COORDINATED OBSERVATIONS OF SPACE DEBRIS AS OPTIMISATION PROBLEM OF INTER-DEPENDENT METRICS

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ABSTRACT

Optimal allocation of sensor resources is addressed in this paper in the frame of space surveillance application. Inspiration is taken from the optimal management of multi-functional sensors and netted surveillance sensors, for which the Sensor Management problem is often addressed as a Markov Decision Process. This approach allows determining the optimal decision at each discrete time instant by quantifying the expected payoff coming from the selected action. An action might be the assignment of the i–th surveillance task to the m–th sensor in the network ('tasking'), the selection of the i–th task at the k–th time slot ('scheduling'), or the activation of a specific sensor configuration for the completion of the i–th task ('resource allocation'). The common objective is the maximization of the global reward coming from the selected sequence of actions over a finite or infinite time horizon. This leads to a sequence of coordinated observations carried out by the sensor(s), which are determined statically or dynamically by the Sensor Manager. In this paper, the allocation of space surveillance resources is analysed as a management problem for sensor(s) with finite resources. The proposed allocation is driven by the operational requirements for space objects cataloguing, such as the object population coverage and the track accuracy. A sequential resource allocation strategy is formulated in order to cope with such inter-dependent, concurring performance metrics. The approach can be also extended to multiple sensors with different performance or nature. Promising results are demonstrated over a phased array radar case study.

Key words: Sensor Management; Task Scheduling; Space Surveillance; Coordinated Observations; Phased Array Radar.

1. SENSOR MANAGEMENT

Sensor Management (SM) is the key enabler for coordinated observations of the underlying dynamic system, which use optimally the available resources. Sensor Management is defined in [1] as the *'control of the degrees of freedom in an agile sensor system to satisfy operational constraints and achieve operational objectives'*. It is also stated [1] that *'to accomplish this, one typically seeks a policy for determining the optimal sensor configuration at each time, within constraints, as a function of information available from prior measurements'*. Thus, SM can be generally seen as a decision process, which involves the acquisition of information (e.g., observations) on a dynamic system and the implementation of actions (e.g., tasking, scheduling or resource allocation) over a discrete time sequence. The quality of our knowledge on the observed system follows from the implemented actions. The sensor manager needs to adaptively select its 'response' to the sensed environment accordingly to a decision policy, which identifies the best action out of a finite set on the basis of the overall objective. Therefore, SM can be tackled as a constrained optimisation problem and a closed-loop, dynamic approach can be adopted, which exploits system outputs, through a feedback path, in order to steer the upcoming decisions.

This is typically the case in Tasking for wireless sensor networks [2], since the available resources are scarce (e.g., battery power or communication bandwidth) and the 'best' sensor to be activated for achieving the overall objective needs to be online selected. In target tracking applications, for instance, it is straightforward to relate such decision to the current knowledge on the observed dynamic scenario ('Information-based Sensor Tasking' [2]).

Conversely, Sensor Scheduling has been often interpreted as a feed-forward [1, 3] process. A set of tasks to be carried out is received by the scheduler, which attempts at optimally allocating the activities over time on the basis of tasks' temporal constraints and performance metrics. Sensor tasks are labelled as time-critical (hard-deadline) or fluid deadline, and a sequence of tasks is sorted out on the basis of their priority level and sensor efficiency criteria. The selection of the action, i.e., the assignment of a task to a certain time slot, is thus based on the prior knowledge of the sensor and the process itself, and it is not error-based. Conflicts are solved on the basis of the versatility of the involved tasks. Typical approaches are described in [4, 5]. The scheduler is thus considered as a module which turns requests into a timeline without higher level decision making capability, and no feedback

Proc. '6th European Conference on Space Debris'
Darmstadt, Germany, 22–25 April 2013 (ESA SP-723, August 2013)

to the tasking unit.

Finally, Resource Allocation can be also considered as a constrained optimisation problem in the frame of SM. On the basis of a performance metric, the future expenditure of resources is determined for a sensor or multiple sensors in a step-wise fashion. As the resources are finite (e.g., the transmitted power or the availability of the receiver), a trade-off among all tasks asking for resources needs to be carried out. As the scenario dynamically evolves over time, a sequence of requests is formed, to which the system attempts at responding with an optimized sequence of resources allocation [6], or a sequence of waveforms to be transmitted. This can be also tackled with a closed-loop decision strategy.

Thus, Sensor Tasking, Scheduling, and Resource Allocation clearly fall in the domain of SM - eventually overlapping. In terms of common solutions, the developed techniques are numerous. Partially Observed Markov Decision Processes (POMDP) [7] have gained recently a key role in many SM applications. Sensor management is in this case approached as a stochastic control problem where a multistage objective function is optimised. Specifically, sequential decisions are made to perform varied actions which can generate varied observations. An optimal decision, whose outcome is uncertain, is sought over the time horizon of future stages, given information from previous observations. A POMDP is a type of stochastic control problem where observations provide incomplete information on the true state of the underlying dynamic system, which is modelled as a Markov process. In this case the relationship between the observed quantities and the underlying state is modelled statistically as the measurements are acquired. The objective of the POMDP problem is to determine the policy which maximises the total reward. Given a finite state problem with finite stages it is possible to tackle a POMDP with dynamic programming [8]. Dynamic programming is based on Bellmans Principle of Optimality: given any starting point on an optimal trajectory, the remainder of the complete optimal trajectory is also optimal for the problem starting from that point. This principle enables the optimisation of the complete problem to be decomposed into the choice of optimal actions for each stage.

In parallel, several information theoretic measures for SM have been investigated. They aim at optimising the information production of the sensor by replacing the optimisation objective function with an information theoretic measure. Different measures have been proposed for differing sensor management problems, such as Shannon entropy [9], the Kullback-Leibler divergence [10] or measures from the error covariance matrix [11]. Such measures can be efficiently used also in case of target tracking applications [12].

Finally, it is worth mentioning the connection between sensor Data Fusion (DF) and sensor management [4, 13]. An illustrative diagram of the numerous interactions is reported in Figure 1. It clearly illustrates that the optimisation - carried out by the sensor manager - cannot depart from the nature of the fused sensor data and the DF architecture itself. Specifically, the sensor manager orchestrates the use of the sensors, the detection and tracking processes (contained in Level 0 and Level 1 blocks), and the detection of inter-relations or anomalies in Level 2/3 steps (e.g., detection of fragmentation or collision). Such SM functionalities might be distributed among the sensing/processing nodes or centralised, or combined in a hybrid way, accordingly to or complementing the strategy conceived for data fusion.

1.1. Management of Radar Resources

The modern multifunction radar [14] has the capability to execute numerous tasks which support differing radar functions. This is made possible by using electronically steered phased arrays, which have an agile beam that can be scanned electronically almost instantaneously. Additionally, a variety of control parameters can be selected, precisely matched to the specific function performed. However, multifunction operation requires the finite radar resource to be effectively distributed between the differing and potentially conflicting tasks.

Volume search is a critical radar function that aims at discovering previously undetected targets in some field of regard for subsequent tracking. The allocation of radiated energy in the field of regard can be optimized by controlling the transmitted waveform, the dwell length and the revisit interval time in each sector or beam position. Additionally, active tracking tasks can be requested in order to get accurate observations of a specific object of interest. Tracking tasks need to be interleaved to the search task, and the time and hence power available to support the radar tasks is limited.

In this work a fixed, rectangular-shaped field-of-regard is assumed for radar observations, which is decomposed into the search of MN sectors, where each sector is referred to as task and where M and N are the number of sector rows and columns respectively. Within each sector the resources are equally distributed among the visited beam positions, which are referred to as jobs. To optimize the volume search we attempt at optimally allocating the available resources among the sectors. To this aim we need a metric that adequately quantifies the performance of the function. If the search function is composed of independent tasks, then the optimisation of the resource allocation for the function can be greatly simplified. However, not all metrics can be decomposed into independent tasks, which complicate the allocation of resource. An example of a particularly useful search metric that cannot be decomposed at task level is the cumulative detection probability [15], as its calculation depends on the control variables in all the sectors through which a target passes. If the search function is required to achieve a specified cumulative detection performance for each object of interest, dependence between the 'resource need' of tasks concurring to this same goal is introduced. This implies that the selection of control parameters for a single task

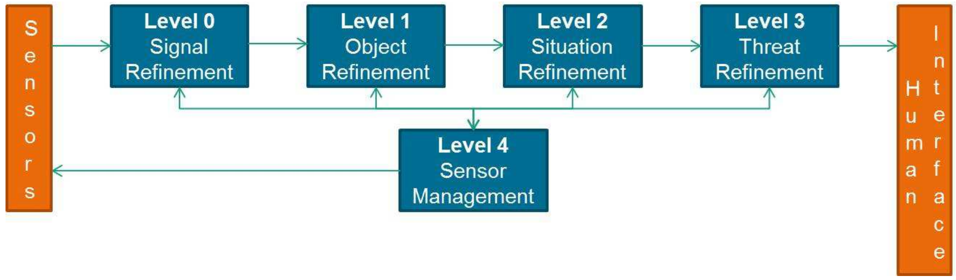

Figure 1. Block Diagram reporting the interconnection between a Data Fusion architecture and the Sensor Manager. Data Fusion functionalities are split in accordance to JDL Data Fusion Model [13]

should dynamically take into account the current state of the other tasks, or exploit statically a model of the interdependence of the tasks. The problem of interdependent metrics is discussed in [16].

In the SM domain, radar use optimisation was first presented in [17], where linear programming was used to determine sensor to track assignments in a sensor network. A cost function that combined both target priorities and track accuracy was suggested to this aim. Generally, the radar resource management problem can be thought of as a branch of sensor management, specifically addressing how the sensors finite resource should be allocated between the numerous tasks which support the varied functions. The constrained optimisation problem searches for the selection of operational parameters for the tasks, such that the combined sensor loading of all tasks does not exceed the capability of the sensor. Existing approaches to the problem loosely fit into two categories, rule based methods [18, 19] or optimisation methods [20, 3]. Generally, rule based methods generate sub-optimal solutions but benefit from light computational demand, whereas optimisation methods can generate optimal solutions but are hindered by excessive computation. Hence, it is desired to mix the desirable characteristics of both methods to produce computationally light algorithms capable of producing quality solutions.

More recently, radar resource management has been addressed through the use of agent systems [21]. Agent systems are self-organising computational societies where the synergy of local interaction between agents produces emergent, global desirable behaviour. By mimicking human interaction mechanisms, agent systems can provide rapid and intelligent adaptation in uncertain and dynamic environments. The automation of human interaction mechanisms in agents systems, such as auctions, can replicate the desirable ability to produce quality behaviour in dynamic and uncertain environments. Specifically, the continuous double auction [21] has evolved over centuries in financial institutions and stock exchanges as a scalable, trusted mechanism for rapidly allocating large resource volumes. Its application to radar resources management through the 'Continuous Double Auction Parameter Selection (CDAPS)' algorithm is described in [21].

1.2. Management of Space Surveillance Sensors

We adopt the definition reported in [23], which states that a *tasker typically generates a list of objects and prioritizes that list for sensors. (...) a scheduler takes that end list of objects and decides when to observe them, given factors such as individual sensor capability and optimality*. These two functionalities are clearly in line with the SM branches described in the previous section.

The use of information theoretic measures for Space Surveillance SM is discussed [23] for a centralised tasker. In case of a centralised architecture the sensor scheduler has no information on the overall performance, while the central tasker receives limited information on the sensor. This means that the selection of low-level jobs is carried out at sensor level by the scheduler, by taking into account sensor-specific parameters such as the target probability of detection. Conversely, the output of the data fusion process (i.e., the catalog entries) are available at central level, hence tasking can exploit global information measures such as the track covariance matrix.

The use of the track covariance matrix for dynamic sensor tasking – specifically the trace of the matrix – is discussed in [24, 25]. The gain coming from an observation is related to the reduction in the 3D position error variance or to the reduction of the largest axes of the position error. In [26] a *synergistic and cooperative cueing for systems such as Space Based Space Surveillance (SBSS) and Space Surveillance Telescope (SST)* is auspicated. Optical sensors with dynamic behaviours are presented in [27], while a closed-loop approach for sensor tasking is presented in [28].

In [29] the effects of the uncertainty estimation on dynamic tasking are discussed. Several techniques for track propagation are nowadays available, and the theoretic accuracy bounds in absence of measurements or the improvement coming from a new observation are derived through Bayesian filtering theory [30]. Another interesting approach in efficiently tasking various devices (radar and optical) is discussed in [31]. The suggested approach relies on agents (e.g. satellites), which engage in a competition for resources (e.g. radar tracking) through a bidding process. A decision-making process attempts to find the best combination of 'bids', resulting in the 'best' allocation of resources. This also allows for the different needs to be taken into account, such as tracking an agent that maneuvers frequently or an agent only used for radar calibration.

As centralised scheduling/tasking is concerned, a description of the difficulties for automatic optimized scheduling for the Space Surveillance Network is reported in [32]. A family of interrelated schedulers is proposed as solution to this constrained management problem. The unavailability of the assets - shared with other missions - and high-priority tasks are also considered by the proposed algorithm.

Since multi-function phased array radars are used or designed within the scope of space surveillance systems [33, 34, 35], the radar resource allocation issue – discussed in the previous paragraph – interacts with the above described sensor tasking and scheduling steps. A Space Surveillance SM strategy should address the three aspects in order to reach the global optimum. A first step is reported in [16], where radar-based observations of Low Earth Orbit (LEO) objects are addressed. We demonstrated in [16] that the scanning strategy of a single agile-beam radar can be optimised to search for space debris, while leaving resources for Active Tracking tasks. Specifically, the search function is considered and the performance is defined in terms of the cumulative probability of detection for the LEO objects. However, the calculation of this probability depends on the control variables in all the sectors through which the target passes, for all of the sensors in the network. As the cumulative detection probability cannot be decomposed into independent tasks, the allocation of resources becomes particularly complicated. This is exacerbated in a sensor network, due to the dependence between the resource need of tasks/sensors concurring to the same goal. This implies that the selection of control parameters for the sensors should dynamically take into account the current state of the other tasks or sensors, or exploit statically a model of tasks inter-dependence. The method proposed in [16] relies on the fact that although the optimisation cannot be decomposed into tasks, it can be decomposed into resource allocation stages. Consequently, an optimisation procedure based on a Markov Decision Process can be developed and applied to the sensor network which searches for space debris. This concept can be used to optimise the joint scanning strategies of a multiple-sensor network. By optimising the sensor-network objective, instead of optimising each sensor separately, redundancy in the sensor resource allocation can be reduced and the overall performance significantly improved.

2. CASE STUDY DESCRIPTION

We consider radar-only observations of space objects in LEO regimes, which are described in [36, 34]. The key parameters for the considered phased array radars are listed in [34, 35]. We first analyse a single sensor (in a mid-latitude location) illuminating a volume of 30° in

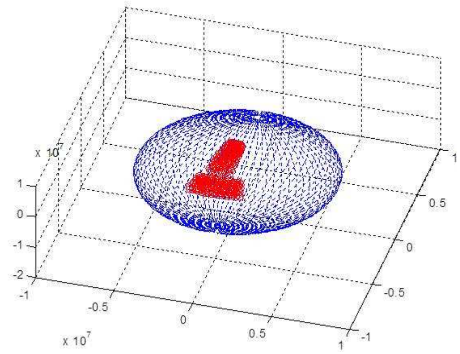

Figure 2. Sketch of sample areas in the sky illuminated by two co-located radar systems. Partial overlap of the two field-of regard is experienced.

azimuth by 20° in elevation at an elevation of 30° over the horizon. Then we add a second sensor observing a volume of 20° in azimuth by 30° in elevation at a higher elevation of 50°, and we scale down accordingly the transmitted power of the sensor pair. A sketch of the illuminated area in the sky is reported in Figure 3.

Each field-of-regard is split into $M \times N$ sectors, giving the global set S of sectors:

$$S^w = \{s_{m,n} | m \in N_M, n \in N_N\}; w = 1, 2 \quad (1)$$

where N_Q indicates the positive integers limited to Q. Search sectors are identified as the vertices of a triangular lattice filling the field-of-regard. Each sector corresponds to N_b adjacent beam directions that are equally spaced in antenna coordinates, i.e. u-v space [14]. For each sector different radar control parameters can be selected.

Thus, the objective is to select control parameters X for the combined surveillance function that optimize the reward function for an object, subject to a resource constraint. The dwell time, τ_c, and revisit interval time, t_r, are the control parameters for each radar. Therefore the control parameter sets are:

$$X = \{X^1, X^2\}; X^w = \{x_s | s \in S^w\}; w = 1, 2 \quad (2)$$

$$x_s = \{t_r, \tau_c\} \quad (3)$$

A static selection of these parameters is sought in the following, which maximizes the global payoff function.

The control parameters which are selected, must not exceed the resource constraint for the surveillance function. The following resource constraint ensures the radar temporal budget is not exceeded for any of the controlled sensors:

$$R(X_w) = \sum_{x \in X^w} r(x) \leq r_m \quad (4)$$

$$r(x) = \left(\frac{\tau_c}{t_r} \right) \quad (5)$$

where r_m is the maximum allowable resource utilization for the search function ($0 \leq r_m \leq 1$).

2.1. Reward Function

The Reward function $v(X)$ can be set on the basis of the operational requirements. If multiple requirements are encountered, a weighted linear combination of multiple metrics can be formulated.

$$v^{(0:j)} = v(X_0, ..., X_j) = \sum_k \alpha_k \cdot m_k(X_0, ..., X_j) \quad (6)$$

$$m_0(X) = \bar{p}(X); \quad m_1(X) = \frac{1}{\bar{\sigma}(X)}; \quad \dots \quad (7)$$

where X_j is the control parameter set at step j, α_k is a weight coefficient between 0 and 1, $\bar{p}(X)$ is the cumulative probability of detection, and $\bar{\sigma}$ is the maximum trace of the track covariance matrix over the population of targets. We adopt in the following, for the sake of simplicity, the expected cumulative probability of detection, which is a good example of inter-dependent metric. The cumulative probability of detection for a constant-altitude trajectory is calculated in [16], and it refers to the probability of at least three detections during each pass of the object through the combined surveilled area, with the constraint that they originate from different sectors. This is desirable, as a more accurate estimate of an object's orbital parameters are achieved with well separated measurements.

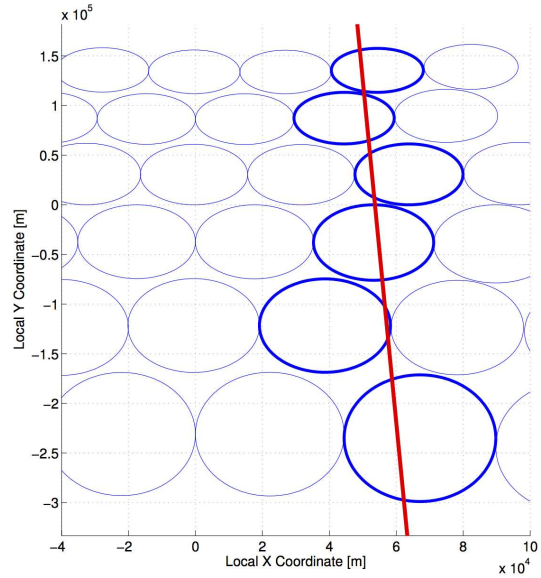

Figure 3. Sample layout of projected sectors in the radar field-of regard, which are intercepted by a sample target trajectory.

2.2. Population Model

The sectors which contribute to the cumulative detection probability depends on the orbital parameters, and the origin point e of the orbit into the field-of-regard. This is illustrated in Fig. 3, which shows an example object trajectory passing through a specific subset of the beam positions in the field-of-regard. The inter-dependence arises as all the emboldened sectors contribute to the cumulative detection probability p, for this specific trajectory under analysis.

Denote ψ as the trajectory inclination (with respect to geographical north), h as the object height, δ as the object diameter and e as an entry point in the field-of-regard. Then, denote Υ as the 4-tuple of object parameters, i.e. $\Upsilon = (\psi, h, \delta, e)$. Probability density functions can be introduced in order to describe the expected object 4-tuple. We resort to public information [36, 37, 38] in order to form likely PDFs, as the ones illustrated in Figure 4. These probability density functions are potentially imprecise, especially as the joint distributions are not considered. However, this is believed to be more precise than assuming a uniform distribution for the target parameters.

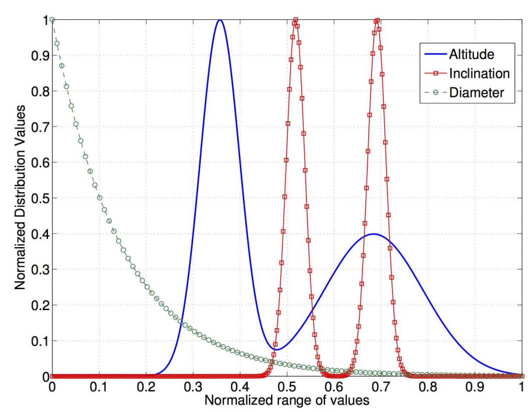

Figure 4. Sample mono/multi-modal distribution functions for target parameters (diameter δ, inclination ψ, altitude h), obtained as superposition of Gaussian-distributed and exponentially-distributed terms. Range of values: $[\delta_m, \delta_M] = [0.01, 25]m, [h_m, h_M] = [200, 2000]km, [\psi_m, \psi_M] = [0, 180]°$.

The origin of a target trajectory with respect to the radar field-of-regard varies over time, as a function of the orbital parameters and the radar location. We assume that over a long observation time all entry points e can be visited by the object of interest. Therefore, equally likely entry points are modelled as being equispaced on a circle that is centred on the centre of the field-of-regard. The radius of this circle is taken as twice the dimension of the field-of-regard. Each entry point is described by the angle made between the entry point and the centre of the field of regard, and so the density function $p_E(e)$ is uniform over the domain $0 \leq e \leq 2\pi$.

These probability density functions can be used to calculate the expected cumulative probability of detecting an object accordingly:

$$\bar{p}(X) = \int_{\Omega} \bar{p}_{\Upsilon}(\Upsilon) p(X, \Upsilon) d\Upsilon \tag{8}$$

where $p_{\Upsilon}(\Upsilon) = p_{\Psi}(\psi) \cdot p_H(h) \cdot p_{\Delta}(\delta) \cdot p_E(e)$, Ω is the domain $\{0 \leq \psi \leq 180°, 200 \leq h \leq 2000km, 0.01 \leq \delta \leq 25m, 0 \leq e \leq 2\pi\}$ and $d\Upsilon$ is a four dimensional volume differential. The expected cumulative probability of detecting an object can be calculated numerically.

2.3. Resource Optimisation

The resource optimisation produces control parameter selections for the surveillance function over a range of resource utilizations. The objective of the optimisation is to produce a set of optimized parameters selections for each stage of resource allocation, i.e. $X^* = \{X_0^*, X_1^*, ..., X_J^*\}$ where J is the total number of resource allocation stages.The implementation of the algorithm is described in [16], and can be summarized as follows:

Step 1. Initialize X_0 as the lowest resource parameter selection, i.e. the minimum possible dwell length and a high revisit interval time.

Step 2. Generate the possible states for stage $j+1$ based on X_j. The possible states are those with an increase in the dwell length or a decrease in the revisit interval time, for each of the sectors.

Step 3. Evaluate the states for allocation stage $j+1$ using Eq. (9).

Step 4. Transition to the state with the highest evaluation if $R(X_{j+1}) \leq r_m$, otherwise end.

Step 5. Go to step 2.

The problem is tackled here by defining sequential stages of increasing resource allocation to each sector. This is allowed, since we demonstrate in [16] that the problem can be decomposed into resource allocation stages, which allows resorting to dynamic programming. However, the number of possible states in allocation stage j, being all possible permutations of allocating j increments of resource, rapidly explodes. This renders a dynamic programming solution intractable. Consequently, a greedy method is applied that maximizes the ratio of the increment in the expected reward and the increment in resource at the allocation stage:

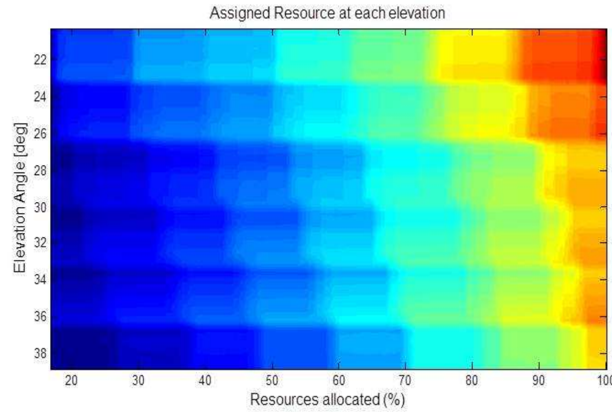

Figure 5. Allocation of single radar resource in elevation for the optimized allocation based on trajectories distributed over diameter δ, inclination ψ, altitude h. Colour code from blue to red encode the increasing amount of assigned resources.

$$\Delta v(X_j) = \frac{v_{j+1}(X_{j+1})}{R(X_{j+1}) - R(X_j)} \tag{9}$$

where

$$v_{j+1}(X_{j+1}) = v^{(0:j+1)} - v^{(0:j)} \tag{10}$$

The resource allocation method operates by increasing the resource allocated to just one of sectors at each resource allocation stage. This increase in resource is representative of a increase in the dwell length τ_c or a decrease in the revisit interval time t_r for the sector. A greedy policy is applied to determine the recipient of the resource increment for each stage. This greedy policy selects the sector that has the highest ratio between the expected cumulative detection probability and the respective increment in resource.

2.4. Numerical Results

The comparison with a non-optimized (uniform) resource allocation is reported in [16]. The advantage for a given resource expenditure is significant. Figures 5 and 6 show the optimized allocation of resources as a function of the elevation angle. It is clear that some sectors should be favoured in case of a single sensor (Figure 5); hence a uniform allocation, given a finite quota of available resources, is far from optimal in the case of a single radar. In case of two collaborative low-power radars pointing at different elevations, the situation changes: the resources are more uniformly allocated for the low-elevation pointing radar and slightly moved towards higher elevation angles, which correspond to smaller sensor-to-target ranges.

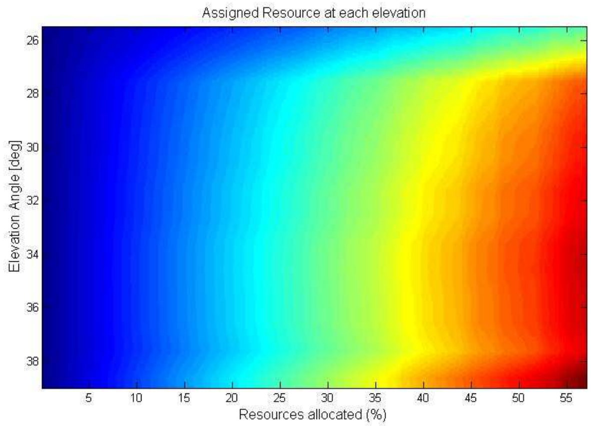

Figure 6. Allocation of single radar resource in elevation for the optimized allocation based on trajectories distributed over diameter δ, inclination ψ, altitude h, in presence of a second collaborating radar observing higher elevation angles. Colour code from blue to red encode the increasing amount of assigned resources.

The overlapping sectors are covered by the former radar, and a small expenditure of resources is suggested for the latter sensor in these sectors. This preliminary analysis of the problem of coordinated observations shows that the proposed method allows taking into account multiple sensors with different characteristics and eventually nature (e.g., radars and telecopes) in the global optimisation problem.

3. CONCLUSIONS

The allocation of resources for space surveillance has been discussed in this paper in the frame of Sensor Management doctrine. A greedy method for sequential allocation of sensor resources has been introduced, which attempts at maximizing an objective function that includes multiple, non-independent performance metrics. Preliminary results on a phased array radar case study demonstrate that the proposed strategy is able to take into account the resource needs from multiple, heterogeneous multifunction sensors.

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