmes d'intelligence artificielle, les algorithmes de programmation dynamique, les algorithmes d'affectation des ressources fondés sur la qualité de service (Q-RAM), les algorithmes fondés sur les formes d'onde et les algorithmes à fréquence de mise à jour variable. Les algorithmes des trois premières catégories sont des algorithmes adaptatifs d'ordonnancement radar, tandis que ceux des deux autres catégories sont des algorithmes fondés sur les ressources. Les problèmes de référence pour les radars à balayage électronique de la Marine américaine ainsi que leurs solutions sont également étudiés. Des commentaires sur chaque catégorie d'algorithmes de RRM sont fournis, et ces commentaires mènent à des recommandations sur les recherches futures.

Portée : L'étude technique a porté sur des solutions possibles au problème de la RRM. Certains des algorithmes étudiés ont servi à mettre à jour le banc d'essai du radar multifonction naval de RDDC et à soutenir l'étude de la commande radar adaptative. Des thèmes de recherches futures ont été recommandés pour répondre aux objectifs du PRA.

Recherches futures : Il est recommandé d'étudier les thèmes suivants dans le futur :

- l'étude des algorithmes de classification adaptatifs pour la RRM;
- la comparaison des algorithmes de logique floue, de réseaux neuronaux et d'entropie;
- l'application de la logique floue à l'ordonnancement des tâches;
- l'évaluation des algorithmes de programmation dynamique et de Q-RAM avec des problèmes de RRM réalistes;
- une enquête sur les bénéfices de la diversité des formes d'onde pour la RRM;
- l'étude des modèles de bruit de mouvement pour la poursuite à fréquence de mise à jour variable;
- le problème de référence n° 3 devrait être étudié et les nouvelles solutions devraient être mises à l'essai et comparées avec la solution existante. De plus, on pourrait envisager l'utilisation de capteurs supplémentaires pour améliorer le rendement de RRM. D'autres

mesures du rendement, comme la charge de traitement et l’obtention de résultats dans des délais opportuns, devraient être incluses.

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1 Introduction

1.1 Motivation

DRDC Ottawa has launched an applied research project (ARP) called "Advanced Concepts for Naval Multi-function Radar (MFR)" [1]. Two major science and technology topics are identified for this project. The first major topic is the radar detection and tracking of small targets in littoral environments. The second major topic is the investigation of the adaptive radar resource management (RRM) problem for the naval MFR. This report presents a survey of the second topic based on existing open literature.

1.2 The Radar Resource Management Problem

A naval MFR performs many functions previously performed by individual, dedicated radars, such as search, tracking and weapon guidance, etc. The radar performs these functions by actively controlling its beams, dwell time, waveform and energy. Details of general phased array radars can be found in references [2-6]. An illustration of the multiple functions is depicted in Figure 1.

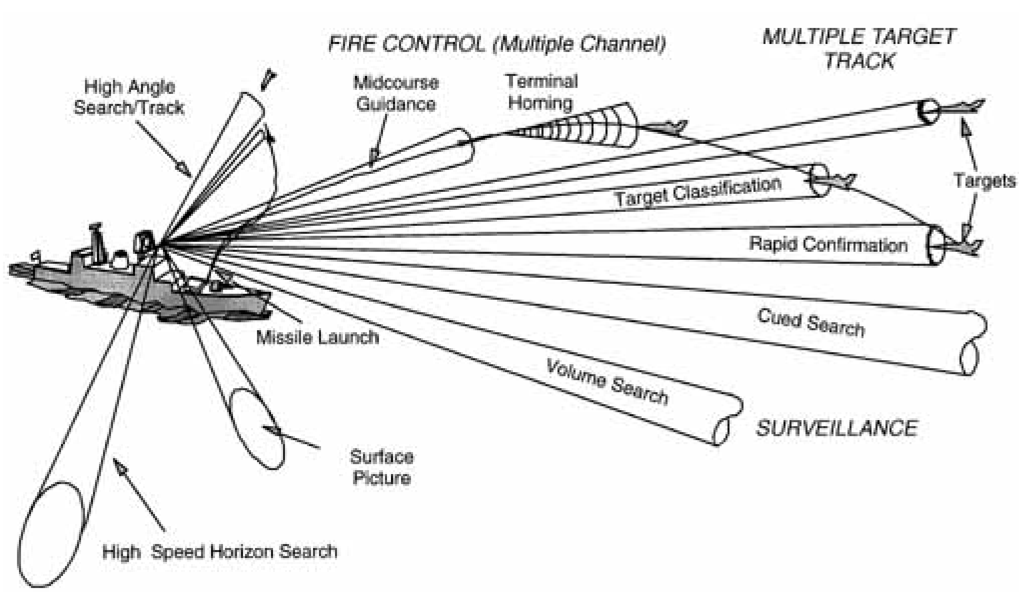

Figure 1: Multiple tasks of typical ship-born radar systems [7].

There are many tasks under each radar function. All the above functions, or equivalently, the tasks, are coordinated by a central component called the RRM in the radar system. This RRM component is critical to the success of a MFR since it maximizes the radar resource usage in order to achieve optimal performance where the optimality is defined according to a cost function. In order to understand the RRM problem and the solutions, a thorough literature search was conducted. A brief version of this survey was presented at the 8th Canadian Conference on Electrical and Computer Engineering [8].

The three major radar resources are shown in Figure 2. The challenge of the RRM arises when the radar resources are not enough to assist all the tasks in all the functions. Lower priority tasks must encounter degraded performance due to less available resources, or the radar may not execute some tasks at all. Each task in the radar requires a certain amount of time, energy and computational resource. The time is characterized by the tactical requirements, the energy is limited by the transmitter energy, and the RRM computer limits the computational resource. All of those limitations have impacts on the performance of the radar resource management.

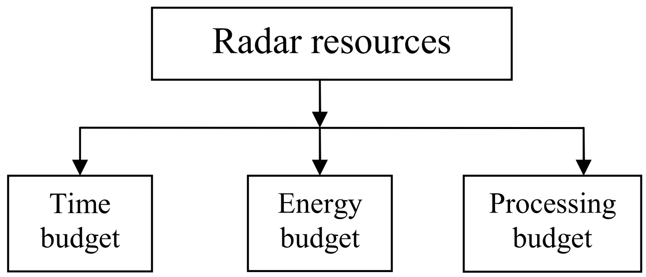

Figure 2: Three radar resources.

An additional challenge is that since the RRM deals with many radar subsystems, evaluation of the RRM algorithms must be done under a more complex and detailed radar model. A general MFR resource management system model is shown in Figure 3. It performs the following steps:

- Get a radar mission profile or function setup;
- Generate radar tasks;
- Assign priorities to tasks by using a prioritization algorithm;
- Manage available resources by a scheduling algorithm so that the system can meet the requirements of all radar functions;
- When there are no detections in the course of non-surveillance tasks, a re-look may be scheduled based on its priority and elapsed time since the last scheduling of the same task;
- The radar scheduler considers radar beams, dwell time, carrier frequency, PRF, energy level, etc.

As can be seen from the above steps, the RRM problem has two basic issues: task prioritization and task scheduling. Some RRM algorithms handle the two issues separately and others handle them simultaneously. The task prioritization is an important factor in the task scheduler. The other factor is the required scheduling time, which is decided by the environment, the target scenario and the performance requirements of radar functions. The required scheduling time could be improved by using advanced algorithms, such as waveform-aided algorithms and adaptive update rate algorithms.

A RRM algorithm can be non-adaptive or adaptive. In a non-adaptive scheduling algorithm, the task priorities are predefined and the radar scheduler includes some heuristic rules. Therefore, the resource performance is not optimized. Adaptive scheduling algorithms are much more complex, and should, theoretically, yield better performance. Since advanced MFRs always use adaptive scheduling algorithms, only adaptive scheduling algorithms are surveyed in this report.

Note that the general sensor management problem is to optimally coordinate the usage of multiple sensors. This is not covered in the report.

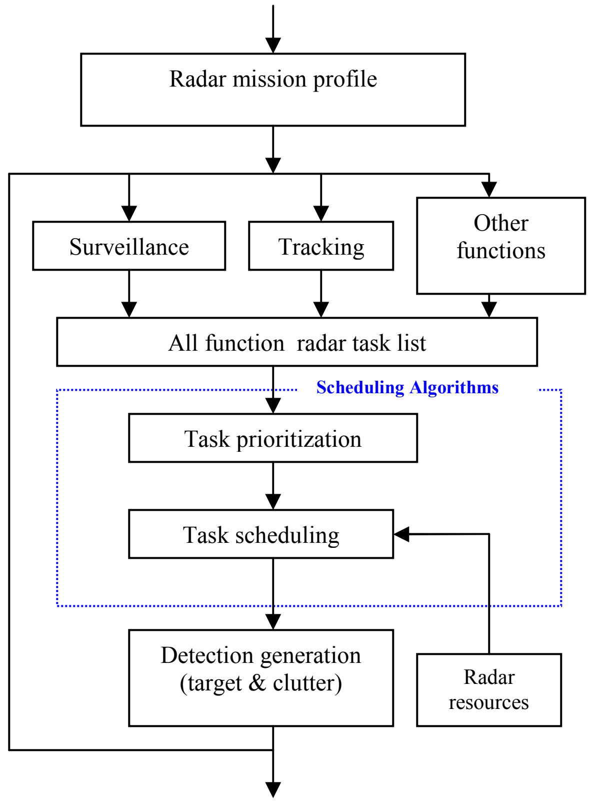

Figure 3: An MFR resource management model.

1.3 Outline of the Report

The RRM algorithms surveyed in this report are divided into five categories, with one chapter devoted to each category. The first three categories are adaptive scheduling algorithms, and the remaining two categories are resource-aided algorithms. When a paper falls into more than one category, it is put into the most suitable category. Categories 4 and 5 are relevant since a better algorithm is able to achieve the same performance with less resource or to achieve a better performance with the same radar resources. Comments are provided for the RRM algorithms in each category.

The five categories are as follows:

- Artificial intelligence algorithms (Chapter 2);
- Dynamic programming algorithms (Chapter 3);
- Q-RAM algorithms (Chapter 4);
- Waveform aided algorithms (Chapter 5); and
- Adaptive update rate algorithms (Chapter 6).

In Chapter 7, the NRL benchmark problems are defined and solutions proposed to date are reviewed. Finally, conclusions and recommendations are presented in Chapter 8.

2 Artificial Intelligence Algorithms

In this category, fifteen papers are noted [9]-[22]. The papers cover neural network approaches [9, 10, 11], expert system approaches [12, 13] and fuzzy logic approaches [14-20]. In addition, an entropy approach for radar scheduling is also discussed [23]. Paper [24] belongs to both the artificial intelligence (AI) category and the waveform-aided algorithm category. It will be discussed in the waveform algorithm category in Chapter 5.

2.1 Neural Networks

Neural networks (NNs) are used for both issues of the RRM: using classification neural networks for task prioritization and optimizing neural networks for task scheduling.

2.1.1 Task Prioritization

Classification neural network algorithms are primarily used for assignment of priorities to tasks. All required radar tasks are the input and the constraints are radar time and energy budgets. Optimization could be the minimization of radar resources, given the search, track and engagement performance requirements, or the maximization of the performance by using the available radar resources.

Komorniczak [9, 10] proposed a neural network priority assignment algorithm. In this algorithm, a feature vector was the input to the multi-layer neurons. Training data set was used to adjust weights of the neural network. In the application phase, the trained neural network generated the priorities based on all given targets' feature data. The arbitrary nonlinear mapping capability of the neural networks was utilized.

The mapping provides target prioritization value, which classifies radar targets into different levels. This is necessary when a lot of targets are competing for radar resources. Accordingly, radar resources are first given to those targets with higher priority. For example, the following target features can be used:

- Membership (friend or foe);
- Range;
- Radial velocity;
- Azimuth;
- Acceleration.

Non-numerical features of the targets are transformed to numerical values, which determine the input vector in the target prioritization process. All the features are put into a joint vector as follows:

x_1 – membership: friend (x_1 = 0), foe (x_1 = 1);

x_2 – range (km);

x_3 – radial velocity of the target (*m/s)*;

x_4 – azimuth (*degrees*);

x_5 – acceleration of the target (m/s^2).

As shown in Figure 4, the components of x vector are multiplied by weights w_i in the NN-block. Then the output is calculated as a weighted sum of x_i , i.e.,

$$u = \sum_{i=1}^{5} w_i x_i \ .$$

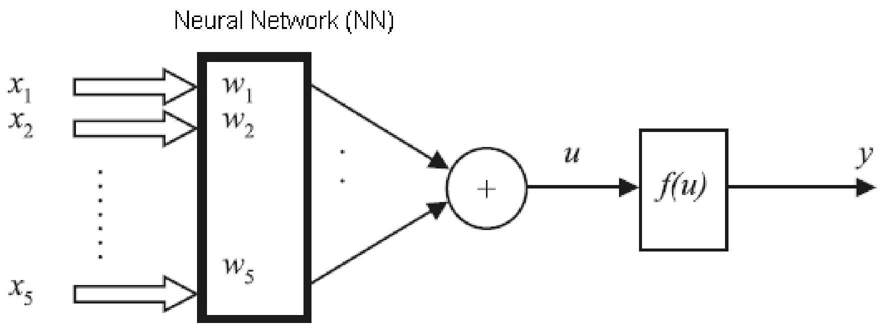

Figure 4: The priority assignment module [11].

The track priority output is calculated by a nonlinear activation function $f(u)$:

$$f(u) = \frac{1}{1+e^{(-bu)}} \ .$$

This function is widely used since it offers continuous priority values in [0, 1]. The slope of the function depends on the parameter *b*. For parameter $b \to \infty$, the function becomes:

$$f(u) = \begin{cases} 1, & u > 0 \\ 0.5, & u = 0 \\ 0, & u < 0 \end{cases} \ .$$

The weight coefficients are generated by a learning method with back propagation. This method relies on minimizing the mean square error. It can be defined as:

$$q = \frac{1}{2} \sum_{j=1}^{N} (\delta^{(j)})^2 \ ,$$

where

$$\delta^{(j)} = z^{(j)} - y^{(j)},$$

and $z^{(j)}$ is the requested value of the target rank in the j^{th} step of learning. $y^{(j)}$ is the output value of the target calculated in the j^{th} step of learning for $w^{(j)}$ weight coefficients, i.e.,

$$y^{(j)} = f\left(\sum_{i=1}^{5} w_i^{(j)} x_i^{(j)}\right),$$

N is the number of learning pairs $< x^{(i)}, z^{(i)} >$ and U is a learning set.

$$U = \left\{< x^1, z^1 >, \cdots, < x^N, z^N >\right\}.$$

According to the gradient method of minimizing error q, the weights are calculated on the basis of the learning data set:

$$w_i^{(j+1)} - w_i^{(j)} = \Delta w_i^{(j)} = -\eta \frac{\delta q^{(j)}}{\delta w^{(j)}},$$

where is η a learning coefficient.

The weight selection algorithm ensures the minimization of the error q for established learning set U. Since the learning method is compatible with the nonlinear neuron model and the nonlinear neuron learning algorithm [10], the system has the ability to generalize the target rank and assign the priorities for other targets, even those not included in learning process. The next stage consists of verification of the module in the RRM.

2.1.2 Task Scheduling

Optimizing neural network algorithms are used for the task scheduling such as pulse scheduling. Izquierdo-Fuente [11] used a Hopfield neural network to optimize the radar pulse scheduler and described the general problem, defined the network and selected the criterion to design the weights. This type of neural network does not need training dataset, however, it needs an energy function abstracted from the scheduling problem. This energy function determines the convergence of the network to a solution of proper assignments. A simulation with 5 targets was done to demonstrate the proposed algorithm. However, this approach tends to converge to local as opposed to global minimum solutions. Also, the convergence rate is very slow, particular with a large number of targets.

2.1.3 Comments

Neural network algorithms were proposed for both task prioritization and task scheduling. In particular, classification neural networks could be useful in RRM and other radar applications such as track classifications. There is no report of neural network algorithms being implemented in any prototype or operational radar systems. However, since neural networks are very effective in many classification applications, this approach may be useful for target prioritization. One known issue is that generating the learning datasets is not a trivial job, which can significantly impact the effectiveness of the neural network algorithms. It is recommended that the neural network based classification algorithms be studied, based on the promising results on task prioritization in [9, 10]. An additional benefit of this recommendation is that the algorithms are useful for track classification or other radar signal classification.

2.2 Expert System

2.2.1 Description of the Expert System Approach

Vannicole [12] and Pietrasinski [13] proposed an expert system with an information database. A high-level expert system diagram is shown in Figure 5. This diagram is useful for radar parameter selection, task prioritization and scheduling. For example, the expert system can be simplified to a scheduler with only a few rules.

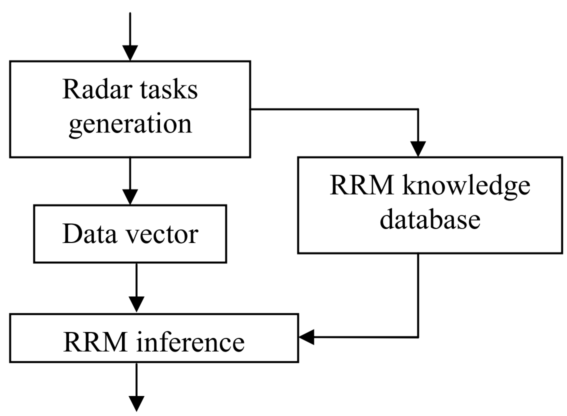

Figure 5: Expert system for RRM.

The authors also presented a knowledge/rule base system, which controlled the parameters and modes for multi-function radars. The expert system performed a situation assessment of the signal/noise environment followed by appropriately prioritized automatic control of the parameters and modes of the radar system. The work involved a radar software development in a simulated environment.

In addition, Vannicole compared a classical solution to a system where an artificial intelligence approach was used. The two approaches were found to offer similar performance. An application of the expert system was also presented and its features were described. The proposed method has been tested in an experimental radar system.

2.2.2 Comments

Expert systems haven’t been found in any real radar applications either. Instead, a similar, but more flexible technology of the fuzzy logic has been preferred, which is discussed in the next section.

2.3 Fuzzy Logic

2.3.1 Fuzzy Logic Approach

References [14-20] describe the use of fuzzy logic to resolve the conflicts of an adaptive scheduler. Here the fuzzy logic allows vague values such as dangerous and friendly to be represented as target priority factors. Fuzzy logic also allows a degree of flexibility to be introduced in tasks for shared resources. Miranda et al [15, 20] proposed a simulation architecture and decision tree with five fuzzy variables (track quality, hostile, weapon systems, threat and position). The fuzzy logic approach provided a valid means for prioritizing radar tasks. An adaptive prioritization assignment and fuzzy-reasoning based algorithm had been developed. This algorithm was responsible for ranking tracks and sectors of surveillance in varying tactical environments.

The priorities of targets were evaluated using the decision tree presented in Figure 6. The required information to assign a priority was provided by a tracking algorithm. Five different variables provided information for the priority:

- Quality of tracks;
- Hostility;
- Degree of threat;
- Weapon system capabilities of the platform;
- Position of the targets.

“Track quality” refers to the accuracy of the predicted position of the target with respect to the desired accuracy.

“Hostile” is a fuzzy variable related to four concepts: range to the targets, absolute target velocity, identity and the way the target is approaching the radar. Thus, depending on the way the target is approaching the radar platform, its absolute velocity, its range and its identity, the priority for tracking may vary.

The variable “weapon systems” represents the importance of a target with respect to the weapon systems of the radar. In order to assess its importance, three concepts can be utilized: the identity of the target, the operational range of the weapon systems and the ratio between the range rate and the absolute velocity of the target.

“Threat” is the linguistic variable, which represents the degree of threat of a target according to its trajectory and identity. Trajectory combines four fuzzy variables: height, manoeuvre, absolute velocity and range rate with respect to the trajectory on which the target is moving. Note that “hostile” and “threat” are closely related concepts, but they combine difference fuzzy variables.

Finally, “position” is a linguistic variable whose value is given by the combination of the fuzzy values of the range and azimuth of a target. Fuzzy values are attributed to each variable. Some examples of the fuzzy values are presented in Table 1. After evaluation of these variables according to a set of fuzzy rules, the priority of the target is determined.

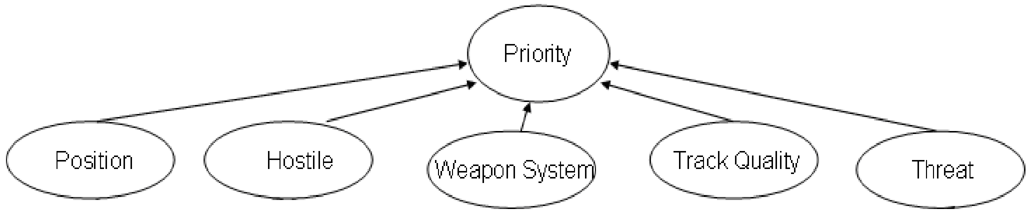

Figure 6: Decision tree for target priority assessment.

Table 1: Examples of fuzzy variables used in the assignment of priorities for targets [15].

Fuzzy variable	Fuzzy values
priority	very low, low, medium–low, medium, medium–high, high, very high
hostile	non-hostile, unknown and hostile
weapons systems	low, medium and high priorities
threat	very low, low, medium–low, medium, medium–high, high and very high
position	close, far, medium

Stoffel [16] used a dynamic fuzzy logic approach for waveform selection and energy management based on the blackboard architecture. A weapon system simulation test-bed and analytical tool were develped.

In a fuzzy logic processing system, three steps are used: fuzzification, fuzzy rules and de-fuzzification. Dawber [22] described the details of the three steps.

2.3.2 Comments

The DRDC's ADAPT_MFR radar test-bed has been recently updated with a fuzzy logic controller under TTCP SEN TP-3. This fuzzy logic controller algorithm was provided by UK [22]. Preliminary experiments showed that this fuzzy controller was able to prioritize targets so that they could be scheduled accordingly. The processing speed of the fuzzy controller is fast and can be useful in real radar systems. The fuzzy logic algorithm is thus an approporate baseline algorithm against which other algorithms could be compared.

2.4 Entropy

2.4.1 Entropy Algorithm

An entropy algorithm was proposed by Berry and Fogg [23]. It used the concept of information entropy for radar resource management. The approach was particularly appropriate for radar systems dominated by uncertainty and subject to time and resource constraints. The proposed algorithm was applied to the scheduling of track updates in phased array radars.

The objective is to track a number of independent targets using a single multifunction phased array radar by observing them at intermittent times so as to determine their locations and update the tracks. The update rate for each target should ideally be as small as possible so as to maximize the probability of the target being within the beam. On the other hand, the dwell time (time on target) should be as long as possible in order to maximize the *SNR,* thereby enhancing the probability of detection, while keeping the false alarm rate low.

However, radar time generally needs to be shared with a number of other targets, as well as the surveillance and weapon guidance tasks. If the update rate or dwell time is too low, then a target may not be detected. Consequently, additional looks will need to be scheduled with higher priorities in order to revisit it. The decision makes complex trade-offs over time to ensure that the radar's resources are used efficiently, and that as the radar becomes overloaded, its performance degrades gracefully.

Suppose there are N targets to be tracked and each target has the following dynamic equation:

$$x(k+1) = F(k)x(k) + v(k).$$

The measurement equation is given by

$$z(k) = H(k)x(k) + w(k),$$

where $v(k)$ and $w(k)$ are sequences of zero-mean, white Gaussian noise processes, as normally specified for Kalman filter trackers. Then, $x(k)$ for times t_k = 0,1, .. , is a multivariate Gaussian distribution which is estimated by its mean $\hat{x}(k)$ and covariance matrix $P(k)$.

For the purpose of beam scheduling to maintain tracks, the interest is in the elements of the covariance matrix representing the error in target azimuth and elevation, i.e., $Q_i(t)$, for the i^{th} target at time t. Then the entropy representing the positional uncertainty is given by

$$h_i(t) = \tfrac{1}{2}\log\left\{4\pi^2 e^2 \,|\, Q_i(t) \,|\right\},$$

where $|\,Q_i(t)\,|$ is the determinant of $Q_i(t)$.

The entropy associated with the joint system of N independent targets at time t is

$$H(t) = \sum_{i=1}^{N} h_i(t) = \tfrac{1}{2} \sum_{i=1}^{N} \log\left\{4\pi^2 e^2 \,|\, Q_i(t) \,|\right\}.$$

This expression provides a method for quantifying the overall uncertainty associated with the targets, and balancing the resources allocated to them. Alternatively, the optimal control problem could be formulated so as to specify an acceptable level of uncertainty as a constraint. Then the RRM problem becomes one of minimizing resources necessary to maintain that level. This is an appropriate formulation for a set of high priority targets, which must be tracked, with remaining radar resources applied to low priority targets and other functions.

2.4.2 Comments

The entropy algorithm provides an additional approach for track prioritization. In practice, a separate task scheduler is needed. As can be seen, the entropy depends on the filter design for the uncertain covariance matrix. In real radar applications, the target dynamics is unknown, and therefore, the entropy calculation would be inaccurate. To be more accurate, this requires an adaptive filter in the tracker implementation, which has not been reported in the current literature. Also, future work is necessary to see if this algorithm performs better than any of other algorithms such as the NN and fuzzy logic approach.

3 Dynamic Programming Algorithms

In the dynamic programming (DP) algorithm category, twenty papers are noted [25-44]. Unlike the AI based approaches, the DP algorithms attempt to solve both the task prioritization and task scheduling problems simultaneously.

3.1 An Example

The dynamic programming approach can be illustrated by a simple three target scheduling problem. Assume that the radar has 5 seconds of time resource to allocate to three targets for possible track updates. Each target has submitted a number of proposals on how it intends to spend the radar time. Each proposal gives the cost of the scheduling (*c*) and the total performance gain (*r*). The following table gives the proposals generated (Table 2):

Table 2: Track scheduling options.

proposal	track 1		track 2		track 3	
	c1	*r1*	*c2*	*r2*	*c3*	*r3*
1	0	0	0	0	0	0
2	1	5	2	8	1	4
3	2	6	3	9	x	x
4	x	x	2	12	2	7

Each target will only be permitted to act on one of its proposals. The goal is to maximize the overall performance gain resulting from the three allocations of the 5 seconds. It is also assumed that any unused time of the 5 seconds is lost, just like the situation of real radar.

A brute-force way to solve this is to try all possibilities and choose the best total performance gain. In this case, there are 3*4*2 = 24 ways of allocating the time. Many of these are infeasible. For instance, the three proposals (#3, #2 and #4) for the three targets cost 6 seconds. Other proposals are feasible, but very poor, such as proposals 1, 1, and 2, which is feasible but performance gain is only 4.

3.2 Computational Challenge

There are many serious disadvantages of the brute-force approach:

- For larger problems, the enumeration of all possible solutions may not be computationally feasible.
- Infeasible combinations cannot be detected *a priori*, leading to inefficiency.
- Information about previously investigated combinations is not used to eliminate inferior, or infeasible, combinations.

Note also that this problem cannot be formulated as a linear problem, for the performance gain is not a linear function of the possible proposals. One of the solutions proposed to this optimization problem is the dynamic programming algorithm, which computes the optimal radar resource assignment for all tracks. Due to the high computational requirement for the high dimensional cases, seeking more efficient algorithms is still an active area of research. It is also noticed that dynamic programming algorithms have become more practical with the increased computation power.

3.3 Some Dynamic Programming Algorithms

Scala and Moran [25] examined the problem of adaptive beam scheduling to minimize target tracking error with phased array radars. It was shown that this could be formulated as a particular type of dynamic programming problem known as the restless bandit problem. Krishnamurthy and Evans [26] derived optimal and sub-optimal beam scheduling algorithms for electronically scanned array tracking systems. The scheduling problem was formulated as a multi-arm bandit problem involving hidden Markov models (HMMs). Wintenby and Krishnamurthy [27] proposed a more general optimization approach, which led to a two timescale scheduling solution and formulated the slow timescale resource allocation as a dynamic programming optimization problem. The radar performance was abstracted into performance measures, defined in terms of predicted track accuracy and track continuity. It was done at slow timescale, and modelled as a discrete time constrained Markov chains. A Lagrangian relaxation algorithm was used to optimize the radar dynamic measures of performance.

Wintenby [28] proposed two approaches for scheduling update and search tasks in a phased array radar system. The first approach was based on dynamic programming from the operations research theory. The other was a temporal reasoning scheme based on temporal logic with a background in artificial intelligence. In [30], Elshafei et al presented a new 0–1 integer programming method for the radar pulse interleaving problem based on Lagrangian relaxation techniques.

Note that two conventional optimization algorithms have also been noticed. The analysis by Orman [33] was centred on a coupled-task specification of the radar jobs. The coupled-task scheduler is unique in terms of use of idle time within a radar job to interleave other radar jobs, and to achieve improved usage of the radar time. The algorithm proposed by Duron and Proth [37] was based on the concept of time balance and was implemented in the experimental MESAR system. Performances of these two algorithms were found to be similar. They also proposed a strategy to maximize the number of useful tasks performed, considering their priorities.

The performance evaluation of RRM algorithms has been difficult due to the varied nature of the radar configuration, the target and clutter situation. Dynamic programming algorithms are exponentially intensive and a lot of effort has been dedicated to develop approximate and faster versions, such as [27, 28]. Proth and Duron [39] defined a formal framework for this real time scheduling problem, and a local search method was introduced to compute efficient schedules for the radar. Based on a V-shape cost function, this algorithm was a good candidate for real time radar scheduling. It also described a set of lower bounds for the scheduling problem.

3.4 Comments

The dynamic programming approach, a nonlinear optimization method, has attracted a lot of attention for adaptive radar control in recent years. It provides a promising solution to the RRM problems. Compared to aforementioned target prioritization algorithms, the dynamic programming algorithms include the radar configurations and parameter dimensions, and optimize the overall performance of all the tracks. However, this is at the cost of increased complexity, in both the mathematical formulation and the numerical optimization. Published results to date make several theoretical assumptions, such as, specific radar configuration and large selective regions of radar parameters. In practice, radar design is limited within some physical and practical boundaries, such as energy, dwell time and PRF. The dynamic programming algorithms are still in the research stage, and the algorithms should be studied with realistic radar constraints.

4 Q-RAM Algorithms

In this category, fourteen papers are noted [45-48]. Similarly to the DP algorithms, the Q-RAM algorithms solve the task prioritization and task scheduling simultaneously.

4.1 Introduction

The Q-RAM algorithms are based on the concept of quality of service (QoS). The radar system is optimized to maintain an acceptable level of QoS, which is a cost function of performance. Due to the varied nature of the environment, QoS-based resource management has to be adaptive to environments, such as temperature, noise, etc. Consequently, a whole range of resource constraints such as power, energy, etc., come into play.

4.2 Mathematical Formulation

The basic problem solved by Q-RAM is as follows. Given a set of tasks $T_1, \cdots, T_n$, assign a setpoint v_i such that the system utility is maximized and no resource utilization exceeds its maximum. Formally, it is written as:

$$\textit{maximize:} \sum_{i=1}^{n} u(v_i)\,,$$

subject to:

$$\begin{aligned}
&\forall\, 1 \le k \le n, 1 \le i \le n \quad r_{ik} = g_{ik}(v_i), \\
&\forall\, 1 \le k \le n \quad \sum_{i=1}^{n} r_{ik} \le r_k^{\max},
\end{aligned}$$

where $g_{ik}(v_i)$ and $u(v_i)$ are the amount of resource *k* required and the utility derived for task T_i at a setpoint v_i, respectively. While finding the optimal resource allocation is NP-hard, the Q-RAM algorithm uses a concave majorant operation to reduce the number of setpoints that must be considered to find a near optimal solution.

4.3 Some Q-RAM Algorithms

4.3.1 A Framework of Q-RAM

A Q-RAM radar management framework (Figure 7) has three main blocks [52]:

1. **Q-RAM** block is a resource allocation tool that employs fast convex optimization using a combination of heuristics and non-linear programming. It assigns parameters to the radar tasks after considering a variety of factors, including task importance and the current resource

utilization level. Q-RAM minimizes the global system error. This objective can also be viewed as utility maximization.

2. The **schedulability envelope** block is a pre-computed schedulability region. It provides Q-RAM with an analytical model of the scheduling operation. Since Q-RAM is a convex optimization engine, the schedulability envelope is transformed into a convex constraint. Satisfaction of this constraint implies that the task set is schedulable with high probability.

3. The last block is a low-level **template-based scheduler** that generates the dwell schedule based on the parameters computed by Q-RAM. Because the schedulability envelope is computed offline and without knowledge of the runtime system state, it is only an approximate schedulability test. The template-based scheduler provides feedback to Q-RAM when it is unable to schedule a task, and Q-RAM uses this information to update its scheduling constraint. Similarly, when the scheduler generates a schedule that under-utilizes the antenna, it signals Q-RAM to adjust the scheduling constraint.

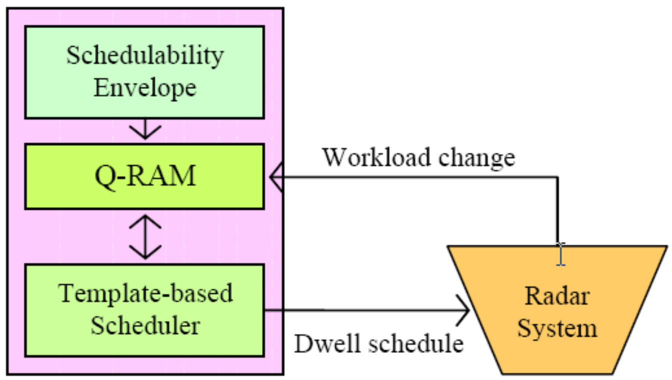

Figure 7: Q-RAM framework [52].

4.3.2 Some Q-RAM Algorithms Based on the Resource Management Framework

Recent studies have focused on performing feasibility analysis of radar tasks for their given execution times in phased-array radar systems. For example, Kuo et al proposed a reservation-based approach for real-time radar scheduling [45]. This approach allows the system to guarantee the performance requirement when the scheduling condition holds.

Shih et al used a template-based scheduling algorithm in which a set of templates was constructed offline, and tasks were fit into the templates at run-time [46, 47]. The templates considered both the timing and power constraints. They also considered interleaving of dwells that allowed beam transmissions (or receptions) on one target to be interleaved with beam transmissions and receptions on another. The space requirements of templates limited the number of templates that could be used, and “service classes” designed offline determine how QoS operating points were assigned to discrete sets of task configurations across an expected operating range. Goddard et al addressed real-time back-end scheduling of radar tracking algorithms using a data flow model [48].

The radar QoS optimization algorithm was based on the work of Q-RAM by Rajkumar et al [49] [50]. The algorithm used an adaptive QoS middleware framework for QoS-based resource allocation and schedulability analysis in radar systems [51].

In [51], Ghosh et al proposed an integrated framework for utility maximization and dwell scheduling. Novel concepts such as the scheduling envelope and temporal distance-constrained task model were proposed. Heuristics were used to achieve a two order of magnitude reduction in optimization time over the basic Q-RAM approach allowing QoS optimization and scheduling of a 100-task radar problem to be performed in 700ms.

A recurring theme in scheduling is the conflict between semantic importance and scheduling priority. Scheduling based on semantic importance alone leads to unpredictable system behavior and poor resource utilization. Here the semantic importance is defined by the target's threat level. On the other hand, real-time scheduling using Earliest Deadline First (EDF) or Rate Monotonic (RM) priorities ignores semantic importance but provide high utilization. The proposed framework reconciled these differences by assigning weights to the tasks based on semantic importance. These weights acted as scaling factors for tracking errors. Since Q-RAM minimizes overall error while ensuring that the system satisfies the scheduling constraint, the system performance would be predictable and the utilization high while honoring the semantic importance of tasks. More details of the algorithm can be found in [52, 55].

4.3.3 Other Q-RAM Algorithms

Gopalakrishnan et al [56, 57] presented a QoS optimization and dwell scheduling scheme for radar tracking application. The QoS optimization was performed using the Q-RAM approach. A finite-horizon scheduling algorithm was also proposed. A simulation model of QoS resource management diagram was proposed and implemented.

Harada et al [58] proposed a novel control method for fair resource allocation and maximization of the QoS levels of individual tasks. In the proposed adaptive QoS controller, the resource utilization was assigned to each task through an online search for the fair QoS level based on the errors between the current QoS levels and their average. The proposed controller eliminated the need for precise detection of the consumption functions as in conventional feedback control methods. The computational complexity of the proposed method was very low compared to straightforward methods solving a nonlinear problem. The algorithm aimed to maximize system utilities for a soft real-time task set. It is unknown how the algorithm will behave for radar applications.

4.4 Comments

The optimization goal of Q-RAM is to select a point, or setpoint, in the operation space for each task so as to maximize the global system utility. The utility obtained from a particular setpoint is a function of the setpoint, the environment, and the user defined utility functions. Q-RAM is capable of quickly finding a near optimal solution. In particular, Q-RAM is designed to work well when the utility curves are concave. This generally holds when there is a "law of diminishing returns" where more and more resources are needed to obtain subsequent increases in utility.

The Q-RAM class of algorithms, a nonlinear optimization method, were originally developed in the context of wireless applications, where QoS is a typical performance measure. In radar applications, these algorithms are also in the research stage. The Q-RAM algorithms should be evaluated and compared with the more mature algorithms mentioned in previous chapters. Currently, the published results present only complicated methods for ideal parameters in a high-dimensional space, leading to an extremely difficult combinatorial problem. For example, an applications that has ten QoS dimensions with ten quality levels means that the radar can be configured in 10^{10} ways. It is suggested that Q-RAM algorithms be evaluated and compared with more mature algorithms mentioned in previous chapters.

5 Waveform-Aided Agorithms

5.1 Introduction

This class of algorithms assumes that there is a task prioritization and scheduling module. It is focussed on improving radar resource requirements by reducing time, energy and processing budgets via waveform selection. Waveform diversity has been a notable way to optimize radar performance in complex littoral environments with jamming resources. In a MFR, different waveforms are scheduled for surveillance, detection, tracking or classification. Waveform selection may use neural networks or other optimization techniques. Waveform selection can be single step or multiple steps ahead. Both fixed and variable waveform libraries have been reported in the literature. Seventeen papers are noted in this category [59-75].

5.2 A Neural Network Algorithm

The radar performance factors such as eclipsing, blind velocity, clutter, propagation and jamming were analyzed by Huizing [24]. These factors were used as the input to a nonlinear function of performance. A multi-layer neural network was used to model the nonlinear function. A training dataset containing pairs of waveform parameters and detection performance was generated with a radar test-bed CARPET. After the training stage, the back propagation network was used to calculate radar detection performance at the selected points in the multidimensional waveform parameter space.

5.3 The Waveform Selected PDA Algorithm

Traditional detection and tracking algorithms can be extended to be waveform selective. An example is the waveform selective probabilistic data association algorithm (WSPDA), which is an extension of conventional probabilistic data association (PDA) tracking algorithm [59]. The WSPDA considers a single target in clutter, based on a previous single target (in clutter) Kalman filter tracker [60]. The assumption of an optimal receiver allows the inclusion of transmitted waveform parameters in the tracking subsystem, leading to a waveform selection scheme where the next transmitted waveform parameters are selected so as to minimize the average total mean square tracking error at the time step. Semi-closed form solutions are given to the local one-step-ahead adaptive waveform selection problem for the case of one-dimensional target motion.

The difference between a conventional active transmission tracking system and the new system is the inclusion of a waveform optimization block after the conventional tracking block, as illustrated in Figure 8. Thus, the tracking system has active control over the transmitted waveform.

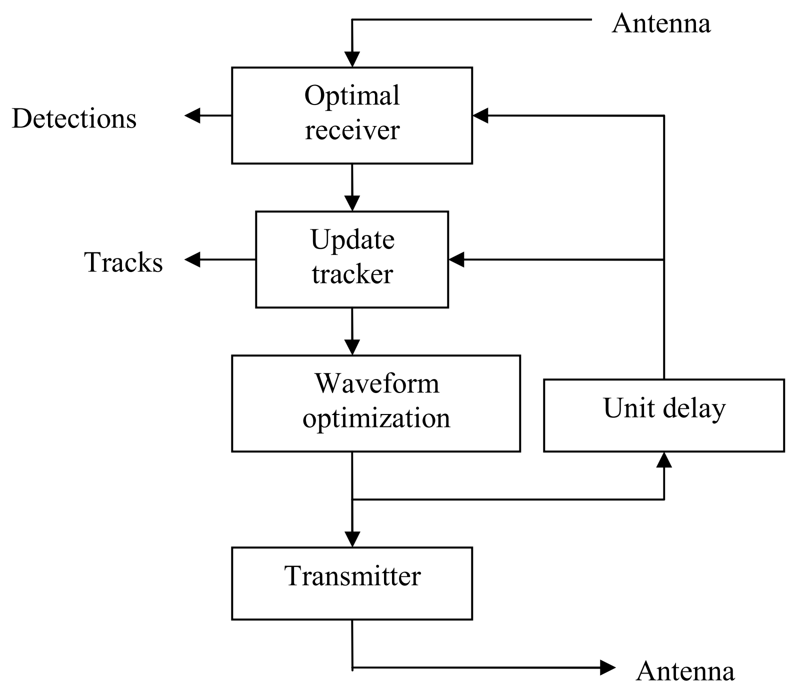

Figure 8: Waveform selective PDA tracking system [59].

5.4 Other Waveform-Aided Algorithms

A waveform-aided interacting multiple model (IMM) tracker was proposed by Howard [61]. The tracker selects a waveform to decrease the dynamic model uncertainty for the target of interest, based on maximization of the expected information obtained about the dynamical model of the target from the next measurement. A design of waveform libraries for target tracking applications was also discussed. Measures of utility of waveforms were defined, and how much the addition of a particular set of waveforms to the library could be determined to improve the library.

Suvoroval et al [62] developed a beam and waveform-scheduling tracker called the Paranoid Tracker. The paper reported an initial study of practical methods for achieving a unification of surveillance and tracking in terms of radar resource management. The proposed method involved the introduction of permanently existing virtual targets, judiciously placed in the field of view of the radar. The tracker's belief in the existence of the virtual or fictitious targets led to the name Paranoid Tracker. The Paranoid Tracker has been offered by DSTO (Australia) to be integrated into DRDC's ADAPT_MFR simulator under the TTCP SEN TP-3 program.

Other waveform-aided detection, tracking and classification algorithms can be found in references [63]-[68]. Scala et al [63] proposed an adaptive waveform scheduling approach for detecting new targets in the context of finite horizon stochastic dynamic programming. The algorithm was able to minimize the time taken to detect new targets, while minimizing the use of radar resources. An algorithm to minimize the tracking errors was proposed by Scala et al [64].

Sowelam and Tewfik [65] suggested that radar waveforms be designed to discriminate between targets. The waveforms minimized decision time by maximizing the discrimination information in the echo signal.

5.5 A Literature Survey of Adaptive Radar

In [74], Haykin et al presented a review of the literature on adaptive radar. The discussion was divided into three groups:

- Controllable parameters for adaptive radar;
- Physical aspects of radar transmission;
- Detection, tracking, and classification.

5.6 A DARPA Research Program on Adaptive Waveform Design for Naval Applications

In 2005, the Defense Advanced Research Projects Agency (DARPA), through Naval Research Laboratory (NRL), sponsored a research program on adaptive waveform design tailored to naval applications [75]. This project investigates Adaptive Waveform Design for Detecting Low-Grazing-Angle and Small-RCS Targets in Complex Maritime Environments. Team members of this project include: University of Illinois at Chicago, Washington University in St. Louis, Arizona State University, University of Maryland, University of Melbourne, Princeton University, Purdue University, DSTO and Raytheon Missile Systems.

The project seeks to achieve substantial improvements in detecting, resolving, and tracking low-grazing-angle (LGA) as well as low radar cross section (RCS) targets in maritime and littoral environments under conditions of severe clutter. Transmit waveforms matched to the environment will be integrated with the development of waveform parameters, libraries, realistic models of complex environments, and signal processing methods for optimal waveform selection in real-time to achieve the substantial performance improvements.

5.7 Comments

Waveform diversity has been widely studied in the radar and communication community. It provides additional flexibilities for solutions to the RRM problem. Different waveforms have been used in many operational systems. These waveforms are limited within a fixed waveform library. The future trend will be adaptive generation of waveforms on-the-fly, which should be sensitive to the environments and target motions. In addition, finding effective waveforms for specific missions or targets is a challenge. A better waveform saves either time or energy, or both, while maintaining the same level of radar performance.

6 Adaptive Update Rate Algorithms

6.1 Introduction

An adaptive update rate algorithm is an extension of traditional trackers with uniform update rates. The update rate is closely related to the clutter characteristics, target manoeuvring level and the required tracking performance. Similar to waveform-aided algorithms, the adaptive update rate algorithms optimize the Kalman filter update intervals. Large intervals result in less usage of the radar resources. Therefore, the adaptive update rate algorithms are resource-aided algorithms. Twenty-three papers are collected in this category [76-98].

6.2 A Foundation for Adaptive Update Rate Tracking

Daum and Fitzgerald [76] investigated the use of covariance coordinates of various kinds for decoupling Kalman trackers, which brought in three benefits:

- Reduced computational cost;
- Alleviation of ill-conditioning;
- Mitigation of nonlinear effects.

This paper provides a foundation for phased array radar tracking where the update rate is variable, and the ill-conditioning and nonlinear issues are more serious.

6.3 Adaptive Update Rate IMM-MHT Algorithm

An adaptive update rate tracking algorithm was proposed by Keuk and Blackman [77]. Based on a simple model of phased array radar, beam scheduling, positioning and radar parameters like *SNR*, detection threshold had been optimized with respect to the computational load. Minimum energy for track maintenance during surveillance was derived.

The revisit time depends on the estimated lack of information regarding the target. Let $\hat{x}(k+1\,|\,k)$ be the predicted target state at time $k+1$, along with its covariance $P(k+1\,|\,k)$, based on all associated measurements up to time k. Let G denote the major axis of the ellipsoid in u, v space defined by covariance $P(\bullet)$. Reflecting target manoeuvrability and position noise, G is an increasing function of the extrapolation time and quite naturally describes the lack of information of the target under track. The relative track accuracy in u, v space is used to calculate the next revisit time $k+1$ from the equation

$$G(k+1\,|\,k) = P_0 \cdot B\,.$$

Therefore, the maximum allowed inaccuracy of the track, related to the beamwidth B, is just P_0, the dimensionless track sharpness parameter. Figure 9 illustrates the behaviour of G as a function of time using the equation. The sawtooth structure reflects the increase in inaccuracy after a processed report. When the inaccuracy G reaches the threshold, a track update is recommended. After the received observation is processed, G is decreased. Due to initial track uncertainty, we first observe a higher data rate (short revisit times), which afterwards settles when more accurate estimates are available.

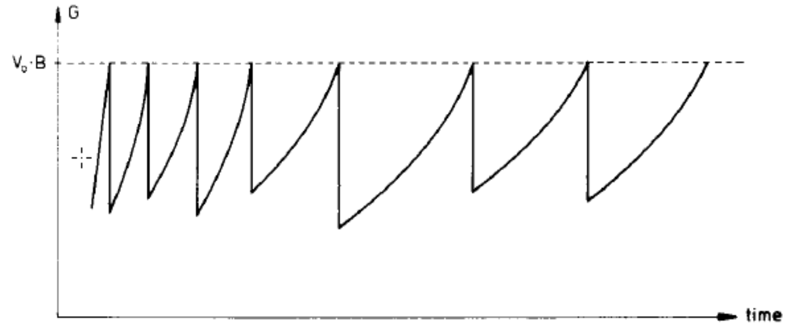

Figure 9: Time behaviour of track errors

In [78], by using adaptive dynamics models and target amplitude information, Koch considered algorithms for efficient control of target revisit intervals, radar beam positions, and energy per dwell with respect to the total sensor allocations and radar energy spent for track maintenance. The performance was evaluated with simulations and benchmark trajectories.

6.4 Other Adaptive Update Rate Algorithms

Shin [79] proposed an adaptive-update-rate IMM algorithm for phased-array radar. The purpose of this IMM algorithm was two fold:

- Estimate and predict the target states;
- Estimate the level of the dynamic process noise.

The update interval is determined so that the number of track updates per unit time in reflection of beam-positioning losses can be reduced. Leung [80] proposed an estimator by solving a formulated dynamic optimization problem using a Hopfield neural network. However, the Hopfield neural network is not practical due to its very low probability of finding the global minimum solution.

Sun-Mog and Young-Hum [81] considered optimal scheduling of track updates to minimize the radar energy, a nonlinear optimal control problem. Keuk and Blackman [77] also proposed a simple model for a multi-target surveillance task. The beam scheduling and radar parameters have been optimized with respect to the radar/computer load. A more realistic rate-based approach was proposed by Tei-Wei [82], where real time dwell scheduling was considered and significant performance improvement was achieved. As to be discussed next, this category of algorithms has some overlap with the NRL benchmark solutions in next chapter and they both considered radar parameter optimization for a better tracking performance.

6.5 Comments

The varying update rate algorithms have been used in many radar systems. However, optimal adaptive rate is still an open topic. One issue with the adaptive rate is that the tracking parameters are more difficult to optimize than algorithms with uniform or near uniform update rate. This is because the noise matrix in a tracking filter has entities with polynomial functions of the update rate. The noise matrix does not match the real target dynamics when the update rate changes dramatically. Therefore, it is necessary to formulate different motion noise models for an adaptive update rate tracker.

7 The NRL Benchmark Problems and Solutions

In this chapter, the phased array radar tracking benchmark problems are reviewed. Eighteen papers are discussed in this context [99-116]. The authors of these papers proposed different solutions to the benchmark problems. Remarks are provided for both the benchmark problems and solutions.

7.1 The NRL Benchmark Problems

Three benchmark problems were developed by Blair, Watson, Hoffman and McCabe [99, 105, 116]. The benchmark codes were written in MATLAB© and the testing tracking algorithms were to be coded in MATLAB©, strictly complying with the input/output format.

The first benchmark problem involves beam-pointing control of phased array radar against highly manoeuvring targets. This benchmark includes the effects of target amplitude fluctuations, beam-shape, missed detections, finite resolution, target manoeuvres and track loss.

The second benchmark problem is an extension of the first in that it considers the presence of electronic counter-measurement (ECM) and false alarms (FAs).

The third benchmark considers closely spaced objects (CSO) and sea-induced multi-path. It also includes the simulation of two additional sensors: the Infra-red search and scan (IRST) and the precision electronic support measurement (PESM).

Some of the benchmark features are summarized as follows:

- Funded by NRL in 1994 (Benchmark 1) [99], 1995 (Benchmark 2) [105] and 1999 (Benchmark 3) [116];
- 60x60 array (3600 elements, Benchmarks 1, 2 and 3);
- 4 GHz mono-pulse radar (Benchmarks 1, 2 and 3);
- 6 manoeuvring targets (Benchmarks 1 and 2) and 12 manoeuvring targets (Benchmark 3);
- Measures of performance (MOP) is the weighted average of energy and time (Benchmarks 1, 2 and 3);
- Consider false alarms (FAs) (Benchmarks 2 and 3);
- Consider electronic counter-measurement (ECM), standoff jammer (SOJ) and range gate pull off (RGPO) (Benchmarks 2 and 3);
- Consider sea-surface-induced multi-path and CSO (Benchmark 3);

- Simulation of other sensors such as IRST and PESM (Benchmark 3).

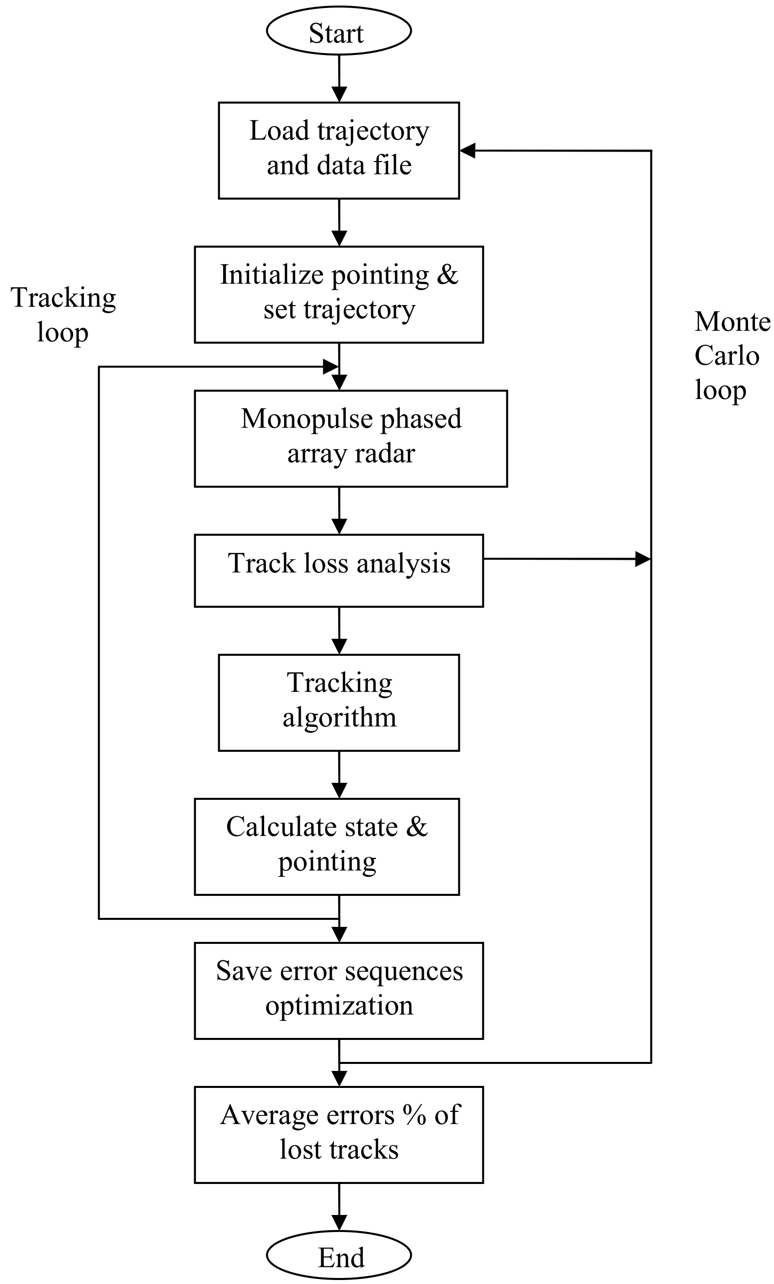

Figure 10: Diagram for Benchmark 1 and Benchmark 2 [99].

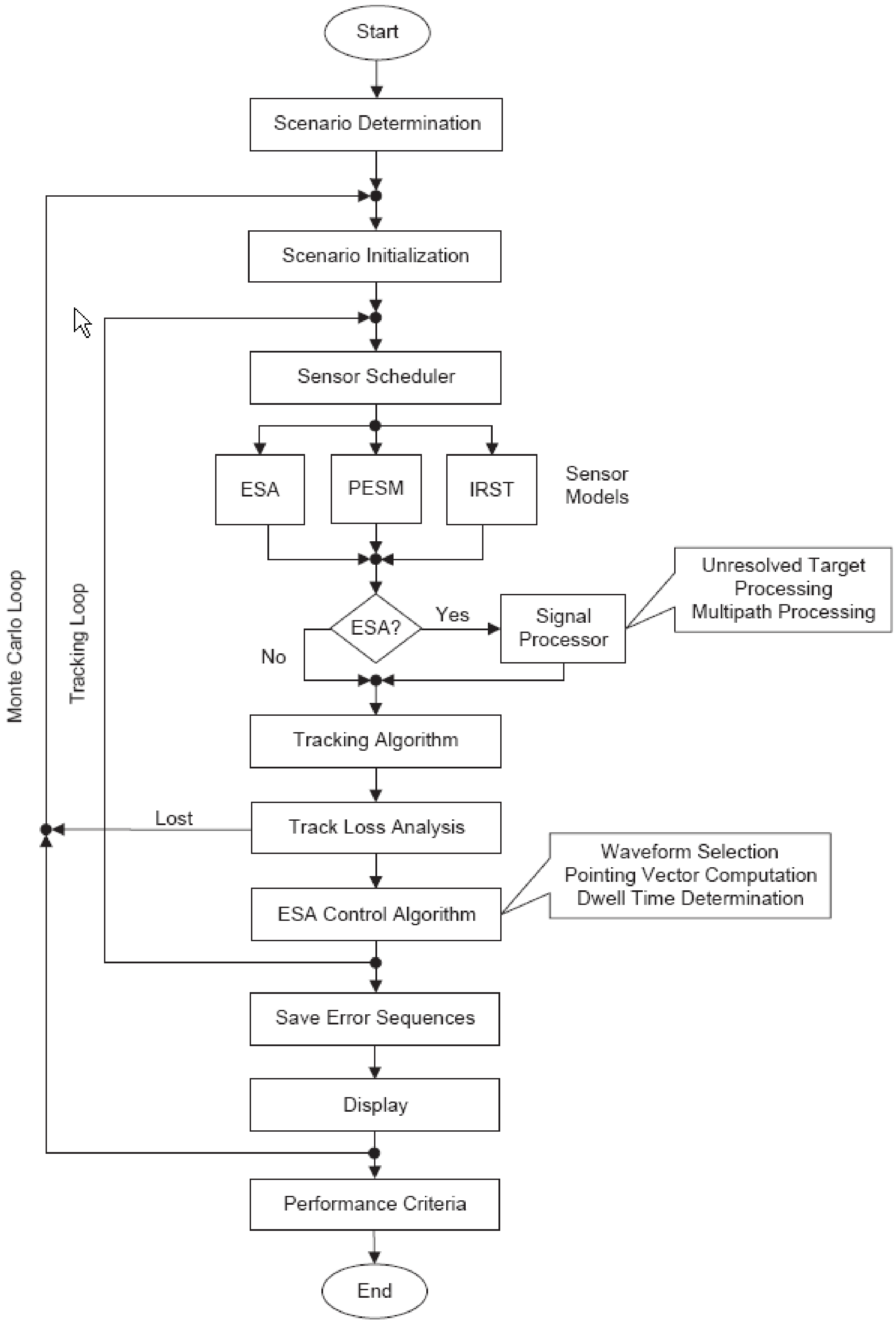

Figure 11 : Diagram for Benchmark 3 [115].

7.2 Solutions to the Benchmark Problems

The flow charts of the benchmark problems are depicted in Figure 10 and Figure 11. Each benchmark participant provides his/her tracking algorithm entitled "Tracking Algorithm". For each experiment, the tracking errors, radar energy and time are saved. After the last experiment of the Monte Carlo simulation, the average tracking errors, average radar energy per second, and average radar time per second are computed for maintained tracks and the percent of lost tracks is also computed. A track is considered lost if the distance between the true target position and the target position estimate exceeds one beamwidth in angle or 1.5 range gates. A constraint of 4% is to be imposed on the number of lost tracks. When FAs and ECM are present in an actual radar system, algorithms for reacquiring the target and "coasting" the target tracks through jamming signals are required in order to maintain a track.

Since the benchmark problems were proposed, many solutions, such as IMM-MHT, a/β tracker, the IMM estimator with probabilistic data association filter (IMMPDAF), adaptive IMM, CSO tracker, have been proposed [106, 107, 108, 114, 116]. The results of these solutions are summarized below.

7.2.1 Solutions to Benchmark 1

More results were published for Benchmark 1 than the other two benchmark problems. Note that the longer the update rates, the better a solution. a/β achieved 0.85 second for update rate. Kalman filter achieved an update rate of 1 second. H-infinity filter also resulted in an update rate of about 1 second. The update rates of the IMM algorithms were found to be:

- Two-model IMM: 1.3 seconds;
- Three-model IMM: 1.5 seconds;
- Adaptive three-model IMM: 2.3 seconds.

7.2.2 Solutions to Benchmark 2

For Benchmark 2, the adaptive Kalman filter achieved an update rate of 1.2 seconds, and IMMPDAF achieved an update rate of 2.4 seconds. IMM-MHT results have been published, but there was no detailed result comparison. Computationally, IMM-MHT takes 5 times longer than the IMMPDAF.

7.2.3 A Solution to Benchmark 3

Benchmark 3 was not publicly available, and there is only one publication to date [116]. In the solution presented in [116], Sinha et al proposed a few algorithms, which are highlighted below.

- Developed both detection and tracking algorithms with enhanced performance, comparing with conventional detection and tracking algorithms;

- Proposed a modified version of the maximum likelihood (ML) angle estimator, which could produce two measurements from a single detection, and a modified generalized likelihood ratio test (GLRT) to detect the presence of two unresolved targets;

- Sea-surface-induced multipath can produce a severe bias in the elevation angle measurement when the conventional monopulse ratio angle extractor method is used. A modified version of the ML angle extractor was proposed, which produced nearly unbiased elevation angle measurements and significantly improved the track accuracy. Efficient radar resource allocation algorithms for two closely spaced targets and targets flying close to the sea surface were also proposed;

- Finally, an IMMPDAF was used. It was found that a two-model IMMPDAF performs better than the three-model version used in the previous benchmark. Also, the IMMPDAF with a coordinated turn model worked better than the one using a Wiener process acceleration model.

The presented signal processing and tracking algorithms, operating in a feedback manner, provide an effective solution to Benchmark 3.

7.3 Comments

In the benchmark problems, the update rate and energy are requested based on the basis of need. There is no consideration given as to whether the required resources are available. This is a drawback for all the benchmark problems.

Benchmark 3 is the most practical among the benchmark problems for naval applications. However, all the three NRL benchmarks are designed for target tracking evaluation, which only considered tracking tasks without track prioritization. It is therefore only part of the RRM solution. In particular, it does not consider beam scheduling over search and prioritized tracking tasks. Each track from the tracker simply asks for a detection, which consumes some radar resources.

The proposed solution to Benchmark 3 does not use the IRST and the PESM for target detection. Further investigation is essential, including the incorporation of additional sensors to enhance the RRM performance.

All the benchmark problems use a simplified performance criterion. The measures of performance (MOP) should be studied. For example, the following measures have been reported, and some of them, such as task occupancy and timeliness, should be considered for the RRM evaluation:

- Number of scheduled surveillance tasks;
- Number of scheduled tracking tasks;
- Total occupancy (%), defined as tracking plus surveillance time to time ratio;
- Tracking occupancy (%), defined as tracking time to time ratio;
- Surveillance occupancy (%), defined as tracking;
- Duty cycle total (%), defined as transmission time to total time ratio;
- Timeliness of tasks;
- Histograms of tracking tasks delays;
- Histograms of surveillance tasks delays;
- Tracking accuracy;

- Search performance (Pd, accuracy, revisit time);
- Track initial range.

8 Conclusions and Recommendations

In this report, a survey of the radar resource management algorithms is presented. The algorithms are divided into five categories: artificial intelligence (AI) algorithms, dynamic programming algorithms, quality of service resource allocation management (Q-RAM) algorithms, waveform-aided algorithms, and adaptive update rate algorithms. Among the five categories, the first three categories are adaptive scheduling algorithms, and the remaining two categories are resource-aided algorithms. Also discussed are the US Navy's phased array radar benchmark problems and solutions.

8.1 Current Status

Following are some general remarks on the current status of the RRM algorithms.

- **Neural network algorithms:** Neural network algorithms were proposed for both task prioritization and task scheduling. To date, they have not been used in developing a realistic RRM solution for real radar systems. However, since classification neural networks are very effective, they are useful for target prioritization. The optimizing neural networks for task scheduling are not mature due to the convergence issues (local minimums and slow speed).

- **Expert system and fuzzy logic algorithms:** The fuzzy logic algorithm is preferred over the expert system approach, because the fuzzy logic provides a better way of handling uncertainty. The fuzzy logic algorithms have been found to be practical and effective. DRDC Ottawa has implemented a fuzzy logic algorithm. Preliminary experiments show that this fuzzy logic controller is able to correctly prioritize targets for scheduling. The fuzzy logic has been used for task prioritization. Therefore, it needs a separate task scheduler, in order to offer a complete solution for the RRM problem. Logically, the fuzzy logic can also be used for task scheduling, an area of future research.

- **A common issue of the AI algorithms:** A common issue of all the AI algorithms (i.e., neural networks, expert systems and fuzzy logic) is the requirement of the knowledge base (such as the learning datasets or the fuzzy rules). This has a major impact on the efficiency and effectiveness of the algorithms.

- **Entropy algorithm:** The entropy algorithm provides a solution for track prioritization. The entropy is calculated from the covariance matrix of the tracking filter. In practice, the target dynamics are unknown, and therefore, the covariance matrix could be inaccurate. An accuracte entropy requires the implementation of a properly designed adaptive filter, another area of future research. In addition, the entropy approach needs a separate task scheduler to offer a complete solution for the RRM problem.

- **Dynamic programming algorithms:** The dynamic programming algorithms has attracted a lot of attention for adaptive radar control in recent years. The task prioritization and scheduling are formulated into one cost function and therefore complete solutions to the RRM problem are provided. Compared to aforementioned target prioritization algorithms, the dynamic programming algorithms include the radar configurations and parameter dimensions, and optimize the overall performance of all the tracks. However, this is at the cost of increased complexity, in both the mathematical formulation and the numerical optimization. Published results to date make several theoretical assumptions, such as, specific radar configuration and large selective regions of radar parameters. In practice, radar design is limited within some physical and practical boundaries, such as energy, dwell time and PRF. The dynamic programming algorithms are still in research stage, and they should be studied with realistic RRM problems.

- **Q-RAM algorithms:** The Q-RAM algorithms were originally developed in the context of wireless applications, where QoS is a typical performance measure. The Q-RAM algorithms also give complete solutions to the RRM problem. In radar applications, these algorithms are also in the research stage. The Q-RAM algorithms should be evaluated and compared with the more mature algorithms mentioned in previous chapters. Currently, the published results present complicated methods for ideal parameters in a high-dimentional space, leading to an extremely difficult combinatorial problem. For example, an application that has ten QoS dimensions with ten quality levels means that the radar can be configured in 10^{10} ways.

- **Waveform-aided algorithms:** Waveform-aided algorithms provide additional flexibilities for the RRM problem. Different waveforms have been used in many operational radar systems. These waveforms are selected from a fixed waveform library. A future trend will be adaptive generation of waveforms on-the-fly, which should be sensitive to the environments and target motions. In addition, finding effective waveforms for specific missions or targets is a challenge. A better waveform saves either time or energy, or both, while maintaining the same level of radar performance.

- **Adaptive update rate algorithms:** The varying update rate algorithms have been used in many radar systems. However, optimal adaptive rate is still an open topic. One issue with the adaptive rate is that the tracking parameters are more difficult to optimize than algorithms with uniform or near uniform update rate. The noise matrix in a tracking filter has entities with polynomial functions of the update rate. The noise matrix does not match the real target dynamics when the update rate changes dramatically. Therefore, it is necessary to formulate different motion noise models for an adaptive update rate tracker.

- **Benchmark problems and solutions:** Three benchmark problems were proposed. Many solutions were presented in the literature. Among the three problems, Benchmark 3 is found to be the most realistic for naval applications. However, only one solution for Benchmark 3 has been proposed, and this solution is not complete. This is because it does not consider radar scheduling and it does not use the IRST and the PESM even though these sensors are available in the Benchmark 3 package. In addition, all the benchmark problems use a simplified performance criterion. The criterion should be extended to a more complete set of measures of performance.

- **General comments:** Neural network, fuzzy logic, and entropy approaches offer solutions to task prioritization. Therefore, a separate task scheduler is needed for each of them to form a complete solution to the RRM problem. Note that task prioritization is the major issue in the RRM problem since task schediuling can be straight forward once the task priority list is available. The dynamic programming and Q-RAM algorithms provide complete solutions for the RRM problem, however, both of them are not mature enough for real applications. The main concern is that the computational load is too high to afford. Simplification and approximation are the ways ahead. The waveform-aided algorithms, the adaptive update rate algorithms and the benchmark solutions are all resource-aided algorithms. They do not directly resolve the RRM problem, but offer solutions to reduce radar resource requirements and make more radar resources available for scheduling.

8.2 Future Work

Based on the survey of the RMM algorithms in the open literature, the following topics are suggested for future research:

- Study of adaptive classification algorithm for RRM;
- Comparison of the fuzzy logic, neural network and entropy algorithms;
- Application of fuzzy logic for task scheduling;
- Evaluation of the dynamic programming and Q-RAM algorithms with realistic RRM problems;
- Investigation of the waveform diversity benefits for RRM;
- Study of the motion noise models for adaptive update rate tracking;
- The Benchmark 3 problem should be studied and future solutions should be tested and compared against the existing solution. Also, additional sensors should be considered to enhance the RRM performance. Other measures of performance (MOP) such as task occupancy and timeliness should be included.

Finally, it is noted that the fuzzy logic approach provides an acceptable solution for the RRM problem, both in terms of performance and computational load. Therefore, it is recommended that the fuzzy logic approach be used as a baseline algorithm for future study.

9 References

[1] Moo, P. (2008), Naval multifunction radar R&D, *Briefing to PMO Destroyer Replacement (DR)*, Power Point Presentation.

[2] Billetter, D.R. (1989), Multifunction array radar, Artech House, 1989.

[3] Sabatini, S. and Tarantino, M. (1994), Multifunction array radar – system design and analysis, Artech House.

[4] Brookner, E. (2006), Phased arrays and radar: past, present and future, *Microwave Journal*, 49 (1), 24-46.

[5] Brookner, E. (2007), Phased-array and radar breakthroughs, In *Proceedings of the IEEE International Radar Conference*, 37-42, Boston: IEEE.

[6] Office of the Federal Coordinator for Meteorological Services and Supporting Research (OFCM), (2006), Federal research and development needs and priorities for phased array radar, CFCM Report.

[7] Genderen, P.V. (1999), State-of-the-art and trends in phased array radar, in *Perspectives on radio astronomy – technologies for large antenna arrays,* edited by Smolders, A.B. and Haarlem, M.P., Netherlands Foundation for Research in Astronomy.

[8] Ding, Z. (2008), A Survey of radar resource management algorithms, In *Proceedings of the 11th Canadian Conference on Electrical and Computer Engineering*, 1559-1564, Niagara Falls: IEEE Canada.

AI Algorithms

[9] Komorniczak, W. and Pietrasinski, J. (2000), Selected problems of MFR resources management, In *Proceedings of the 3rd International Conference on Information Fusion,* 3-8, Paris, France: International Society of Information Fusion.

[10] Komorniczak, W., Kuczerski, T. and Pietrasinski, J. (2001), The priority assignment for detected targets in multifunction radar, *Journal of Telecommunications and Information Technology,* 2001 (1), 30-32.

[11] Izquierdo-Fuente, A. and Casar-Corredera, J.R. (1994), Optimal radar pulse scheduling using a neural network, In *Proceedings of the IEEE World Congress on Neural Networks and Computational Intelligence,* 4588-4591.

[12] Vannicole, V. (1991), Expert system for sensor resource allocation, In *Proceedings of the IEEE International Radar Conference*, 1005-1008.

[13] Pietrasinski, J.F. and Komorniczak, W. (1990), Application of artificial intelligence in radar resource management, In *Proceedings of the 12th International Conference on Microwaves and Radar*, 138-142.

[14] Vine, M.T. (2001), Fuzzy logic in radar resource management, *Multifunction Radar and Sonar Sensor Management Techniques*, IEE 26, 1-4

[15] Miranda, S.L.C., Baker, K., Woodbridge, K. and Griffiths, H.D. (2007), Fuzzy logic approach for prioritisation of radar tasks and sectors of surveillance in multifunction radar, *IET Proceedings – Radar, Sonar and Navigation*, 1 (2), 131-141.

[16] Stoffel, A.P. (1994), Heuristic energy management for active array multifunction radars, In *Proceedings of the IEEE National Telesystems Conference*, 71-74, San Diego: IEEE.

[17] Komorniczak, W., Pietrasinski, J. and Solaiman, B. (2002), The data fusion approach to the priority assignment in the multifunction radar, In *Proceedings of the 14th Conference on Microwave, Radar and Wireless Communication,* 647-650.

[18] Miranda, S.L.C., Baker, K., Woodbridge, K. and Griffiths, H.D. (2006), Knowledge-based resource management for multifunction radar, *IEEE Signal Processing Magazine*, 66 (1), 66-76.

[19] Miranda, S.L.C., Baker, K., Woodbridge, K. and Griffiths, H.D. (2005), Simulation methods for prioritizing tasks and sectors of surveillance in phased array radar, *Journal of Simulation,* 5 (1-2), 18-25.

[20] Miranda, S.L.C., Baker, K., Woodbridge, K. and Griffiths, H.D. (2004), Phased array radar resource management: a comparison of scheduling algorithms, In *Proceedings of the IEEE International Radar Conference,* 79-84.

[21] Kanetos, Woodbridge, K. and Baker, C. (2002), Tracking optimization for multifunction radar, In *Proceedings of the London Communications Symposium*.

[22] Dawber, B. (2005), Fuzzy logic module, *TTCP Power Point Presentation.*

[23] Berry, P.E. and Fogg, D.A.B. (2003), On the use of entropy for optimal radar resource management and control, In *Proceedings of the IEEE International Radar Conference*, 572-577.

[24] Huizing, A.G. and Spruyt, J.A. (1992), Adaptive waveform selection with a neural network, In *Proceedings of the IEEE International radar conference*, 419-421.

Dynamic Programming Algorithms

[25] Scala, B.L. and Moran, B. (2005), Optimal target tracking with restless bandits, *Elsevier Digital Signal Processing*, 2006 (16), 479-487.

[26] Krishnamurthy, V. and Evans, R.J. (2001), Hidden Markov model multiarm bandits: a methodology for beam scheduling in multitarget tracking, *IEEE Transactions on Signal Processing,* 49 (2), 2893-2908.

[27] Wintenby, J. and Krishnamurthy, V. (2006), Hierarchical resource management in adaptive airborne surveillance radars, *IEEE Transactions on Aerospace and Electronic Systems*, 42 (2), 401-420.

[28] Wintenby, J. (2003), Resource allocation in airborne surveillance radar, *Ph.D. dissertation, Chalmers University of Technology*, Sweden.

[29] Strőmberg, D. and Grahn, P. (1996), Scheduling of tasks in phased array radar, In *Proceedings of the IEEE International Symposium on Phased Array Systems and Technology*, 318-321.

[30] Elshafei, M., Sherali, H.D. and Smith, J.C. (2003), Radar pulse interleaving for multi-target tracking, *Naval Research Logistics*, 51 (1), 72-94.

[31] Washburn, R.B., Schneider, M.K. and Fox, J.J. (2002), Stochastic dynamic programming based approaches to sensor resource management, In *Proceedings of the International Conference on Information Fusion,* 608-615, Annapolis, Maryland: International Society of Information Fusion.

[32] Howard, S., Suvorova, S. and Moran, B. (2004), Optimal policy for scheduling of Gauss-Markov systems, In *Proceedings of the International Conference on Information Fusion*, 888-892, Stockholm, Sweden: International Society of Information Fusion.

[33] Orman, A.J., Potts, C.N., Shahani, A.K. and Moore A.R. (1996), Scheduling for a multifunction phased array radar system, *European Journal of Operational Research*, 90 (1), 13-25.

[34] Orman, A.J., Shahani, A.K. and Moore A.R. (1998), Modelling for the control of complex radar system, *Computer Operations Research*, 25 (3), 239-249.

[35] Orman, A.J. and Potts, C.N. (1997), On the complexity of coupled-task scheduling, *Discrete Applied Mathematics*, 72 (1), 141-154.

[36] Butler, J.M., Moore, A.R. and Griffiths, H.D. (1997), Resource management for a rotating MFR, In *Proceedings of the IEEE International Radar Conference*, 568-572.

[37] Duron, C. and Proth, J.M. (2002), Multifunction radar: task scheduling*, Journal of Mathematical Modelling and Algorithms*, 1, 105-116.

[38] Duron, C. and Proth, J.M. (2002), Linked task scheduling: algorithms for the single machine Case, *INRIA Report*.

[39] Duron, C. and Proth, J.M. (2004), Insertion of a random bitask in a schedule: a real-time approach, *Computers & Operations Research*, 31, 779-790.

[40] Winter, E. and Lupinski, L. (2006), On scheduling the dwells of a multifunction radar, In *Proceedings of the IEEE International Conference on Radar*, 1-4.

[41] Filippi, R. and Pardini, S. (1990), An example of resources management in a multifunctional rotating phased array radar, In *Proceedings of the IEE Colloquium on, Real-Time Management of Adaptive Radar Systems*, 1-3.

[42] Butler, J.M. (1998), Multi-function radar tracking and control, *Ph. D. thesis*, University College London.

[43] Kuo, C.F., Kuo, T.W. and Chang, C. (2003), Real-time digital signal processing of phased array radars, *IEEE Transactions on Parallel and Distributed Systems*, 14 (5), 433-446.

[44] Lee, C.G., Kang, P.S., Shih, C.S. and Sha, L. (2006), Schedulability envelope for real-time radar dwell scheduling, *IEEE Transactions on Computers*, 55 (12), 1599-1613.

Q-RAM Algorithms

[45] Kuo, T.W., Chao, A.S., Kuo, C.F., Chang, C. and Su, Y. (2002), Real-time digital signal processing of phased array radars, In *Proceedings of the IEEE International Radar Conference*, 160-171.

[46] Shih, C., Gopalakrishnan, S., Ganti, P., Caccamo, M. and Sha, L. (2003), Scheduling real-time dwells using tasks with synthetic periods, In *Proceedings of the IEEE Real Time Systems Symposium*, 210-219.

[47] Shih, C., Gopalakrishnan, S., Ganti, P., Caccamo, M., Sha, L. (2003), Template-based real time dwells scheduling with energy constraints, In *Proceedings of the IEEE Real Time and Embedded Technology and Applications Symposium,* 19-27.

[48] Goddard, S. and Jeffray, K. (1997), Analyzing the real-time properties of a dataflow execution paradigm using a synthetic aperture radar application, In *Proceedings of the IEEE Real Time and Embedded Technology and Applications Symposium*, 60-71.

[49] Rajkumar, R., Lee, C., Lehoczky, J. and Siewiorek, D. (1997), A resource allocation model for QoS management, In *Proceedings of the IEEE Real Time Systems Symposium*, 290-307.

[50] Lee, C., Lechoczky, J. and Siewiorek, D. (1998), On QoS optimization with discrete QoS options, In *Proceedings of the IEEE Real Time and Embedded Technology and Applications Symposiu,* 276-286.

[51] Ghosh, S., Rajkumar, R., Hansen, J. and Lehoczky, J. (2006), Integrated QoS-aware resource management and scheduling with multi-resource constraints, *Real-Time System*, 33, 7-46.

[52] Ghosh, S. (2004), Scalable QoS-based resource allocation, *Ph. D. thesis*, Carnegie Mellon University.

[53] Hansen, J.P., Rajkumar, R., Lehoczky, J. and Ghosh, S. (2006), Resource management for radar tracking, In *Proceedings of the IEEE International Radar Conference*.

[54] Ghosh*, S.,* Hansen, J.P., Rajkumar*,* R. and Lehoczky, J. (2004), Integrated resource management and scheduling with multi-resource constraints, In *Proceedings of the 25th IEEE International Real-Time Systems Symposium,* 12-22.

[55] Hansen, J.P., Ghosh, S., Rajkumar R. and Lehoczky, J. (2004), Resource management of highly configurable tasks, In *Proceedings of the 18th International Parallel and Distributed Processing Symposium*, 140-147.

[56] Gopalakrishnan, S., Shih, C.S., Ganti, P., Caccamo, M. and Sha, L. (2004), Radar dwell scheduling with temporal distance and energy constraints, In *Proceedings of the IEEE International Radar Conference*, 1-34.

[57] Gopalakrishnan, S., Caccamo, M., Shih, C.S., Lee, C. and Sha, L. (2006), Finite-horizon scheduling of radar dwells with online template construction, *Real-Time Systems*, 33 (1), 47-75.

[58] Harada, K., Ushio, T. and Nakamoto, Y. (2007), Adaptive resource allocation control for fair QoS management, *IEEE Transactions on Computers*, 56 (3), 344-357.

Waveform-Aided Algorithms

[59] Kershaw, D.J. and Evans, R.J. (1997), Waveform selected PDA, *IEEE Transactions on Aerospace and Electronic Systems*, 33 (4), 1180-1188.

[60] Kershaw, D.J. and Evans, R.J. (1994), Optimal waveform selection for tracking systems, *IEEE Transactions on Information Theory*, 40 (5), 492-496.

[61] Howard, S., Suvorova, S. and Moran, B. (2004), Optimal policy for scheduling of Gauss-Markov systems, In *Proceedings of the 7th International Conference on Information Fusion*, 888-892, Stockholm, Sweden: International Society of Information Fusion.

[62] Suvorova1, S., Howard, S.D. and Moran, W. (2006), Beam and waveform scheduling approach to combined radar surveillance and tracking the paranoid tracker, In *Proceedings of the International Waveform Diversity and Design Conference,* Lihue, Hawaii: IEEE

[63] Scala, B.L., Moran, B. and Evands, R. (2003), Optimal adaptive waveform selection for target detection, In *Proceedings of the IEEE International Radar Conference*, 492-496, Adelaide: IEEE.

[64] Scala, B.L., Rezaeian, M. and Moran, B. (2005), Optimal adaptive waveform selection for target tracking, In *Proceedings the 8th International Conference on Information Fusion*, 25-28, Philadelphia: International Society of Information Fusion.

[65] Sowelam, S.M. and Tewfik, A.H. (2000), Waveform selection in radar target classification, *IEEE Transactions on Information Theory,* 46 (3), 1014-1029.

[66] Howard, S., Suvorova, S. and Moran, B. (2004), Waveform libraries for radar tracking applications, In *Proceedings of the 1st International Conference on Waveform Diversity and Design*, 1424-1428, Edinburgh, UK: IEEE.

[67] Moran, B., Suvorova, S. and Howard, S. (2005), Sensor management for radar: a tutorial, In *Proceedings of the Sensing for Security Workshop,* 1-23, Ciocco, Italy: NATO ASI.

[68] Harada, F., Ushio, T. and Nakamoto, Y. (2007), Adaptive resource allocation control for fair QoS management, *IEEE Transactions Computer*, 56 (3), 344-357.

[69] Suvorova, S., Musicki, D., Moran, B., Howard, S. and Scala, B. L. (2005), Multi step ahead beam and waveform scheduling for tracking of maneuvering targets in clutter, In *Proceedings of International Conference Acoustics, Speech, Signal Processing (ICASSP),* 889-892, Philadelphia: IEEE.

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

[71] Sira, S., Papandreou-Suppappola, A. and Morrell, D. (2007), Dynamic configuration of time-varying waveforms for agile sensing and tracking in clutter, *IEEE Transactions on Signal Processing,* 55 (7), 3207-3217.

[72] Sira, S., Cochran, D., Papandreou-Suppappola, A., Morrell, D., Moran, W., Howard, S. and Calderbank, R. (2007), Adaptive waveform design for improved detection of low-RCS targets in heavy sea clutter, *IEEE Journal of Selected Topics in Signal Processing, 1 (1), 56-66*.

[73] Hurtado,M., Zhao, T. and Nehorai, A. (2008), Adaptive polarized waveform design for target tracking based on sequential Bayesian inference, *IEEE Transactions on Signal Processing,* 56 (3), 1120-1133.

[74] Haykin, S., Currie, B. and Kirubarajan, T. (2003), Literature search on adaptive radar transmit waveforms (DRDC Ottawa CR-2003-094), McMaster University, Hamilton, Ontario.

[75] DARP Adaptive Waveform Design, http://signal.ese.wustl.edu/DARPA/publications.html (Access date: 25 Nov. 2008).

Adaptive Update Rate Algorithms

[76] Daum, F. and Fitzgerald, R. (1983), Decoupled Kalman filters for phased array radar tracking, *IEEE Transaction on Automatic Control*, 28 (3), 296-283.

[77] Keuk, G. and Blackman, S. (1993), On phased array radar tracking and parameter control, *IEEE Transactions on Aerospace and Electronic Systems*, 29 (1), 186-194.

[78] Koch, W. (1999), On adaptive parameter control for phased-array tracking, In *Proceedings of the SPIE Conference on Signal and Data Processing of Small Targets*, Vol. 3809, 444-455.

[79] Shin, H.J. (1995), Adaptive-update-rate target tracking for phased-array radar, *IEE Proceedings – Radar, Sonar and Navigation,* 142 (3), 137-143.

[80] Leung, H. (1997), A Hopfield neural tracker for phased array antenna, *IEEE Transactions on Aerospace and Electronic Systems*, 33 (1), 301-307.

[81] Sun-Mog, H. and Young-Hun, J. (1998), Optimal scheduling of track updates in phased array radars, *IEEE Trans. Aerospace Electronics Systems*, 34 (3), 1016-1022.

[82] Tei-Wei, K., Yung-Sheng, C., Kuo, Chin-Fu and Chang, C. (2005), Real-time dwell scheduling of component-oriented phased array radars, *IEEE Transactions Computer*, 54 (1), 47-60.

[83] Keuk, G. (1978), Software structure and sampling strategy for automatic target tracking with phased array radar, In *Proceedings of the AGARD*, 21-32.

[84] Cohen, S.A. (1986), Adaptive variable update rate algorithm for tracking targets with a phased array radar, *IEE Proceedings – Radar, Sonar and Navigation,,* 133 (3), 277-280.

[85] Vannicola, V.C., and Mineo, J.A. (1990), Expert system for sensor resource allocation, *the 33rd Midwest Symposium on Circuits and Systems*, 1005-1008.

[86] Mune, M., Harrison, M., Wilkin, D., and Woolfson, M.S. (1992), Comparison of adaptive target-tracking algorithm for phased array radar, *IEE Proceedings – Radar, Sonar and Navigation,* 139 (5), 336-342.

[87] Sarunic, P.W. (1995), Adaptive variable update rate target tracking for a phased array radar, In *Proceedings of the IEEE International Radar Conference*, 317-322.

[88] Sarunic, P.W. and Evans, R.J. (1997), Adaptive update rate tracking using IMM nearest neighbour algorithm incorporating rapid re-looks, *IEE Proceedings - Radar, Sonar and Navigation* , 144 (4), 195-204.

[89] Noyes, S.P. (1998), Calculation of next time for track Update in the MESAR phased array radar, *IEE Colloquium on Target Tracking and Data Fusion*, 2/1-2/7.

[90] Jeffrey, T.W. (1998), Phased array radar tracking with non-uniformly spaced measurements, In *Proceedings of the IEEE International Radar Conference*, 44-49.

[91] Coetzee, S.L., Woodbridge, K. and Baker, C.J. (2003), Multifunction radar resource management using tracking optimization, In *Proceedings of the IEEE International Radar Conference*, 578-583.

[92] Gopalakrishnan, S., Shih, C.S., Ganti, P., Caccamo1, M. and Sha, L. (2004), Radar dwell scheduling with temporal distance and energy constraints, In *Proceedings of the IEEE International Radar Conference.*

[93] Lee, C.G. (2005), A novel framework for quality-aware resource management in phased array radar systems, In *Proceedings of the 11th IEEE Real Time and Embedded Technology and Applications Symposium*, 322-331.

[94] Zwaga, J.H., Boers, Y. and Driessen, H. (2003), On tracking performance constrained MFR parameter control, In *Proceedings of the 6th International Conference on Information Fusion*, 712-718, Cairns, Queensland, Australia: International Society of Information Fusion.

[95] Zwaga, J.H. and Driessen, H. (2005), Tracking performance constrained MFR parameter control: applying constraints on prediction accuracy, In *Proceedings of the 8th International Conference on Information Fusion*, 25-28, Philadelphia: International Society of Information Fusion.

[96] Boers, Y., Driessen, H. and Zwaga, J. (2006), Adaptive MFR parameter control: fixed against variable Pd, *IEE Proceedings - Radar, Sonar and Navigation,* 153 (1), 2-6.

[97] Lee, C.G., Shih C.S. and Sha, L. (2006), Schedulability envelope for real-time radar dwell scheduling, *IEEE Transactions Computer*, 55 (12), 1599-1613.

[98] Benoudnine, H., Keche, M., Ouamri, A. and Woolfson, M.S. (2006), Fast adaptive update rate for phased array radar using IMM target tracking algorithm, In *Proceedings of the IEEE International Symposium on Signal Processing and Information Technology*, 277-282.

Benchmark Algorithms

[99] Blair, W.D., Watson, G.A. and Hoffman, S.A. (1994), Benchmark problem for beam pointing control of phased array radar against maneuvering targets, In *Proceedings of the the American Control Conference,*2071-2075*,* Baltimore: American Automatic Control Council.

[100] Blair, W.D., Watson, G.A, Kirubarajan, T. and Bar-Shalom, Y. (1998), Benchmark for radar resource allocation and tracking in the presence of ECM, *IEEE Transactions on Aerospace and Electronic Systems,* 34 (4), 1097-1114.

[101] Blair, W.D. and Watson, G.A. (1994), IMM algorithm for solution to benchmark problem for tracking maneuvering targets, In *Proceedings of the SPIE Acquisition, Tracking and Pointing Conference,* 476-488*,* Orlando: SPIE.

[102] Watson, G.A. and Blair, W.D. (1994), Tracking performance of a phased array radar with revisit time controlled using the IMM algorithm, In *Proceedings of the American Control Conference,*160-165*,* Baltimore: American Automatic Control Council.

[103] Daeipour E., Bar-Shalom, Y. and Li, L. (1994), Adaptive beam pointing control of a phased array radar using an IMM estimator, In *Proceedings of the American Control Conference,* 2093-2097, Baltimore: American Automatic Control Council.

[104] Kirubarajan T., Bar-Shalom Y. and Daeipour E. (1994), Adaptive beam pointing control of phased array radar using an IMM estimator, In *Proceedings of the American Control Conference,* 2616-2620, Baltimore: American Automatic Control Council.

[105] Blair, W.D., Watson, G.A. and Hoffman, S.A. (1995), Benchmark problem for beam pointing control of phased array radar against maneuvering targets in the presence of ECM and false alarms, In *Proceedings of the American Control Conference,* 2601-2605, Seattle: American Automatic Control Council.

[106] Blackman, S.S., Bush, M., Demos, G. and Popoli, R. (1995), IMM/MHT tracking and data association for benchmark tracking problem, In *Proceedings of the American Control Conference,* 2606-2610, Seattle: American Automatic Control Council.

[107] Kalata P. (1994), An *a/β* target tracking approach to the benchmark tracking problem, In *Proceedings of the American Control Conference,* 2076-2080, Baltimore: American Automatic Control Council.

[108] Kirubarajan, T., Bar-Shalom, Y. and Daeipour, E. (1995), Adaptive beam pointing control of a phased array radar in the presence of ECM and false alarms using IMMPDAF, In *Proceedings of the American Control Conference,* 2616-2620, Seattle: American Automatic Control Council.

[109] Hoffman, S.A. and Blair, W.D. (1995), Guidance, tracking and radar resource management for self defense, In *Proceedings of the IEEE Conference on Decision and Control*, 2772-2777, New Orleans: American Automatic Control Council.

[110] Efe, M. and Atherton, D.P. (1996), Adaptive beam pointing control of a phased array radar using the AIMM algorithm, In *Proceedings of the IEE Colloquium on Target Tracking and Data Fusion*, 11/1-11/8.

[111] Popoli, R.E., Blackman, S.S. and Busch, M.T. (1996), Application of multiple hypothesis tracking to agile beam radar tracking, In *Proceedings of the SPIE Conference on Signal and Data Processing of Small Targets*, 418-428.

[112] Kirubarajan, T., Bar-Shalom, Y., Blair, W.D. and Watson, G.A (1998), IMMPDAF for radar management and tracking benchmark with ECM, *IEEE Transactions on Aerospace and Electronic Systems,* 34 (4), 1115-1134.

[113] Angelova, D., Semerdjiev, E., Mihaylova, L. and Li, X. (1999), An IMMPDAF solution to benchmark problem for tracking in clutter and standoff jammer, *Information and Security*, 2, 1-8.

[114] Burns, P.D. and Blair, W.D. (2004), Optimal phased array radar beam pointing for MTT, *Aerospace Conference*, 1851-1858.

[115] Watson, G.A. and McCabe, D.H. (1999), Benchmark problem with a multisensor framework for radar resource allocation and tracking of highly maneuvering targets, closely-spaced targets, and targets in the presence of sea-surface-induced multipath". *Technical Report NSWC-DD/TR-99/32*, NSWC, Dahlgren, VA, March.

[116] Sinha, A., Kirubarajan, T. and Bar-Shalom, Y. (2006), Tracker and signal processing for the benchmark problem with unresolved targets, *IEEE Transactions on Aerospace and Electronic Systems*, 42 (1), 279-300.

List of symbols/abbreviations/acronyms/initialisms

AI	Artificial Intelligence
CFP	Canadian Patrol Frigate
CSO	Closely Spaced Objects
DND	Department of National Defence
DRDC	Defence Research & Development Canada
DRDKIM	Director Research and Development Knowledge and Information Management
DSTO	a defence agency, Australia
ECM	Electronic Countermeasures
ES	Expert System
FA	False Alarm
IFF	Identification Friend or Foe
IMM	Interacting Multiple Models
IRST	Infra-Red Search and Track
LGA	Low Grazing Angle
MFR	Multifunction Radar
MHT	Multiple Hypothesis Tracking
MOP	Measures of Performance
NN	Neural Network
NRL	Naval Research Lab, US
PDA	Probabilistic Data Association
PDF	Precision Direction Finding
PESA	Passive Electronically Scanned Array
PESM	Precision Electronic Support Measures
QoS	Quality of Service
Q-RAM	QoS Resource Allocation Methodology
R&D	Research & Development
RAM	Resource Allocation Manager or Management
RCS	Radar Cross Section
RF	Radio Frequency
RGPO	Range Gate Pull Off
RRM	Radar Resource Management
SNR	Signal Noise Ratio
SOJ	Standoff Jammer
TR or T/R	Transmit/receiver module
WSPDA	Waveform Selective PDA

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DRDC Ottawa has launched an applied research project (ARP) called “Advanced Concepts for Naval Multi-function Radar (MFR)”. Two major science and technology topics are identified for this project. The first major topic is the radar detection and tracking of small targets in littoral environments. The second major topic is the investigation of the adaptive radar resource management (RRM) problem. This report presents a survey of the second topic based on existing open literature. The surveyed algorithms are grouped into five categories: artificial intelligence algorithms, dynamic programming algorithms, quality of service (QoS) resource allocation management (Q-RAM) algorithms, waveform-aided algorithms and adaptive update rate algorithms. The first three categories are adaptive radar scheduling algorithms and the remaining two categories are resource-aided algorithms. The US Navy’s phased array radar benchmark problems and solutions are also reviewed. Comments are provided for each category of the RRM algorithms, which lead to recommendations for future study.

RDDC Ottawa a lancé un projet de recherche appliquée (PRA) intitulé « Concepts avancés pour radar multifonction (MFR) naval ». Ce projet comporte deux thèmes majeurs de science et technologie : l’étude du problème de gestion des ressources radar (RRM) adaptative ainsi que la détection et la poursuite radar de petites cibles dans des environnements littoraux. Le présent rapport comprend une étude documentaire du deuxième thème selon les sources publiées. Les algorithmes étudiés sont groupés selon cinq catégories : les algorithmes d’intelligence artificielle, les algorithmes de programmation dynamique, les algorithmes d’affectation des ressources fondés sur la qualité de service (Q-RAM), les algorithmes fondés sur les formes d’onde et les algorithmes à fréquence de mise à jour variable. Les algorithmes des trois premières catégories sont des algorithmes adaptatifs d’ordonnancement radar, tandis que ceux des deux autres catégories sont des algorithmes fondés sur les ressources. Les problèmes de référence pour les radars à balayage électronique de la Marine américaine et leurs solutions sont également étudiés. Des commentaires sur chaque catégorie d’algorithmes de RRM sont fournis, et ces commentaires mènent à des recommandations sur les recherches futures.

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multifunction radar, Adapt_MFR, artificial intelligence, dynamic programming, Q-RAM, waveform, benchmark, adaptive update rate, filtering, target tracking, radar resource management, radar scheduling, track prioritization, survey

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