An Evaluation of Task and Information Driven Approaches for Radar Resource Allocation

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2021 IEEE Radar Conference (RadarConf21) | 978-1-7281-7609-3/20/$31.00 ©2021 IEEE | DOI: 10.1109/RadarConf2147009.2021.9455168

***Abstract*—This paper describes an evaluation of different methods of radar resource allocation. The evaluation operates in a cognitive fully adaptive radar framework, specialized to concurrent tracking and classification of multiple airborne targets using a single airborne radar platform. The framework is based on the perception-action cycle of cognition and includes a perceptual processor that performs multiple radar system tasks and an executive processor that allocates system resources to the tasks to decide the next transmission of the radar on a dwell-by-dwell basis. We compare allocation algorithms using task-based and information-based strategies. Our main contribution is the illustration of the allocation algorithms in a MATLAB-based testbed and a comparison of the performance and the sensor task selections made by each.**

***Index Terms*—Fully Adaptive Radar, Cognitive Radar, Resource Allocation, Sensor Management, Tracking**

I. Introduction

The modern contested environment presents challenges for conventional wide-area search and queued tracking approaches to radar resource allocation (RRA) which stems from the large number of targets and the relative unpredictability of target kinematics. These properties require a closed-loop sense and respond approach to fully take advantage of the unprecedented flexibility available in modern digital radars. The concept of fully adaptive radar (FAR), also called cognitive radar, is to exploit all available degrees of freedom on transmit and receive in order to optimize radar system performance and efficiency. Cognitive radar systems [1]–[6] mimic the perception-action cycle (PAC) of cognition [7], [8] to adapt the radar sensor to collect data to achieve a system performance goal. This requires developing a perception of the current system status, predicting the effect of different sensing actions, and choosing the next sensing action, all in real-time.

Recently, a number of perception-action approaches to the RRA problem have been proposed, including [9]–[12]. These algorithms rely on two fundamental steps. First, they capture (perceive) the state of the surveillance area probabilistically. Next, they use this probabilistic description to select future sensing actions by determining which actions are expected to have maximum utility. Recent work in this area has been referred to as FAR or cognitive radar [12]. In the past, related work has been referred to as sensor management and/or resource allocation [9], [13].

This material is based upon work supported by the Air Force Research Laboratory (AFRL) under Contract No. FA8649-20-P-0940. Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the AFRL

This work extends past efforts in this direction. Specifically, here we model an agile multimode radar and apply RRA techniques to select from dozens of possible transmission waveforms.

A key challenge of any RRA algorithm is to balance the multiple competing objectives of target detection, tracking, classification, and other radar tasks. This is addressed through the objective function used in the optimization step to select the next radar actions. There are two approaches to this optimization: task-driven [14] and information-driven [13]. In the task-driven approach, performance quality of service (QoS) requirements are specified, while in the information-driven approach, an information measure is optimized.

In the task-driven method, a composite objective function is constructed by weighting the various objectives, such as the expected time to detect and the tracking root mean square error (RMSE) given a detection. This has the benefit of explicitly laying out the relative importance of the objectives, but as such does require specification of QoS levels for each of the requirements and selection of weights which mix these incommensurate quantities [12]. An alternative approach uses an information theoretic objective function, which maximizes the information flow. Common measurements of information include entropy, mutual information (MI), Kullback-Leibler divergence (KLD), and Rényi (alpha) divergence (RD) [10], [15]. Information metrics implicitly balance different types of information that a radar may acquire. This has the desirable property of a common measuring stick (information flow) for all actions [16], but does not explicitly optimize a mission criterion such as RMSE. As such, the information theoretic measures can be difficult for the end-user to understand and attribute to specific operational goals [17].

This paper describes a MATLAB-based fully adaptive radar resource allocation (FARRA) algorithm for concurrent tracking and classification of multiple targets which illustrates and compares task-driven and information-based algorithms for allocating system resources. Our major findings can be summarized as follows:

- Definition of the executive processor objective function is critical. The objective function must balance task performance and the cost of using the sensor as well as accurately reflect user preferences. The objective function should result in an optimization problem with low computational complexity.

- The task and information-based algorithms had similar performance but selected different actions to achieve their solutions. We show the task and information-based algorithms are actually based on common information-theoretic quantities, so the distinction is in the granularity of the metrics used to quantify system performance and the degree to which the metrics were weighted.
- Information-based algorithms do not require the user to specify task requirements and they directly combine the value of disparate tasks based on the expected information gained. However, without additional ad-hoc weighting, they do not allow for separate control of tasks and may produce solutions that over-emphasize some tasks at the expense of others or select sensor actions that provide only marginal gain when judged by user preference.
- The task-based algorithms are able to separately control task performance and to achieve specified performance requirements. However they require the user to specify requirements and sensor costs and require judgment in constructing cost/utility functions and weightings for combining disparate task performance metrics.
- The main compute burden stems from enumerating all possible actions and not the computation of the task or information-based metrics. Developing efficient methods for addressing this piece is important for a real-time implementation.

This paper is organized as follows. First, Section II describes the Fully Adaptive Radar framework. Section III describes the task and information-based objective functions we employ. Third, in Section IV we give simulation results comparing the allocation approaches. Finally, section V presents the conclusions from this effort.

II. Fully Adaptive Radar Framework

The FAR framework for a single PAC is shown in Figure 1. The PAC consists of the perceptual processor and the executive processor. The dual-processor construction aligns with Fuster's neuropsychological cognitive structure [7] and the JDL fusion levels model [18]. The PAC interacts with the external environment through the sensor and with the radar system through the perceptual and executive processors. The perceptual processor receives data from the hardware sensor and processes it into a perception of the environment. The perception is passed to the executive processor as well as to the radar system. The executive processor receives the perception from the perceptual processor along with requirements from the radar system, and solves an optimization problem to determine the next sensor action. The executive processor informs the hardware sensor of the settings for the next observation, the sensor collects the next set of data, and the cycle repeats.

We assume the system objective is to estimate the state of a target at time t_k, denoted as $\boldsymbol{x}_k$. The hardware sensor observes the environment and produces a measurement vector $\boldsymbol{z}_k$ that depends on the target state $\boldsymbol{x}_k$ and the sensor parameters $\boldsymbol{\theta}_k$.

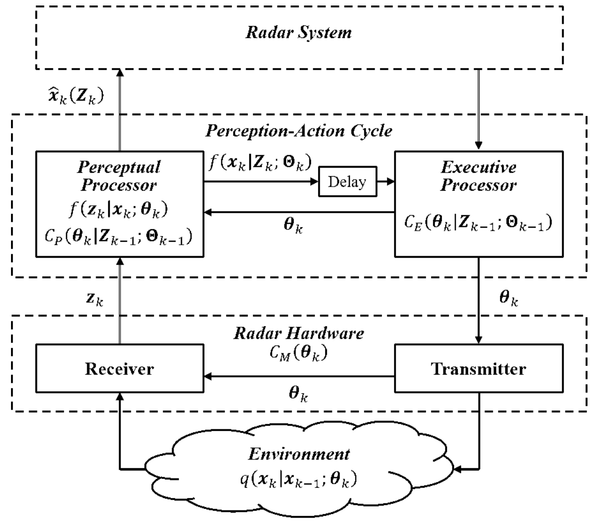

Fig. 1: Single PAC FAR framework

The estimate of the target state at time t_k is a function of the observations up to time t_k, which in turn depend on the sensor parameters up to time t_k, which we denote as $\boldsymbol{Z}_k \doteq \boldsymbol{z}_1, \boldsymbol{z}_2, \cdots, \boldsymbol{z}_k$ and $\boldsymbol{\Theta}_k \doteq \boldsymbol{\theta}_1, \boldsymbol{\theta}_2, \cdots, \boldsymbol{\theta}_k$, respectively.

The state transition model is assumed to be a first order a Markov model with initial target state probability density function (PDF) $q(\boldsymbol{x}_0)$ and transition PDF $q(\boldsymbol{x}_k|\boldsymbol{x}_{k-1};\boldsymbol{\theta}_k)$, which represents the probability that a target in state $\boldsymbol{x}_{k-1}$ will evolve to state $\boldsymbol{x}_k$. The transition density may depend on the sensor parameters. This will occur, for example, when the choice of sensor parameters affects the time difference $t_k - t_{k-1}$. The measurement model is described by the conditional PDF, or likelihood function, $f(\boldsymbol{z}_k|\boldsymbol{x}_k;\boldsymbol{\theta}_k)$. The cost of obtaining an observation and any constraints on the sensor parameters are modeled by the measurement cost function $C_M(\boldsymbol{\theta}_k)$. The perceptual processor processes the data and produces a perception of the target state in the form of a posterior PDF $f^+(\boldsymbol{x}_k) \doteq f(\boldsymbol{x}_k|\boldsymbol{Z}_k;\boldsymbol{\Theta}_k)$ and a target state estimate $\hat{\boldsymbol{x}}_k(\boldsymbol{Z}_k)$. It may also compute a perception of the environment. The performance of the perceptual processor is characterized by the processor cost function $C_P(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1})$, which depends on the sensor parameters and the previously received data. The executive processor decides on the next value for the sensor parameters by minimizing the executive cost function $C_E(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1})$, which balances the processor performance against the cost of using the sensor.

The information-updated posterior density $f^+(\boldsymbol{x}_k)$ is computed using the standard Bayes-Markov recursion. In the executive processor, we assume that we have received the observations up to time t_{k-1} and want to find the next set of sensor parameters to optimize the performance of the state estimator that will include the next observation $\boldsymbol{z}_k$ as well as the previous observations $\boldsymbol{Z}_{k-1}$. We define the *joint conditional* PDF of $\boldsymbol{x}_k$ and $\boldsymbol{z}_k$ conditioned on $\boldsymbol{Z}_{k-1}$ as

$$f^\uparrow(\boldsymbol{x}_k, \boldsymbol{z}_k) = f^+(\boldsymbol{x}_k) f(\boldsymbol{z}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_k). \tag{1}$$

We define the *predicted conditional (PC)-Bayes risk* for the estimator $\hat{\boldsymbol{x}}_k(\boldsymbol{Z}_k)$ by taking the expectation of the error function with respect to the joint conditional PDF,

$$R^{\uparrow}(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}) = E_k^{\uparrow}\{\epsilon(\hat{\boldsymbol{x}}(\boldsymbol{Z}_k),\boldsymbol{x}_k)\}, \quad (2)$$

where $E_k^{\uparrow}\{\cdot\}$ denotes expectation with respect to $f^{\uparrow}(\boldsymbol{x}_k,\boldsymbol{z}_k)$. We can also write the PC-Bayes risk as

$$R^{\uparrow}(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}) = E_{\boldsymbol{z}_k|\boldsymbol{Z}_{k-1}}\{R^{+}(\boldsymbol{Z}_k;\boldsymbol{\Theta}_k)\}, \quad (3)$$

where the expectation is with respect to $f(\boldsymbol{z}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_k)$.

It is important to emphasize that the PC-Bayes risk is a function of the known past observations $\boldsymbol{Z}_{k-1}$ but not the unknown next observation $\boldsymbol{z}_k$ since it has been averaged over both $\boldsymbol{z}_k$ and $\boldsymbol{x}_k$. It is also a function of all the sensor parameters in $\boldsymbol{\Theta}_k$, however we separate the dependence on the unknown next sensor parameter $\boldsymbol{\Theta}_k$ from the known past sensor parameters $\boldsymbol{\Theta}_{k-1}$ so that we can optimize over $\boldsymbol{\theta}_k$.

In many applications, the PC-Bayes risk may be difficult to compute and in general will not have a closed form analytical expression. We discuss surrogate functions that are analytically tractable and provide a good indication of the quality of the target state estimate in the next section.

The processor cost function is a scalar function derived from the PC-Bayes risk or a surrogate. The measurement and processor costs are then combined into a single executive optimization cost function via some combining function $F\{\,\}$,

$$C_E(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}) = F\{C_P(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}), C_M(\boldsymbol{\theta}_k)\}, \quad (4)$$

and $\boldsymbol{\theta}_k$ is chosen to minimize the executive cost function

$$\boldsymbol{\theta}_k = \arg\min_{\boldsymbol{\theta}} C_E(\boldsymbol{\theta}|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}). \quad (5)$$

The framework described by Figure 1 and the equations above can be applied to a large class of problems. In this paper, we specialize to an airborne multimode radar which is used to track and classify multiple airborne targets. By way of background, we define the elements of the problem as:

- **Target State Vector,** $\boldsymbol{x}$: We assume a known and fixed number of targets. For each target, the state vector is $\boldsymbol{x} = [x, \dot{x}, y, \dot{y}, z, \dot{z}, s, c]$, where s is the received signal-to-noise ratio (SNR) and c is the discrete target class.
- **Target State Parameterization**: We model the kinematic component using a Gaussian and the class component using a PMF over the discrete set of possible classes.
- **Motion Model,** $q(\boldsymbol{x}_k|\boldsymbol{x}_k;\boldsymbol{\theta}_{k-1})$: We use a linear, additive white Gaussian noise motion model on target state and a $N_c \times N_c$ transition matrix for the class transition.
- **Controllable Parameters,** $\boldsymbol{\theta}$: We enumerate W possible waveforms the radar can use. Some are tracking waveforms characterized by bandwidth, pulse repetition frequency (PRF) and total pulses. Others are classification waveforms characterized by duration.
- **Measurements,** $\boldsymbol{z}_k$: In tracking mode, noisy measurements of target range, range-rate, azimuth, and elevation are made with probability of detection P_D, and measurement RMSE defined by the radar waveform parameters. In classification mode, received data is processed to provide a classification call and the correct classification probability is related to the waveform duration.

With this as background, we now turn our attention to the definition of the perceptual processor error function.

III. FARRA Objective Functions

A key challenge of any radar resource allocation algorithm is to balance the multiple competing objectives of target detection, tracking, classification, and other radar tasks. This is addressed through the objective function used in the optimization step to select the next radar actions. Objective functions may also be referred to as payoff, criteria, value, or cost functions. Articulating the system goals in a mathematical form suitable for optimization is thus critical to the operation of a FARRA system. As the number of parameters available for adaptation and the number of radar system tasks grow, this becomes increasingly difficult.

In this paper, we develop both task-driven and information-driven methods for specifying the objective function used by the perceptual processor. The task-driven approach, described in subsection III-A, uses performance quality of service (QoS) requirements as the objective function. The information-driven approach, described in subsection III-B, instead maximizes expected information flow to the executive processor. It should be noted here that in both approaches, the optimization is in a global sense and may not be the optimal solution for a particular radar task.

A. QoS Approach

Following the development in [12], we assume there are M tasks. The perceptual processor for the m^{th} task computes a perception of its environment, which may include quantities such as target location, target class, target SNR, etc. The executive processor for the m^{th} task evaluates the performance of the perceptual processor in terms of a task QoS metric, which is denoted by $G_m(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1})$. The QoS metric for the current frame will in general depend on the QoS metric of the previous frame, the perception from the previous frame, the previous sensing actions, and the current sensing action. Each task QoS metric has a task QoS requirement, denoted $\bar{G}_m$. The task QoS metrics and requirements are physically meaningful quantities with appropriate physical units.

For a tracking task, we use the position RMSE extracted from the state mean square eror (MSE) matrix, and the requirement is an upper limit on the RMSE. In most cases, it is not possible to evaluate the MSE matrix analytically. However, the Bayesian Cramér-Rao lower bound (BCRLB), the inverse of the Bayesian information matrix (BIM), provides a (matrix) lower bound on the MSE matrix of any estimator [19] and is usually analytically tractable. For tracking applications, this yields the posterior Cramér-Rao lower bound (PCRLB) [20].

The PCRLB provides a lower bound on the global MSE that has been averaged over $\boldsymbol{x}_k$ and $\boldsymbol{Z}_k$, thus it characterizes tracker performance for all possible data that might have been received. Here we use a PC-BIM, $\boldsymbol{B}_k^{\uparrow}(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1})$, and a predicted conditional Cramér-Rao lower bound (PC-CRLB) to bound the PC-MSE matrix, which is averaged over the joint density of $\boldsymbol{x}_k$ and $\boldsymbol{z}_k$ conditioned on $\boldsymbol{Z}_{k-1}$. The PC-CRLB differs from the PCRLB in that it characterizes performance conditioned on the actual data that has been received.

As the task-based metric for scheduling tracking waveforms uses the PC-CRLB at its core, it is directly connected to information theoretic quantities we will discuss later. In addition, for classification waveforms we use the conditional entropy as the performance metric, providing a similar connection. The main distinction with QoS scheduling is that we convert the objective to a quantity with physical units and then normalize it with respect to a goal. Specifically, for each task the QoS metric is converted to a utility $U_m(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1})$, which is a unitless quantity on the interval $[0,1]$. It represents the level of satisfaction with the QoS and is determined from the task utility function,

$$U_m(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1})=u_m(G_m(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}),\bar{G}_m). \quad (6)$$

The executive processor combines and balances the task utilities along with resource constraints to determine the resource allocation for the next frame. The mission utility, or mission effectiveness, is a measure of the radar system's ability to meet all of its requirements. It is a weighted sum of the task utilities, where the task weighting, w_m, represents the relative importance of the m^{th} task to the overall mission, and the weights sum to one. The mission utility is given by

$$U(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}) = \sum_{m=1}^{M} w_m U_m(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}). \quad (7)$$

Constraints are described by the function $g_c(\boldsymbol{\theta}_k)$, constructed so the constraint may be expressed as the inequality $g_c(\boldsymbol{\theta}_k) \leq 0$. The next action vector is then determined by maximizing the mission utility subject to the constraint

$$\boldsymbol{\theta}_k = \arg\max_{\boldsymbol{\theta}} U(\boldsymbol{\theta}|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}) \qquad s.t. \;\; g_c(\boldsymbol{\theta}) \leq 0. \quad (8)$$

B. Information-Based Approach

In the information gain approach, the relative merit of different sensing actions is measured by the corresponding expected gain in information [10], [13], [21]–[23]. As in the task-based approach, the goal is to select, in advance, the action $\boldsymbol{\theta}_k$ that will result in maximum benefit. In the information-based approach, we first define a metric based on information theory for computing the benefit a measurement will yield. We must predict, before the measurement is actually made, the expected value of the metric, therefore we next perform a statistical expectation with respect to the conditional sensor model. Finally, we choose the next sensing action that maximizes the expected value of the metric.

Assume, temporarily, that at time t_k an resource allocation strategy has selected action $\boldsymbol{\theta}_k$, it has been executed, and measurement $\boldsymbol{z}_k$ has been received. To judge the value of this action, we compute the information gained by that measurement; specifically the information gain between the predicted PDF on target state before the measurement was taken $f^-(\boldsymbol{x}_k) \doteq f(\boldsymbol{x}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_k)$ and the posterior PDF after the measurement has been received $f^+(\boldsymbol{x}_k) \doteq f(\boldsymbol{x}_k|\boldsymbol{Z}_k;\boldsymbol{\Theta}_k)$. The most popular approach uses the Kullback-Leibler Divergence. The KLD between $f^+(\boldsymbol{x}_k)$ and $f^-(\boldsymbol{x}_k)$ is defined as

$$D(f^+(\boldsymbol{x}_k)||f^-(\boldsymbol{x}_k)) \doteq \int f^+(\boldsymbol{x}_k) \ln \frac{f^+(\boldsymbol{x}_k)}{f^-(\boldsymbol{x}_k)} d\boldsymbol{x}_k. \quad (9)$$

There are a number of generalizations of the KLD in the literature, including the RD, the Arimoto-divergences, and the f-divergence [23]. The KLD has a number of nice theoretical and practical properties, including (a) the ability to compare actions which generate different types of knowledge (e.g., knowledge about target class versus knowledge about target position) using a common measuring stick: information gain; (b) the asymptotic connection between information gain and risk-based optimization; and (c) the avoidance of weighting schemes to value different types of information.

Taking the expectation with respect to $f(\boldsymbol{z}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_k)$, we obtain the EKLD (which is equal to the MI),

$$I_{\boldsymbol{xz}}(\boldsymbol{\theta}_k|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}) \doteq E_{\boldsymbol{z}_k|\boldsymbol{Z}_{k-1}} \int f^+(\boldsymbol{x}_k) \ln \frac{f^+(\boldsymbol{x}_k)}{f^-(\boldsymbol{x}_k)} d\boldsymbol{x}_k. \quad (10)$$

The next action vector is then determined by maximizing the expected information

$$\boldsymbol{\theta}_k = \arg\max_{\boldsymbol{\theta}} I_{\boldsymbol{xz}}(\boldsymbol{\theta}|\boldsymbol{Z}_{k-1};\boldsymbol{\Theta}_{k-1}). \quad (11)$$

For our model, the MI is a function of the determinant of the PC-CRLB.

IV. Simulation Results

We now describe simulations comparing the objective functions. Our simulation includes three moving targets and a moving sensor as illustrated in Figure 2.

The measuring platform can adaptively select between a "tracking" mode and an "classification" mode. When in tracking mode, it can choose a PRF, bandwidth (BW), and pulse count (N_p) from a list of possibilities. The measurement process results in detection-level data of target range, range-rate, azimuth, and elevation. Tracking measurements are made with a probability of detection P_D, which is a function of SNR, which is in turn a function of waveform. When in classification mode, the radar can select among modes which trade probability of correct classification (p_{cc}) with dwell time. When this measurement modality is selected, the observation is a classification call. The available waveforms,

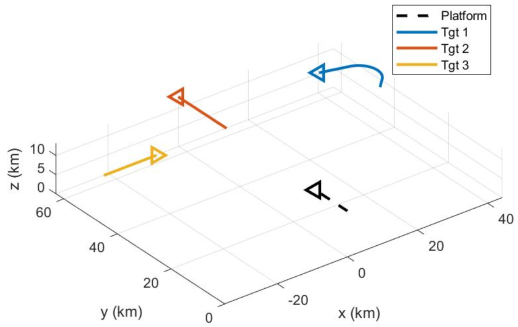

Fig. 2: Simulation scenario

their parameters, and dwell times are listed in Table I. Also included is the "do nothing" waveform #0.

TABLE I: Waveform Parameters and Dwell Times

Waveform	BW (MHz)	PRF (kHz)	N_p	T (ms)
0		N/A		0.0
1,2,3	1,5,10	20	1	0.05
4,5,6	1,5,10	10	1	0.1
7,8,9	1,5,10	20	10	0.5
10,11,12	1,5,10	10	10	1.0
13,14,15	1,5,10	20	20	1.0
16,17,18	1,5,10	10	20	2.0
19,20,21	1,5,10	20	50	2.5
22,23,24	1,5,10	10	50	5.0

Waveform	p_{cc}	T (ms)
25	.3	1.0
26	.6	2.5
27	.75	5.0

Targets are tracked using detection data coupled with an Extended Kalman Filter. We use a Singer model for target motion in the tracker. The simulation is discretized to 100ms. We assume 90ms are used for surveillance (search) dwells and the remaining 10ms are for the purposes of tracking and classification of the three known targets. The resource allocation algorithm may elect to measure each target during the dwell or any subset of the targets as long as the total measurement time fits into the allocated time budget. For each target, the sensor may select from the following options:

- **Do nothing** Choose waveform #0. This takes zero time and generates zero utility. It frees up the timeline to dedicate extra dwell time to other targets.
- **Perform a track dwell**. Choose from waveforms #1−24. This takes variable time given by N_p/PRF and provides variable utility depending on the waveform parameters.
- **Perform a classification dwell**. Choose from waveforms #25 − 27. This takes variable time and provides variable utility.

The predicted utility of a sensing action is scored using either the QoS metric in (8) or the information theoretic metric in (11). The objective is then maximized subject to the timeline. Our computational approach is to enumerate all possible sensing actions (triplets) that can be performed in the timeline and select the one that maximizes total utility. In practice this is far fewer than 28^3 combinations.

A. Comparison of QoS and MI in a Tracking Scenario

We first illustrate QoS-based scheduling and MI allocation in a tracking-only (i.e., no classification) scenario. In this case, only waveforms 0 − 24 are meaningful. Figure 3 shows the RMSE over 100 Monte Carlo trials for each method. The trials have the sensor and target trajectories fixed, but a random realization of the measurements is drawn anew each time. This, in turn, affects the adaptive resource allocation calculations leading to different allocations and RMSE each time.

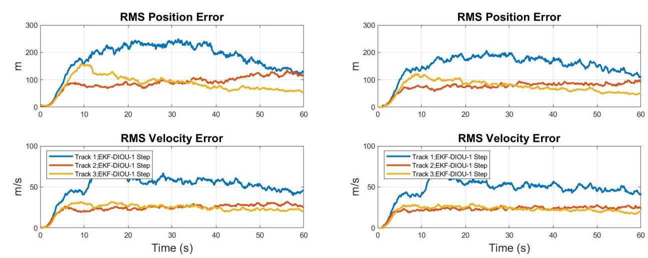

Fig. 3: MI (left) and QoS (right) tracking RMSE

This example illustrates that in the tracking-only scenario with our definition of QoS, the QoS and MI based scheduling techniques lead to similar RMSEs for the three targets. Figure 4 shows how the resource allocation algorithm selected to use the sensors over time by looking at what fraction of the 10ms timeline is used for each target at each time.

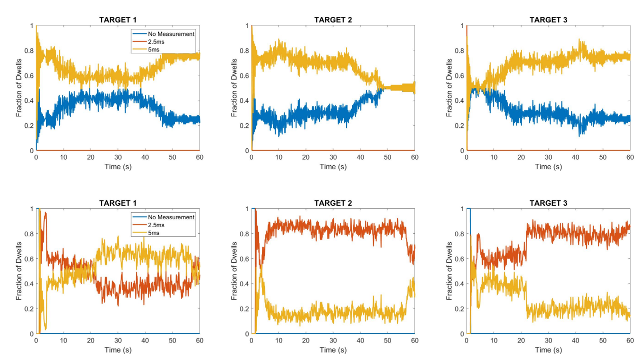

Fig. 4: MI (top) and QoS (bottom) selection of measurements

The methods the scheduling algorithms deploy to reach the roughly equal RMSE performance are different. Broadly speaking, the MI approach prefers to make 5ms dwells. It does this by typically measuring two targets at 5ms and skipping one target to allocate its 10ms scan time. This generates larger P_D dwells for two targets at the expense of not measuring a third. In contrast, the QoS method typically measures one target at 5ms and the other two at 2.5ms.

An additional distinction is a consequence of good localization at initialization. The QoS method elects to perform no measurements at the very beginning of the simulation because the target has been well localized at initialization meaning the QoS metric is met even without a measurement. In contrast, the MI does perform measurements.

B. MI Allocation in a Tracking and Classification Scenario

We now include a classification mode (waveforms $25-27$). The mode utility is also computed using the MI. The FARRA algorithm now selects from the following options: not measure a target, measure in tracking mode, or measure in classification mode. Both the tracking mode and classification mode have a multiple waveforms to select from as indicated in Table I.

Figure 5 shows the time sequence of measurement modalities selected for each of the three targets. Note that the target class is static so once the class is identified no further classification measurements are needed. Broadly speaking, we find that algorithm interleaves track and classification dwells during the first portion of the simulation to maintain track accuracy but also learn about the target class.

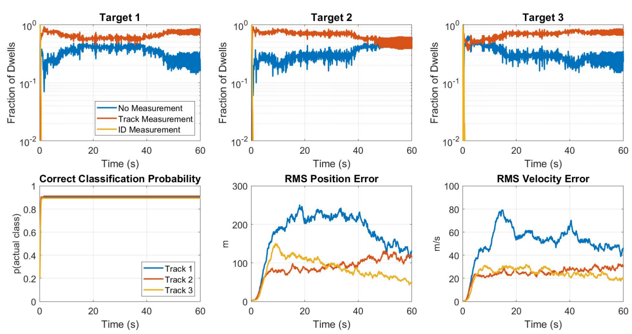

Fig. 5: Top: MI mode selection for the three targets; Bottom: classification probabiloity, position and velocity RMSE

With these parameters, the scheduler chooses to use the 2.5ms classification dwell (waveform 26) about 40% of the time and the 5ms classification dwell (waveform 27) about 60% of the time. Typically, the scheduler uses a 2.5ms classification dwell followed by two 5ms classification dwells. When all three of those measurements are the same, it no longer performs classification dwells as the uncertainty has been reduced sufficiently. If, however, those three measurements are not identical, the scheduler uses an additional 2.5ms classification dwell followed by a 5ms classification dwell to determine the target class. The algorithm stops performing classification dwells once the target class is well known.

V. Conclusion

This paper has described an evaluation of different methods of radar resource allocation in the fully adaptive radar resource allocation framework. Our analysis is specialized to concurrent tracking and classification of multiple airborne targets using a single airborne radar platform. The approach is based on the perception-action cycle of cognition and includes a perceptual processor that performs multiple radar system tasks and an executive processor that allocates system resources to the tasks to decide the next transmission of the radar on a dwell-by-dwell basis. We described a fundamental connection between our task-based and information-based methods and showed that although the two methods opt for different sensor usage strategies, they in fact have similar performance.

References

[1] S. Haykin, "Cognitive radar: a way of the future," *IEEE Signal Processing Magazine*, vol. 23, no. 1, pp. 30–40, 2006.
[2] S. Haykin, Y. Xue, and M. Setoodeh, "Cognitive radar: step toward bridging the gap between neuroscience and engineering," *The Proceedings of the IEEE*, vol. 100, no. 11, pp. 3102–3130, 2012.
[3] S. Haykin, *Cognitive Dynamic Systems: Perception-action Cycle, Radar and Radio*. Cambridge University Press, 2012.
[4] ——, "Cognitive Dynamic Systems," *The Proceedings of the IEEE*, vol. 102, no. 14, pp. 3102–3130, 2014.
[5] J. R. Guerci, *Cognitive Radar: The Knowledge-Aided Fully Adaptive Approach*. Artech House, 2010.
[6] S. Gurbuz, H. Griffiths, A. Charlish, M. Rangaswamy, M. Greco, and K. Bell, "An Overview of Cognitive Radar: Past, Present, and Future," *IEEE Aerospace and Electronic Systems Magazine*, vol. 34, no. 12, pp. 6–18, 2019.
[7] J. M. Fuster, *Cortex and Mind: Unifying Cognition*. Oxford University Press, 2003.
[8] ——, "The cognit: a network model of cortical representation," *International Journal of Psychophysiology*, vol. 60, no. 2, pp. 125–132, 2006.
[9] M. Hernandez, T. Kirubarajan, and Y. Bar-Shalom, "Multisensor Resource Deployment using Posterior Cramer-Rao Bounds," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 40, no. 2, pp. 399–416, 2004.
[10] C. Kreucher, K. Kastella, and A. O. Hero, "Multi-target sensor management using alpha-divergence measures," in *Information Processing in Sensor Networks*, 2003, pp. 209–222.
[11] K. Bell, C. Baker, G. Smith, J. Johnson, and M. Rangaswamy, "Cognitive Radar Framework for Target Detection and Tracking," *IEEE Journal on Selected Topics in Signal Processing*, vol. 9, no. 8, pp. 1427–1439, 2015.
[12] A. Charlish and F. Hoffmann, "Cognitive radar management," in *Novel Radar Techniques and Applications Volume 2: Waveform Diversity and Cognitive Radar, and Target Tracking and Data Fusion*. Institution of Engineering and Technology, 2017, pp. 157–193.
[13] C. Kreucher, A. Hero, and K. Kastella, "A comparison of task driven and information driven sensor management for target tracking," in *Proc. IEEE Conference on Decision and Control*, 2005, pp. 4004–4009.
[14] R. Nadjiasngar and A. Charlish, "Quality of service resource management for a radar network," in *Proc. 2015 IEEE Radar Conference*, vol. 5, 2015, pp. 344–349.
[15] T. Cover and J. Thomas, *Elements of Information Theory*. Wiley, 1991.
[16] C. Kreucher and A. Hero, "Non-myopic approaches to scheduling agile sensors for multistage detection, tracking and identification," in *Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing*, vol. 5, 2005, pp. 885–888.
[17] D. A. Castañón, R. Mahler, K. J. Hintz, J. Reich, I. Kadar, M. Farooq, and T. Kirubarajan, "Issues in resource management with applications to real-world problems," in *Proc. SPIE*, 2006.
[18] C. L. Steinberg, A. N. Bowman and F. E. White, *Revisions to the JDL data fusion model*. CRC Press, 2008, pp. 65–88.
[19] H. L. Van Trees, K. L. Bell, and Z. Tian, *Detection, Estimation, and Modulation Theory, Part I*. Wiley, 2013.
[20] H. L. Van Trees and K. L. Bell, *Bayesian Bounds for Parameter Estimation and Nonlinear Filtering/Tracking*. Wiley, 2007.
[21] C. Kreucher, K. Kastella, and A. O. Hero III, "Multi-platform information-based sensor management," in *Proc. SPIE*, 2005, pp. 141–151.
[22] R. Romero and N. Goodman, "Cognitive radar network: cooperative adaptive beamsteering for integrated search-and-track application," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 49, no. 2, pp. 915–931, 2013.
[23] C. Yang, I. Kadar, E. Blasch, and M. Bakich, "Comparison of information theoretic divergences for sensor management," in *Proc. SPIE*, 2011.