Towards an online, adaptive algorithm for radar surveillance control

Fotios Katsilieris*, Alexander Charlish§ and Yvo Boers*

*Thales Nederland B.V.
Hengelo, the Netherlands
Email: {Fotios.Katsilieris, Yvo.Boers} @nl.thalesgroup.com

§Fraunhofer FKIE
Wachtberg, Germany
Email: Alexander.Charlish@fkie.fraunhofer.de

***Abstract*—Multifunction radars are highly configurable and possess some form of beam agility, allowing maintenance of a large number of tasks supporting varied functions. However, the surveillance function is commonly executed using a fixed periodic pattern, not utilising the full hardware potential. In this paper, a new method of surveillance control is proposed which utilises a particle filter to estimate a probability density of the undetected target location. Subsequently, the finite resource available for surveillance is allocated between sectors, based on information extracted from this probability density, using the Continuous Double Auction Parameter Selection algorithm. This method is successfully demonstrated through simulation on a surveillance control problem.**

I. Introduction

The multifunction radar (MFR) is subject to increasing appeal due to its ability to configure nearly instantaneously an array of radar parameters, subject to the requirements of different radar functions. This includes the ability to control an agile beam, which enables a dynamic time-energy resource allocation. Consequently, the MFR is able to maintain a large number of individual tasks, which are supporting a variety of differing radar functions such as target tracking, surveillance and weapon guidance. The automated control and management of such a sensor, given that the resources available for the numerous tasks are finite, remains a significant challenge.

The majority of the literature on MFR resource management is focused on the control and scheduling of tracking tasks, and various solutions have been presented with local optimisation [1], [2], [3] or consideration of the global optimisation [4]. However, much less consideration has been given towards the surveillance function, which is often implemented using a periodic search or simple rule based approaches. Such surveillance control schemes are unable to generate behaviour that adapts to changes in the environment or operational requirements and so do not fully exploit the hardware potential.

Recently, a number of works have addressed the problem of surveillance control for multifunction radar. In [5] the track and search functions of an MFR are scheduled according to a threat-based criterion. For scheduling surveillance tasks, the authors use ghost targets that dictate volume or horizon search instead of tracking tasks. In [6] the authors use a *search-to-track* ratio that the user has to set. Accordingly, the sensor manager schedules the corresponding tasks of the radar. For performing surveillance, an estimate of the spatial density of previously undetected targets is utilized. The sensing action that maximizes the expected number of newly detected targets is chosen whenever a search function is scheduled. In [7] an a priori probability distribution of the target to be detected is specified by a set of discrete target position probabilities corresponding to each search beam. The proposed method suggests making the next look in the search cell that will provide the maximum value of the incremental search energy and S/N payoff ratios for all cells and that will maximize the duty factor of each cell. Despite the successes of these previous works, resource is allocated myopically in general, without direct consideration of the finite resource constraint.

In [8] the continuous double auction parameter selection (CDAPS) algorithm is introduced and demonstrated on the long-range surveillance function. CDAPS utilises a market mechanism to find the global optimum parameter selection, in terms of utility maximisation, given the global finite resource constraint. However, in [8], the CDAPS algorithm is applied using a simple model of the cumulative detection range with assumed expected target parameters. In [9][1] a particle filter is proposed to estimate a probability density of the undetected target location in the surveillance volume. This probability density, as it depends on the received data, is a better basis for resource allocation than the simple model used in [8]. The undetected target location has also been proposed for surveillance control in [10] using a multi-target Poisson density and a (quasi) Newton method. In contrast, this paper utilises a single target density of the undetected target location and applies the CDAPS algorithm. Additionally, this method is compared to the two myopic management criteria proposed in [9], being the maximum expected Kullback-Leibler divergence

F. Katsilieris is also a PhD student at the Dept. of Applied Mathematics of the Univ. of Twente, Enschede, the Netherlands.

[1] Also available at http://eprints.eemcs.utwente.nl/21638/

and maximum expected probability of detecting a target.

In Sec. II the parameter selection problem is formulated. The proposed solution of applying CDAPS based on the undetected target density is described in Sec. III. The generation of surveillance performance measures from the undetected target density is described in Sec. IV, which is critical for the interface to the CDAPS algorithm. In Sec. V analysis of simulated results is given and final conclusions are presented in Sec. VI.

II. Problem formulation

Consider an MFR that has to perform surveillance along with its other tasks (target tracking, weapon guidance etc.). The considered problem amounts to finding the surveillance parameters $\mathbf{u}_i^{opt}$ for each sector i that will maximize a surveillance criterion J_i given a global resource constraint r_{max}:

$$\mathbf{u}^{opt} = \arg\max_{\mathbf{u}} \mathbf{J}(\mathbf{s}_k, \mathbf{Z}_k, \mathbf{u}) \tag{1}$$

$$\text{subject to} \sum_{i=1}^{N_S} r_i(\mathbf{u}_i) \leq r_{max} \tag{2}$$

where

- $k = 1, 2, \ldots$ is the time index
- $i = 1, 2, \ldots, N_S$ is the sector index
- $\mathbf{s}_k \in \mathbb{R}^{N_s}$ is the state vector of the target at time k
- $z_k \in \mathbb{R}^{N_z}$ is the received measurement and $\mathbf{Z}_k = \{z_1, ..., z_k\}$ is the measurement history
- $\mathbf{u} = [\mathbf{u}_1, \ldots, \mathbf{u}_{N_s}] \in \mathcal{U}$ is a generic parameter selection across all sectors and $\mathcal{U} \in \mathbb{R}^{N_u}$ is the set of all the available surveillance parameters
- $\mathbf{u}^{opt} = [\mathbf{u}_1^{opt}, \ldots, \mathbf{u}_{N_s}^{opt}] \in \mathcal{U}$ is the optimal parameter selection across all sector
- $\mathbf{J} = [J_1, \ldots, J_{N_S}]$ is the vector of the criteria to be optimized
- $r_i(\mathbf{u}_i)$ is the resource loading per sector i due to the surveillance parameters $\mathbf{u}_i$ expressed as percentage throughout
- r_{max} is the global resource constraint expressed as percentage throughout

This is a challenging multiobjective, constrained optimization problem.

III. Proposed solution

The proposed solution is to allocate the finite resource available for surveillance using the CDAPS algorithm, using information extracted from the estimated probability density of the undetected target.

A. Continuous Double Auction Parameter Selection (CDAPS)

The CDAPS algorithm has been developed in order to solve multi-objective constrained optimization problems in an efficient way [11]. The CDAPS algorithm is an agent based approach to optimization where distributed agents, each representing single tasks, produce the global optimum resource allocation under a global resource constraint. The optimum is defined in terms of maximisation of utility, where utility functions can be defined for each task, which map from task quality to utility space. The optimization is performed using a continuous double auction, where each agent is able to buy or sell resource, given the performance of its represented task.

In this paper, each agent represents the task of surveillance of a given sector and the surveillance parameters are the dwell time τ_c and the revisit interval t_f.

A full description of the CDAPS algorithm can be found in [11] and the algorithm is demonstrated for radar surveillance function in [8] and the active tracking function in [12]. The CDAPS algorithm requires that the resource loading, task quality and utility from each potential parameter selection can be calculated. The method of extracting these from the undetected target probability density is described in Sec. IV.

CDAPS tackles the multi-objective constrained optimization problem by assuming that each criterion J_i can be mapped to a concave utility function V_i of the resource and requiring that the sum of the individual utility functions V_i be maximized. The problem described by Eq. (1) and (2) is now simplified to a concave, single objective, constrained optimization problem:

$$\mathbf{u}^{opt} = \arg\max_{\mathbf{u}} \left[\sum_{i=1}^{N_S} V_i(\mathbf{u}) \right] \tag{3}$$

$$\text{subject to} \sum_{i=1}^{N_S} r_i(\mathbf{u}_i) \leq r_{max} \tag{4}$$

As a concave maximization problem can be formulated as a convex minimization problem, convex optimization theory can be applied. In addition, as the possible parameter selections will be discrete, the solution is optimal for the given discrete parameter set, but only near optimal in contrast to continuous parameter selections.

B. Estimating the "undetected target" density

The CDAPS algorithm is able to find the global optimum resource allocation; however, this allocation is only as good as the performance model or estimate it is based upon. Therefore, it is desirable to incorporate as much information as possible, such as prior information or information from previous measurements, into the performance estimate. This can be achieved by the recursive estimation of a probability density function that describes the location of the undetected target. This methodology along with a particle filter implementation have been presented in [9].

The input of the algorithm presented in [9] is the density and the chosen sensing action at time $k-1$. First, the prediction step is performed using the Chapman-Kolmogorov equation in order to obtain the predictive density:

$$p(\mathbf{s}_k|\mathbf{U}_{k-1}) = \int p(\mathbf{s}_k|\mathbf{s}_{k-1}) \cdot p(\mathbf{s}_{k-1}|\mathbf{U}_{k-1}) \, d\mathbf{s}_{k-1} \tag{5}$$

where $p(\mathbf{s}_k|\mathbf{s}_{k-1})$ is determined by the kinematic model of the target (in this paper a constant velocity model is assumed) and $\mathbf{U}_{k-1}$ is the parameter selection history.

Then the predictive density is updated using negative information [13] and Bayes' rule:

$$p(\mathbf{s}_k|\mathbf{U}_k) = \frac{p(\mathbf{s}_k|\mathbf{U}_{k-1}) \cdot [1 - P_d(\mathbf{s}_k, \mathbf{u}_k)]}{\mathcal{C}} \tag{6}$$

$$\text{where} \quad \mathcal{C} = \int p(\mathbf{s}_k|\mathbf{U}_{k-1}) \cdot [1 - P_d(\mathbf{s}_k, \mathbf{u}_k)] \; d\mathbf{s}_k$$

The output updated density $p(\mathbf{s}_k|\mathbf{U}_k)$ at time k can be used to assess the performance of different sensing actions, as described in Sec. IV-B.

IV. Surveillance Performance

The CDAPS algorithm requires that the resource loading and utility can be calculated for each potential parameter selection. The parameters under control considered in this paper are the revisit interval t_f and the dwell length τ_c of each sector. Modern radar systems allow for other parameters to be controlled, such as the waveform bandwidth and pulse repetition frequency, however the revisit interval and dwell length are critical assuming maximum duty factor and waveform bandwidth operation. The proposed method can be readily extended to include additional parameter dimensions.

This section details how the resource loading, task quality and utility can be extracted from the probability density of the undetected target.

A. Resource Loading

The resource loading of each parameter selection for any sector, expressed as percentage throughout, is given by:

$$r^{j,l} = \frac{\tau_c^j}{t_f^l} \tag{7}$$

where $j = 1, \ldots, N_{\tau_c}$ is the dwell length index and $l = 1, \ldots, N_{t_f}$ is the revisit interval index.

B. Task Quality

The task quality that is achieved, for a given parameter selection, is calculated using the output of the particle filter, which is the density $p(\mathbf{s}_k|\mathbf{U}_k)$. To produce this density, the filter is propagated over period of time N_k using the parameter selection $\mathbf{u}_{i,k}^{j,l}$.

An intuitive criterion was chosen as the task quality for performing search, being the maximum cumulative probability of detecting a target at each sector i:

$$J_i = \sum_{k=1}^{N_k} \left[\int P_d(\mathbf{s}_k, \mathbf{u}_{i,k}^{j,l}) \cdot p(\mathbf{s}_k|\mathbf{U}_{k-1}) \; ds_k \right] \tag{8}$$

where $P_d(\mathbf{s}_k, \mathbf{u}_{i,k}^{j,l})$ is the probability of detecting a target with states $\mathbf{s}_k$ if the parameters $\mathbf{u}_{i,k}^{j,l}$ are chosen and $p(\mathbf{s}_k|\mathbf{U}_{k-1})$ is the predictive probability density function of the target states at time k.

The length of the simulation time used can affect the task quality values calculated for each possible sensing action. As this is the input to the CDAPS algorithm, the simulation time

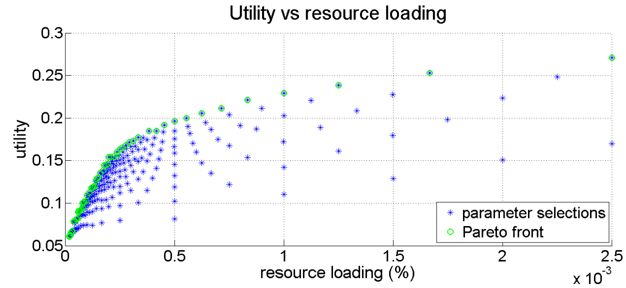

Fig. 1. Each point in the graph (of the $N_{\tau_c} \times N_{t_f}$ in total) represents how much utility is gained and how much resource loading is exerted by all possible combinations of parameters. The optimal points, also known as the *Pareto front*, are highlighted.

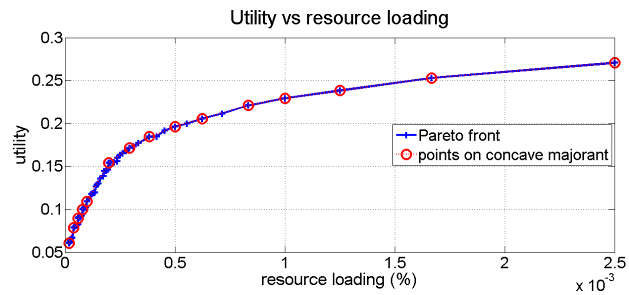

Fig. 2. After extracting the Pareto front from Fig. 1, the points that lie on a concave majorant are selected and passed to the corresponding agent in the CDAPS algorithm.

N_k also affects the parameter selection, which is discussed further in Sec. V-A.

C. Utility

A utility function is required which maps task quality into utility. In this case an exponential utility function was chosen, which is a function of the cumulative probability of detecting a target:

$$V_i = 1 - \exp[-\alpha \cdot J_i] \tag{9}$$

and α is a sensitivity parameter. This utility function is chosen relatively arbitrarily, except for maintaining concavity. In practice, this utility function can be adapted to suit the requirement of the represented task.

D. Resource-utility space

The CDAPS algorithm uses the resource and utility values of potential parameters selections. Figure 1 shows an example where the N_j points for a sector are plotted in the utility vs resource loading space. As it can be seen, there are some points that have a larger utility value for the same resource as other points. These better points are known as the *Pareto front* in the literature and they can be extracted easily, using for example [14].

Because a discrete set of parameter selections is used, the Pareto front will not always be strictly concave. In order to solve this problem, the points that do not lie on a strictly concave majorant are removed and only the remaining points will be passed to the corresponding agent in the CDAPS algorithm, see Fig. 2.

V. Simulations

In the simulations, the following dwell lengths and revisit intervals are considered:

$$\tau_c = [0.2, 0.4, \ldots, 2] \text{ msec} \quad (10)$$

$$t_f = [0.4, 0.8, \ldots, 10] \text{ sec} \quad (11)$$

for simulation times of

$$\begin{aligned} N_k &= [1, 3, 5, 10, 15, 20, 25] \cdot \max(t_f) \\ &= [10, 30, 50, 100, 150, 200, 250] \text{ sec} \end{aligned} \quad (12)$$

and the sensitivity parameter is set as $\alpha = 0.1$.

The density is initialized at $k = 0$ by uniformly distributing the particles in a disk of 300 km radius. The velocities v_x and v_y are chosen such that the radial speed of the targets is uniformly distributed in $[0,\ 400]$ m/s and they move towards the radar. This initialization process resembles the real life scenario of the moment when the radar is turned on and there is no information about the targets location, meaning that targets might be anywhere. A constant velocity model is used with $b_x = b_y = 2$ $(\text{m/s}^2)^2$ as the power spectral densities of the acceleration noise in the $x - y$ direction. Furthermore, target birth is modelled at the border of the field of view of the radar by means of replacing a fixed percentage of particles with new ones at the border during the resampling process.

The aforementioned parameters are tested in a scenario where an MFR has to perform surveillance of 8 sectors of 10×10 degrees. Using a $b_w = 1.5^\circ$ beamwidth and $0.8 b_w$ spacing means that there are 81 beam positions per sector. Therefore, the total resource utilization percentage for given combinations of $\tau_c^{j_i}$ and $t_f^{l_i}$ per sector will be:

$$r = \sum_{i=1}^{N_S} \frac{\tau_c^{j_i}}{t_f^{l_i}} \cdot 81 \cdot 100\% \quad (13)$$

and a global resource constraint of $r_{max} = 10\%$ is imposed.

The standard radar range equation can be used to calculate the SNR. Realistic radar parameters are used according to the standard texts [15], [16] to give an instrumented range of 300 km for a target with RCS $= 1$ m^2. The probability of detection can then be calculated assuming a Swerling 1 target and a probability of false alarm P_f:

$$P_d = P_f^{\left(\frac{1}{1+SNR}\right)} \quad (14)$$

Although the selection of parameters affects the performance of the radar, the conclusions that will be drawn are relevant over a range of possible parameter choices.

A. Effect of simulation time

The first step is to assess the effect of the simulation time N_k needed to evaluate the utility of each parameter selection. As this evaluation of the utility, extracted from the particle filter, is passed to the CDAPS algorithm, it can greatly affect the resulting parameter selection.

Figure 3 shows the different resource utility curves that are passed to the CDAPS algorithm for the various simulation times. It can be seen that changing the length of the simulation time greatly changes the task utility. The reason for this great variation is that when the simulation time is short, it is only evaluating over the initialisation stage of the particle filter. In this stage, it is necessary to detect targets close to the radar; however, for the longer simulation times these close-in targets have already been detected and the algorithm focuses on detecting the distant targets.

A scenario where there is no external information, much like in [9, Subsec.V-A], is used to produce the optimal parameter selections chosen by CDAPS for each value of N_k, as shown in Table I. It can be seen that shorter simulation times result in a short dwell length and short revisit interval, whereas longer simulation times result in longer dwell lengths and revisit intervals. This is intuitive, as the shorter simulation time, which is evaluated over the initialisation stage, is required to detect many targets close to the radar. However, the steady selection, which is observed for longer simulation times, needs to detect targets far away from the radar.

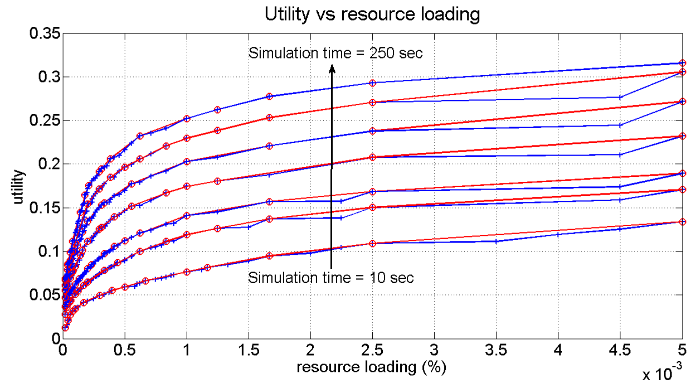

Fig. 3. The procedure explained in Fig. 2 is demonstrated for varying simulation times. It can be observed that changing the length of the simulation time greatly changes the task utility.

TABLE I
THE OPTIMAL DWELL LENGTHS AND REVISIT TIMES FOR DIFFERENT SIMULATION TIMES

method	Sim. time (sec)	revisit int. (sec)	dwell length (msec)	resource (%)
1)	10	1.2(a) & 2(b)	0.2	9
2)	10	1.4	0.2	9.26
3)	30	3.6(a) & 4.8(b)	0.6	9
4)	50	6	0.8	8.64
5)	100	10	1.4	9.07
6)	150	10	1.2(a) & 1.6(b)	9
7)	150	10	1.4	9.07
8)	200	10	1(a) & 2(b)	9
9)	200	10	1.4	9.07
10)	250	10	1.4	9.07

TABLE II
THE COMPARISON RESULTS OF THE VARIOUS METHODS FOR SURVEILLANCE - PART 1

Method	Avg. number of detected targets	Avg. percentage of detected targets (%)	Variance of detected targets percentage
1a)	269.32	89.77	21.67
1b)	268.09	89.36	22.35
2)	268.68	89.56	22.97
3a)	281.91	93.97	14.18
3b)	281.65	93.88	14.01
4)	285.2	95.07	12.36
5)	290.59	96.86	10.22
6a)	288.54	96.18	12.90
6b)	290.87	96.96	6.36
7)	293.01	97.67	6.17
8a)	287.37	95.79	8.76
8b)	290.89	96.96	8.14
9)	295.34	98.45	4.61
10)	291.43	97.14	6.17
E[P_d]	293.72	97.91	5.52
E[KLD]	293.37	97.79	7.57
Periodic	287.9	95.97	9.44

B. Performance evaluation

An assessment of the surveillance performance is generated in a scenario where the MFR will have to detect 300 targets that have RCS $= 1$ m^2 and move following a constant velocity model. The initial velocities of all the targets are chosen such that the radial speed of the targets is uniformly distributed in $[0,\ 400]\ m/s$ and they move towards the radar. The azimuth of the targets is uniformly distributed in $[0, 2\pi)$. Furthermore, the targets are divided into 3 groups according to their initial distance to the radar:

- Group 1: 100 targets with initial range in $[0, 50]$ km
- Group 2: 100 targets with initial range in $(50, 100]$ km
- Group 3: 100 targets with initial range in $(100, 300]$ km

The aforementioned parameter selections will be compared with performing periodic search such that a probability of detection of 0.7 at 10 km is achieved[2] for a target with RCS $= 1$ m^2, assuming the Swerling I model and false alarm rate of $P_{FA} = 1.4 \cdot 10^{-9}$. This requirement results to revisit time of 8 sec and dwell length of 1 msec.

They will also be compared to performing myopic search every 2 sec using the two criteria[3] discussed in [9] for choosing the sector to be searched and the optimal dwell length. The revisit interval for each sector can then be derived indirectly.

We performed 100 Monte Carlo runs. Each run was terminated either when all targets had been detected or when 20 minutes of radar surveillance had passed. The results are reported in Tables II and III.

In Tables II and III it can be observed that longer revisit intervals and longer dwell times result in detecting targets at long distances faster and with higher probability. On the other hand, short revisit intervals and dwell times result in fast detection of the targets that are close to the radar.

These results can be explained by the fact that for short simulation times, the detection of targets at short ranges is favored over the detection of targets at long ranges. On the other hand, if long simulation times are used then the density reaches a steady-state condition where targets are expected to be only at long distances from the radar and long dwell times are needed for their detection. Consequently, long revisit intervals are also chosen in order to satisfy the resource constraint. The aforementioned results demonstrate the importance of the simulation time due to its connection to the ranges that the targets are expected to be found.

The myopic criteria do not offer the flexibility of adapting the resource consumption according to where the undetected targets might be. Because they are myopic, they always choose the longest dwell time and therefore their performance depends only on the search period that the user sets.

The periodic search, designed such that a certain probability of detection is achieved, produced results that lie between the results obtained for simulation times of 50 and 100 seconds. This is intuitive since the revisit interval and dwell time of the periodic search also lie between the corresponding selections chosen by the CDAPS algorithm.

VI. CONCLUSIONS AND FUTURE WORK

A novel algorithm for selecting the surveillance parameters of an MFR has been presented. The presented algorithm extracts resource utility measures for a number of surveillance sectors from a density of the undetected target location. These resource utility measures are used to allocate the finite radar resource using the Continuous Double Auction Parameter Selection algorithm.

As a first step in evaluating the performance of the presented algorithm, the effect of the simulation time of the "undetected target" density on the parameter selection was studied. The results show that for short simulation times the joint algorithm chooses parameters that are suited for detecting quickly targets close to the radar. On the other hand, for long simulation times the joint algorithm chooses parameters that are suited for detecting targets that are far away from the radar.

In the future, we would like to get a better insight into the benefits of using non-myopic, adaptive methods instead of myopic or naive methods, such as periodic scanning, for performing surveillance. Towards this goal, the algorithm can be extended to include external information, such as map information about airports, and be tested in such scenaria.

Another aspect of the algorithm that needs to be tested is its ability to select the best parameters online, as the operational requirements change. For this reason, it can be tested in scenaria where the targets are expected to be found at different

[2]This probability of detection can appear to be low for the considered distance. However, it happens due to the selected radar parameters and does not affect qualitatively the conclusions that will be drawn.

[3]The criteria are the maximum expected probability of detecting a target and the maximum expected Kullback-Leibler divergence between the posterior and the predictive "undetected target" density.

TABLE III
THE COMPARISON RESULTS OF THE VARIOUS METHODS FOR SURVEILLANCE - PART 2

Method	Group 1 avg. number of detected targets (%)	Group 1 avg. time until detection (sec)	Group 2 avg. number of detected targets (%)	Group 2 avg. time until detection (sec)	Group 3 avg. number of detected targets (%)	Group 3 avg. time until detection (sec)
1a)	100	1.59	100	3.83	69.32	216.78
1b)	100	2.45	100	6.13	68.09	235.63
2)	100	1.77	100	4.50	68.68	224.95
3a)	100	3.67	100	7.26	81.91	161.31
3b)	100	4.76	100	9.37	81.65	171.92
4)	100	5.85	100	10.64	85.2	158.84
5)	100	11.15	100	17.53	90.59	138.63
6a)	100	11.22	100	18.31	88.54	153.67
6b)	100	11.18	100	17.21	90.87	129.11
7)	100	10.75	100	17.29	93.01	130.74
8a)	100	11.38	100	18.93	87.37	164.56
8b)	100	10.94	100	17.74	90.89	126.49
9)	100	10.82	100	16.24	95.34	107.00
10)	100	10.91	100	17.59	91.43	140.32
E[P_d]	100	18.74	100	27.43	93.72	142.11
E[KLD]	100	18.30	100	26.66	93.37	141.82
Periodic	100	8.39	100	14.62	87.9	135.4

places as the time passes by. In these cases, the best parameters will have to be re-evaluated every few time instances.

The surveillance criterion J_i is an important part of the algorithm and it has to be chosen according to the operational requirements. For this reason, selecting the most suitable surveillance criterion is an important research topic.

It would also be of interest to include more parameters in the optimization procedure (e.g., waveform bandwidth) in order to create an even more realistic model.

ACKNOWLEDGMENT

The research leading to these results has received funding from the EU's Seventh Framework Programme under grant agreement n° 238710. The research has been carried out in the MC IMPULSE project: https://mcimpulse.isy.liu.se

The authors thank Dr. Hans Driessen (Thales Nederland B.V.) for his helpful comments while writing this publication.

REFERENCES

[1] G. van Keuk and S. Blackman, "On phased-array radar tracking and parameter control," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 29, no. 1, pp. 186–194, Jan 1993.
[2] W. Koch, "On adaptive parameter control for phased-array tracking," in *Proceedings of Signal and Data Processing of Small Targets*, 1999.
[3] Y. Boers, H. Driessen, and J. Zwaga, "Adaptive MFR parameter control: fixed vs. variable probabilities of detection," in *Proceedings of Signal and Data Processing of Small Targets*, 2005, pp. 2–6.
[4] J. Hansen, R. Rajkumar, J. Lehoczky, and S. Ghosh, "Resource management for radar tracking," in *IEEE International Radar Conference*, Verona, NY., May 2006, pp. 140–147.
[5] F. Bolderheij and P. Van Genderen, "Mission driven sensor management," in *Proceedings of the 7th International Conference on Information Fusion*, 2004.
[6] K. White, J. Williams, and P. Hoffensetz, "Radar sensor management for detection and tracking," in *Proceedings of the 11th International Conference on Information Fusion*, 2008, pp. 1–8.
[7] D. Matthiesen, "Efficient beam scanning, energy allocation, and time allocation for search and detection," in *IEEE International Symposium on Phased Array Systems and Technology (ARRAY)*, oct. 2010, pp. 361 –368.
[8] A. Charlish, K. Woodbridge, and H. Griffiths, "Agent based multi-function radar surveillance control," in *Proceedings of the IEEE Radar Conference (RADAR)*, vol. 1, 2011, pp. 824 – 829.
[9] F. Katsilieris, Y. Boers, and H. Driessen, "Optimal search: a practical interpretation of information-driven sensor management," in *Proceedings of the 15th International Conference on Information Fusion*, 2012, pp. 439–446.
[10] J. L. Williams, "Search theory approaches to radar resource allocation," in *Proceedings of the 7th U.S./Australia Joint Workshop on Defense Applications of Signal Processing (DASP)*, 2011.
[11] A. Charlish, "Autonomous agents for multi-function radar resource management," Ph.D. dissertation, University College London (UCL), 2011.
[12] A. Charlish, K. Woodbridge, and H. Griffiths, "Multi-target tracking control using continuous double auction parameter selection," in *Proceedings of the 15th International Conference on Information Fusion*, 2012, pp. 1269–1276.
[13] W. Koch, "On exploiting 'negative' sensor evidence for target tracking and sensor data fusion," *Information Fusion*, vol. 8, no. 1, pp. 28–39, 2007.
[14] Y. Cao, "Identification of the Pareto Front from a set of points," July 2008. [Online]. Available: http://www.mathworks.de/matlabcentral/fileexchange/17251-pareto-front
[15] S. Blackman and R. Popoli, *Design and Analysis of Modern Tracking Systems*. Artech House, 1999, ch. 15, pp. 967–1067.
[16] M. I. Skolnik, Ed., *Radar Handbook*, 3rd ed. New York: McGraw-Hill, 2008.