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Interval Algebra – An effective means of scheduling surveillance radar networks

Richard W. Focke [a,b,*], Johan P. de Villiers [a,c], Michael R. Inggs [b]

[a] Council for Scientific and Industrial Research, Pretoria, South Africa
[b] University of Cape Town, Cape Town, South Africa
[c] University of Pretoria, Pretoria, South Africa

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ABSTRACT

Interval Algebra provides an effective means to schedule surveillance radar networks, as it is a temporal ordering constraint language. Thus it provides a solution to a part of resource management, which is included in the revised Data Fusion Information Group model of information fusion. In this paper, the use of Interval Algebra to schedule mechanically steered radars to make multistatic measurements for selected targets of importance is shown. Interval Algebra provides a framework for incorporating a richer set of requirements, without requiring modifications to the underlying algorithms. The performance of Interval Algebra was compared to that of the Greedy Randomised Adaptive Search Procedure and the applicability of Interval Algebra to nimble scheduling was investigated using Monte-Carlo simulations of a binary radar system. The comparison was accomplished in terms of actual performance as well as in terms of computation time required. The performance of the algorithms was quantified by keeping track of the number of targets that could be measured simultaneously. It was found that nimble scheduling is important where the targets are moving fast enough to rapidly change the recognised surveillance picture during a scan.

Two novel approaches for implementing Interval Algebra for scheduling surveillance radars are presented. It was found that adding targets on the fly and improving performance by incrementally growing the network is more efficient than pre-creating the full network. The second approach stemmed from constraint ordering. It was found that for simple constraint sets, the Interval Algebra relationship matrix reduces to a single vector of interval sets. The simulations revealed that an Interval Algebra algorithm that utilises both approaches can perform as well as the Greedy Randomised Adaptive Search Procedure with similar processing time requirements. Finally, it was found that nimble scheduling is not required for surveillance radar networks where ballistic and supersonic targets can be ignored. Nevertheless, Interval Algebra can easily be used to perform nimble scheduling with little modification and may be useful in scheduling the scans of multifunction radars.

1. Introduction

Multisensor management deals with the task of queueing sensors to make measurements that best serve the mission that a multisensor data fusion (MDF) system is intended to complete [1,2]. In the case of a surveillance system, this means controlling the sensors so as to gather the most pertinent information about the sensed area.

Multisensor management is contained entirely in level 4, process refinement, of the Joint Directors of Laboratories (JDL) data fusion model [3], as refining the process of information fusion can best be achieved by controlling the inputs to the process. This is when the only inputs to the information fusion system are the sensor measurements. Recently, the updated Data Fusion Information Group (DFIG) data fusion model was proposed [3–5], where resource and mission management replaces process refinement. Resource management is a subset incorporating aspects such as tuning all information fusion functionality. Furthermore, it also looks at how to control information collected by other means, such as military intelligence.

Two preliminary steps can be used to formulate a solution for multisensor management. The first is to model the sensors, their

* Corresponding author at: Council for Scientific and Industrial Research, Meiring Naude Road, Pretoria, South Africa.

E-mail addresses: rfocke@csir.co.za, richard.focke@uct.ac.za (R.W. Focke), jdvilliers1@csir.co.za, pieter.devilliers@up.ac.za (J.P. de Villiers), michael.inggs@uct.ac.za (M.R. Inggs).

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environment and the goals they must achieve. The second is the choice of architecture, which dictates how the multisensor manager will be designed and employed.

Modelling a sensor manager can be achieved using two methods [6]. The first choice is to make use of a myopic simplification and thus deal with only a very simple model of the past and the future. The alternative choice is to employ longer-term planning, which considers more historic information and generates long-term predictions. Common solutions for the latter choice include partially observed Markov decision processes (POMDPs) [7,8] and multiple-armed bandits (MABs), a simplification of the Markov decision process (MDP) [9,10]. These are both types of Bayesian networks and, while they are promising, they often lead to numerically difficult solutions. Thus, as longer-term planning is desirable, there is still work required to make these practically feasible in all cases.

There are various architectures used for creating a mulstisensor manager. Traditionally, a centralised architecture has been used, where a central information fusion system feeds a centralised multisensor manager with information so as to control all sensors. Another possibility is a decentralised architecture, where typically both the information fusion system and multisensor manager are distributed across each discrete sensor or suite of sensors [2,11,12]. These architectures represent the current state of the art, as distributed problems are difficult to solve. A hybrid of these approaches has been proposed by various authors [13,14], which usually consists of two or more distinct levels. On the lowest level sensor management is distributed and must keep sensors busy and tune sensor parameters for high-level tasks. The higher level, sensor coordination, is centralised and ensures that collectively the sensors are optimally achieving the sensor fusion system goals.

Sensor coordination consists of planning and scheduling [2], and can be sub-divided into three functions [15]. The first function of sensor coordination must solve the problem of generating tasks for each sensor. The next function of sensor coordination is to prioritise the generated tasks. Together the first two functions perform the required planning. The final function of the sensor coordination is to place the best set of tasks in the timeline of sensing actions for each sensor. This is known as the scheduling function, which is the focus of this work.

A sensor coordination algorithm is considered a *nimble scheduler* when it is able to rapidly adapt to changes in the surveyed area. This means that, if there are fast-moving or rapidly accelerating targets, the scheduler will incorporate the updated target locations in real time. These targets will not only affect planning but also scheduling within very short time intervals. Thus the scheduler must be able to recalculate the schedule of tasks for the sensors concurrently with the execution of these tasks by the sensors. The updated schedule of tasks can leverage the improved situational picture as it is generated by the information fusion system.

1.1. Current scheduling solutions

Sensor scheduling treats the sensor resources as a timeline extending from the present towards the future. As such, scheduling is a combinatorial optimisation problem very similar to the knapsack problem. The goal is to fill the timeline with tasks such that the sensor is never idle. Idle time is wasteful since this time is better spent catching up on tasks that may later cause a bottleneck.

A good overview of types of algorithms for sensor scheduling can be found in the work of Xiong and Svensson [2] and Musick and Malhotra [15], as well as a more recent work by Ding [16]. There are many approaches that can be followed to schedule individual sensors. However, not all of them are directly applicable to multisensor scheduling, which is required for an MDF system.

Early in the history of sensor management scheduling was performed by human operators with only minimal assistance provided by the system that was being managed [17]. Next, heuristic approaches that captured much of the domain knowledge of human operators were employed. These approaches are still very popular today as they require minimal computation time and are easy to develop [14,18–20].

As research in the field broadens to encompass additional functions of sensor coordination, this aspect is sometimes handled intrinsically by task prioritisation algorithms [9,21–24]. Examples are split among those using information and decision theory. This has the benefit of not wasting computation especially if the mission of the MDF system changes on a high level. In this case, instead of handling a timeline of tasks, the sensor manager only deals with the current task to schedule. On the other hand, if a centralised fusion centre is used and stops operating or if communication is lost in a decentralised system, there will be no timeline of tasks to continue with in the interim. Just doing arbitrary tasks during this time can have detrimental effects, not only on the optimality of the scheduling solution, but also on the mission of the MDF system as a whole.

The scheduling problem can be solved through the use of optimisation algorithms when information-theoretic approaches to task prioritisation are used [25]. These optimisation algorithms fall into two categories: mathematical programming [19,26–28] and artificial intelligent search techniques [29,30]. Simulation techniques are another possibility, where possible future timelines are investigated using multiple trials [31–33]. Sometimes random approaches are followed and these are typically used as an electronic countermeasure [34].

Artificial intelligence techniques have also been proposed in the past and have predominantly used reasoning/expert systems. Examples include fuzzy-set based reasoning [35,36] and fuzzy decision trees [36] all within the context of an expert system. In these systems, the scheduling rules are captured by analysing linguistic rules of thumb provided by human sensor operators.

1.2. Multistatic radars

An interesting application of multisensor management for radars is the possibility of making multistatic measurements [37,38], which can be used to increase the probability of detection of small targets in heavy clutter scenarios. Increasingly, there is a trend where small boats are used in piracy and terrorist activities to attack larger vessels. Coordinating the measurements of multiple radars could potentially mitigate some of these problems, by ensuring that these targets are detected and tracked. However, most radars of the affected vessels are not very sophisticated, and thus require a simple solution to benefit from multistatic measurements.

Multistatic measurements are possible by adequately scheduling each radar to measure the target simultaneously. Each radar must also be able to receive the transmitted signals of the other radars, or the signals must combine coherently through constructive interference to increase the energy on the target. Receiving radars can always make a monostatic measurement by computing the monopulse angle of the target and the delay experienced by the signals it transmits. More sophisticated receiving radars can also discern the Doppler shift induced by the target motion.

For multistatic radars, where a radar can distinguish the signals of the other radars, this receiving radar can then also make a bistatic measurement. This is done by pinpointing the position of the target using intersecting ellipsoids with the receiving and transmitting radars as the ellipsoid foci. Thus, each radar is able to make more measurements of the target. Each radar has an increased probability of detection and can make more accurate