Precision Target Tracking and Adaptive Sensor Resource Management for Maritime Surveillance

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1 Introduction

The self-defence capability of the Canadian forces is essential to the completion of a mission as well as for personnel safety. Regardless of the role and risk involved, a unit’s self-defence capability will need to be multi-dimensional in nature. The potential threat to Canadian naval units may come from air, surface, subsurface, or electromagnetic environments. Moreover, the proliferation of a number of potential weapon systems of different types and capabilities throughout the world is unlikely to subside in the future, and their capabilities will continually improve, adding to the already difficult problem of sorting friends, neutrals, and foes during operations in a dense environment. Besides, the spread of supersonic versions of anti-ship missiles and their increasing stealthiness make shorter reaction time for defence even more crucial than at present.

The defence against various threats will require both a multi-dimensional and a multi-layered approach, employing a variety of systems, optimizing detection techniques, “hard kill”, “soft kill”, and avoidance capabilities. Moreover, given the projected capabilities of future weapon systems, the self-defence envelope must expand well beyond the 7-10nm area around each surface platform if a unit were to have any chance of defending itself successfully. Key to providing a suitable self-defence capability will be an effective early detection strategy. Although, avoiding or defeating the incoming weapon can be effective in many instances, the ability to deter, and if necessary to engage, an attacking unit must also be recognized as a vital part of a robust self-defence capability.

To counter these threats and enhance the capability for a robust self-defence, the navy must defend itself with units dispersed over hundreds of square miles. This is especially true in a littoral environment, where the natural environment and its effects on sensor range in addition to the exposure to a variety of weapons are not normally encountered in an open ocean environment. Each unit will possess one or several sensors, and each sensor will observe a somewhat different view of the situation because of its unique characteristics and vantage point. A network of these units must create an identical picture at each unit with sufficient quality to be treated as local data for engagements. The key characteristics of such coordinating units will be speed, range and precision. In the case of hard kill weapon systems, the additional characteristics of lethality will be important.

Amid this disparity in knowledge among the units efforts are being made to correlate target tracks and identification data. The timely availability and accuracy of the tracks and identities will allow better planning and quick (re)action. The objective of our project is to develop a state-of-the-art distributed fusion system testbed with advanced algorithms for multisensor-multitarget tracking and
identification to support Canada’s defence efforts in a network- or information-centric world. One important aspect in the development of this testbed is the evaluation of the algorithms on realistic scenarios [20, 34]. The experience gained from the benchmark problem presented in this paper will be taken into account in our development of the Canadian testbed.

2 Multisensor-Multitarget Tracking and Fusion Literature

Different aspects of multisensor-multitarget tracking, the process of estimating the states of moving objects using the data from multiple sensors like, for example, radar, ESM or optical, has been handled by a number of researchers (see [2], [3], [6] for theory and applications). Typical applications of multisensor-multitarget tracking are in ground target tracking [26], air traffic control (ATC) [38], coastal monitoring [36], space surveillance [2], radar tracking in the presence of electronic countermeasures [11], [25], and visual tracking [29], to name a few. Most practical systems consist of a number of heterogeneous and asynchronous sensors (i.e., different types of sensors resulting in measurements at different times) that may be geographically distributed. Then the task is to combine or fuse the noisy information from these different sensors and find the best possible state estimates of the targets of interest that are mobile.

Multisensor tracking and fusion systems can be broadly categorized as centralized and decentralized (or distributed). In the centralized architecture, all raw data from individual sensors are sent to a single fusion center where they are statistically combined to obtain a single set of track estimates. In a centralized system, which produces the optimal (best) global estimates, the major bottleneck is the communication load to transfer the entire raw data from the sensors to the fusion center. In distributed scenarios multiple airborne or ship-mounted sensors, the centralized architecture may not be practicable [2]. In contrast, in the decentralized architecture, each sensor processes its own data and sends only the resulting estimates (and its covariances or uncertainties) to the fusion center. The fusion center carries out a track-to-track association to combine the estimates from different sensors. In some cases, the fusion center may send its fused estimates back to the individual sensors, in which case one has a centralized fusion system with feedback [2]. In addition the sensor-to-fusion center communication may be done "on-demand", that is, as needed. While the decentralized architecture requires less communication bandwidth, its performance is sub-optimal to that of the centralized architecture even if the track-to-track fusion is done optimally by accounting for all possible errors [13], [14] (results are available only for the case of homogeneous sensors). Simulation studies using homogeneous sensors have validated these results [14]. In a networked environment, as in many practical systems today, the architecture is hierarchical; that is, fusion may be carried out in more than one fusion center and in more than one level (e.g., raw data, estimates and decision) - the basic fusion architectures (centralized and decentralized) are just the building blocks in the overall fusion topology.

In addition to the evaluation of performance of different fusion architectures, a number of other issues are of interest. Sensor registration is one such crucial issue in multisensor tracking. Because of sensor misalignment or processing errors, a bias may be introduced into the measurements, which may result in biased state estimates and degraded performance. The problem is exacerbated further in the case of multiple geographically distributed sensors [1], [31]. Proper measurement registration techniques have to be used to estimate the bias component of each sensor and then the de-biased measurements can be used to obtain improved state estimates. Typically, targets of opportunity (friendly targets with known locations) are used for sensor registration, which may not be very practicable in a hostile environment [16]. In multisensor tracking systems the problem of out-of-sequence measurements, where sensor reports may arrive at the fusion center not in a time-ordered manner, needs to
be handled systematically as well [30].

Distributed sensor networks may require modification to the standard state estimation algorithms to handle the underlying fusion architectures. In addition, the hierarchical nature of a sensor/fusion system has to be taken into account. In [12] a Probabilistic multitarget tracker was proposed for distributed sensor networks. This work modifies the tracker to handle the centralized fusion architecture with multiple homogeneous sensors. In addition, the paper presents a solution for a particular data association (the process of matching measurements to targets in the presence of measurement origin uncertainty) mechanism. In [19] and [23] a multiple model based estimation algorithm was proposed for multisensor tracking. In [27] a new algorithm for efficient multisensor fusion was proposed for multitarget tracking geographically distributed sensors. Again, [27] dealt with a specific data association mechanism using multidimensional assignment [17], [32].

Another issue of interest is the fusion of heterogeneous sensors with possible feature information. For example, one sensor (e.g., radar) may provide position measurements that are related to the actual target state while another sensor (e.g., high resolution radar) may provide target profile feature information that may not be related directly to target state. This is known as feature-aided tracking [21], which has gained importance with the availability of inexpensive feature-capable sensors like high-resolution radar (HRR) and imaging sensors. In the case of multiple heterogeneous sensors it is not obvious how the features from disparate sensors can be fused - developing an algorithm that can fuse features from not only multiple sensors but also feature-aided estimates from different fusion centers [21, 22] is of significant value.

In tracking a large number of targets using multiple sensors, one important task is sensor resource allocation. The idea is to select the best group, sequence or mode of sensors, with the minimal usage cost, which can be used to accomplish a given surveillance task. Effective sensor resource management enables the best utilization of existing sensor resources while ensuring the accurate handling of the targets of interest in the surveillance region. A sensor resource manager can decide which sensor to use at which time and in which mode or with which parameters in order to track the targets with a given accuracy [11], [25], [39]. Even with a single sensor, for example, a multifunction radar, resource management may be beneficial in selecting revisit time, mode, parameters [25] and even the platform location [4].

Finally, one important aspect in any algorithm development, especially for multisensor-multitarget tracking, is the evaluation of the algorithms on realistic scenarios. In [11] a realistic benchmark system was developed for evaluating different algorithms for single target tracking and single (multifunction) sensor resource management. It was later extended to two sensors and two targets [40]. In [14] a homogeneous multisensor-multitarget benchmark problem was used to evaluate tracking and fusion performances without sensor resource management. A realistic simulation or prototype environment for heterogeneous multisensor-multitarget tracking and sensor resource management performance evaluation is highly desirable.

3 Research Issues in Network-Centric Maritime Surveillance

3.1 Algorithms for Preprocessing Multisensor Data for Networked Systems

In order to maximize the benefits of multisensor fusion, the sensor data need to be preprocessed to avoid or handle properly the inconsistencies therein. One important inconsistency, even in single sensor systems, is registration error, which results from sensor’s self-location determination errors or from pointing errors. This typically introduces a bias in the measurements that, if not removed or accounted for properly, could lead to degraded estimation results and eventually to track loss [1]. The problem is even more severe in multisensor systems where the registration errors can accumulate and
result in deteriorated data association and estimation results. One common registration strategy is to use "targets of opportunity" with known locations and motion parameters. Since this may not be practicable in hostile environments, a more systematic approach is needed. This need to be achieved by estimating online the registration errors for various sensors and compensating for them before track estimation. Note that the registration algorithm needs to handle different types of sensors. Another preprocessing problem is out-of-sequence measurements, where a measurement that originated at an earlier time reaches the fusion center after a measurement that originated later [30]. This may happen because of communication delays through the network and processing delays at sensor or fusion nodes. With out-of-sequence measurements the problem is to update a state, which is at a later time, using an earlier measurement. While a number of attempts have been made at solving this problem, a general heterogeneous sensor solution for hierarchical networks (with single and multiple lags) needs to be found - this is the next objective under this topic.

3.2 Fusion of Disparate Types of Data in a Networked Environment

Most estimation algorithms assume simple centralized or decentralized fusion architectures. With distributed sensor networks, modifications to handle the additional layer (or hierarchy) of information are needed. In distributed architectures, the exact cross-correlations between the local state estimation errors need to be accounted for in order to fuse the measurements and the estimates optimally [2]. In addition, modifications are needed for standard estimators like the IMM estimator and the PDAF in networked configurations. This is because of the requirement that each estimate be consistent (i.e., has a covariance that is neither optimistic nor pessimistic). This is the first objective under this topic.

The other issue is the fusion of disparate types of data from heterogeneous sensors. Some of the sensors in the system measure the state of the target directly (e.g., a radar or ESM measure the range and/or azimuth). Other sensors may give measurements unrelated directly to the target state (e.g., HRR giving range profiles). Other measurements (features) of this nature are radar cross-section, signal intensity, shape, etc. In this case, a consistent fusion framework needs to be developed in order to update target states with state related measurements and features. Furthermore, in a networked environment fusion will be carried out in different levels (measurement to measurement, measurement to track, track to track, etc.). Techniques for deriving consistent likelihood measures to fuse different types of data (e.g., measurements, features, track estimates) in different fusion levels need to be developed.

3.3 Network-Centric Fusion Architectures and Their Performance Evaluation

With multiple sensors and different options for fusing data (measurements, estimates and decisions) at different levels, it is essential to have an efficient architecture that results in better utilization of existing resources. In order to achieve this, proper design and performance evaluation techniques have to be devised. While network centric architectures may exist in some cases, analytical performance evaluation techniques do not. Current performance evaluation techniques, for example, as in [14], assume homogeneous, asynchronous sensors and simplistic state estimators like the a-b filters. In contrast, state-of-the-art systems use heterogeneous sensors with sophisticated trackers like the Interacting Multiple Model (IMM) estimator [3]. To be of practical use, a fusion architecture and the corresponding fusion algorithm have to be general enough to work with heterogeneous and asynchronous sensors. In addition, current performance evaluation techniques assume simple centralized architectures while the real-world systems involve hierarchical topologies. Analytical performance evaluation and its verification by simulation are essential before implementation. The first aim of our work is to rectify this shortcoming by investigating different network centric architectures for common sensor types (e.g.,
radar, ESM, imaging) and practically useful trackers like the Kalman filter and the IMM estimator. Analytical performance evaluation techniques, which will be validated by simulations, are planned. Our work will complement Raytheon Canada’s on-going efforts on the network-centric surveillance system development by providing new and advanced algorithms and by providing means of system performance evaluation.

3.4 Resource Management Algorithms in Heterogeneous, Multisensor Environments

Scenarios Making the best possible use of existing sensor and network resources is essential in order to minimize the operational cost while maintaining the required performance. The resource manager selects the minimal set of the sensors, their operational parameters (e.g., waveform, frequency, mode) at the usage (revisit) times subject to an optimization criterion [11]. For example, in a radar system the waveform and the SNR can be selected to satisfy a constant false alarm rate. Similarly, the revisit interval can be selected subject to a certain maximum prediction error [25]. The difficulty arises when there are heterogeneous sensors and the network architecture itself needs to be factored into the optimization process. In addition, communication bandwidth, delays and time constraints for decision making in precision engagement have to be considered as well. In this project, we aim to handle this problem in a systematic manner using optimal subset selection algorithms. For different architectures, the communication load to transfer raw measurements or state estimates together with the associated covariances will be used as part of the optimization criterion (in addition to the required prediction accuracy). Our objective is to consider the multitude of sensors available in a practical system with time constraints. Specifically, different combinations of angle-only, radar, Doppler and imaging sensors will be considered for optimization.

3.5 Testbed for Maritime Surveillance

In addition to evaluating the performance of surveillance system analytically, which is usually limited because of mathematical tractability, it is essential to validate the performances of various algorithms using simulations (and, if possible, real data). Toward this end, we aim to develop a realistic simulation environment (prototype) for generating multisensor-multitarget tracking scenarios, design different fusion architectures, implement various tracking and fusion algorithms and evaluate their performance. This will facilitate the transition of the new algorithms to practical systems as well. As part of this effort, a number of research issues for the efficient and robust implementation will have to be addressed. Typically, the straightforward implementation of estimation and fusion algorithms may result in excessive computational and communication loads and numerically unstable systems (e.g., standard implementation of the Kalman filter vs. the Joseph form implementation to improve numerical stability; information filter implementation to improve computational efficiency [3]). The ability to implement the algorithm effectively and efficiently will in turn force changes in tracker/fusion architecture designs. For this reason it is extremely important to develop a comprehensive simulation environment. The approach will be to develop a skeletal tracker/fusion framework first and then integrate the individual implementations from the tasks listed earlier - this effort and the other tasks in our effort complement one another and they will proceed concurrently. The objective here is to develop a platform independent track manager with support for data preprocessing, estimation, fusion and performance evaluation [41]. Special care will be taken to minimize testbed development time and expenses.
4 US Navy’s Ship Self-Defense Benchmark Problem

Large-scale target tracking with applications to, for example, air traffic surveillance and air traffic control, is a well studied problem in the literature. Some specific problems of interest in the single-target, single-sensor case are tracking maneuvering targets [3], tracking in the presence of clutter [2] and electronic countermeasures (ECM) [15]. In addition to these tracking issues, to be complete, a tracking system for a sophisticated electronically steered antenna radar has to consider radar scheduling, waveform selection and detection threshold selection. Although many researchers have worked on these issues and many algorithms are available, there was no standard problem to compare the performances of the various algorithms. Rectifying this, Blair et al. developed the first benchmark problem [8], which considered only the problem of tracking a maneuvering target and pointing/scheduling of a phased array radar. Of all the algorithms considered for this problem, the interacting multiple model (IMM) estimator yielded the best performance [7, 18, 24, 35]. The second benchmark problem [10] included false alarms (FA) and ECM, specifically, a standoff jammer (SOJ) and range gate pull off (RGPO) as well as several possible radar waveforms (from which the resource allocator has to select one at every revisit time). Preliminary results for this problem showed that the IMM and multiple hypothesis tracking (MHT) algorithms were the best solutions [5, 25, 33]. The MHT algorithm, while 1–2 orders of magnitude costlier computationally than the IMMPDAF (IMM estimator with probabilistic data association filter — PDAF — modules [2]) for the problem considered (as many as 40 hypotheses are needed), yielded comparable results with the IMMPDAF. The benchmark problem of [10] was upgraded in [11] to require the radar resource allocator/manager to select the operating CFAR and include the effects of the SOJ on the direction of arrival (DOA) measurements; also the SOJ power was increased to present a more challenging benchmark problem. While, in [10], the primary performance criterion for the tracking algorithm was minimization of radar energy, the primary performance was changed in [11] to minimization of a weighted combination of radar time and energy. In [11], a framework based on the IMMPDAF for radar scheduling and control, target tracking and neutralizing techniques for ECM is presented. The tracking algorithm is designed to control the beam pointing of the phased array radar adaptively in order to maximize the revisit interval for the target while meeting a maximum allowed track loss probability. Also, the SOJ has to be tracked (at as low a rate as possible) so its interference with target returns does not cause loss of the target track. The time and the pointing direction for the next radar dwell are determined by the radar resource allocation algorithm. This also selects the type of dwell, waveform for active dwells and the threshold for measurement detection. The radar can carry out target track dwells (illuminating in the direction of the predicted location of an existing track), search dwells (to detect and initialize tracks) and passive dwells to track a jammer. Six target tracks are considered in this problem. The targets exhibit radar cross-section (RCS) fluctuations according to the Swerling type 3 model and perform maneuvers with lateral accelerations up to 7g and longitudinal accelerations up to 2g. Target ranges vary from 20km to 100km and the elevation angles vary between 2° and 80°. The jammer stays at ranges greater than 150km and performs accelerations up to 2g. As an additional ECM, the target under track employs RGPO so as to pull the tracker’s range gate off the target by creating false returns.

The tracking algorithm is required to maintain tracks with a maximum track loss of 4%. A track is declared lost if the estimation error is greater than the two-way beamwidth in angles or 1.5 range gates in range. To compare the relative performance of different algorithms, the average radar power per target, average radar time per second, average sampling interval and the average root mean square (RMS) error of the position and velocity estimates are used. The IMM estimator, combined with other data association techniques, has been shown to be an effective technique for tracking maneuvering targets in the presence of false alarms based on real data [28, 38]. Any algorithm that handles this tracking problem needs to have the following:
the ability to identify the beginning and the end of maneuvers

• the ability to discount false alarms while associating target-originated measurements correctly to the track.

The first requirement, known as maneuver detection, involves swift switching of the filter gain and/or state model [3]. The next one, known as data association, involves assignment and/or weighting of multiple measurements. The first requirement can be met with the approach of random maneuver modeling where the unknown input command is assumed to be a random process, which is treated as a process noise with several intensities and structures [3]. The IMM estimator accommodates both discrete and continuous uncertainties. This is ideally suited for tracking maneuvering targets which exhibit discrete uncertainties in flight mode as well as continuous ones. In [11], the IMM is combined with the PDA technique, which handles data association via weighting, to perform automatic track formation and maintenance. The PDA technique associates each validated measurement probabilistically to the estimated track. The probabilistic nature of the IMMPDAF allows the straightforward inclusion of neutralizing techniques for ECM within the same framework. The adaptive scheduling and detection techniques are also described in [11].

5 Lessons Learnt From US Navy Benchmark

An invited session was organized at the 1994 American Control Conference (ACC) with the first benchmark as the theme for the session. The benchmark problem was presented along with four approaches to the problem. The results of the invited session [18, 24, 35] and other studies such as [7] provided relative comparisons of different tracking algorithms on the first benchmark. The results of the first benchmark are summarized in Figure 1, where the average revisit period of each algorithm is given versus the computational cost of implementing the algorithm. In Figure 1, the computational cost is given in units of the computational cost of implementing an $\alpha$-$\beta$ filter. When reviewing Figure 1, note that a tracking algorithm that requires an average revisit period of 2.0s will allow the radar to track twice as many targets as an algorithm that requires an average revisit period of 1.0s. The $\alpha$-$\beta$ filter provided an average revisit period of 0.85s, while a standard Kalman filter with a nearly constant velocity motion model was found to provide an average revisit period of about 1s. Thus, for an order of magnitude increase in computations, the Kalman filter provided only a 20% increase in the average revisit period. A two-model IMM estimator was found to provide an average revisit period of 1.3s, while a three-model IMM estimator was found to provide an average sample period of 1.5s. Incorporating adaptive revisit times with a three-model IMM estimator was found to provide an average revisit period of 2.3s for computational cost of about 60 $\alpha$-$\beta$ filters. An H-Infinity filter solution was originally included in the invited session at the 1994 ACC, but the authors withdrew the paper when they concluded that the H-Infinity filter provided no significant advantage over the Kalman filter [37].

Many of the deficiencies associated with the first benchmark problem were corrected to produce the benchmark problem presented in [9] with MATLAB code to implement the benchmark and summarized in [11]. This second benchmark extends the first benchmark to include the effects of FAs and ECM. The inclusion of FAs was accompanied with multiple radar waveforms so that the waveform energy can be coordinated with the tracking algorithm. The ECM includes Range Gate Pull Off (RGPO) on the target and a Standoff Jammer (SOJ) broadcasting wideband noise. The radar model simulation includes the effects of target amplitude fluctuations, beam shape, missed detections, finite resolution, and FAs. The targets exhibit Radar Cross Section (RCS) fluctuations according to the Swerling 3 type and perform as much as $7g$ of lateral acceleration and $2g$ of longitudinal acceleration. Eight radar
waveforms that differ primarily in the pulse length are available for control (i.e., selection) from the tracking (and radar management) algorithm. Since a waveform with a longer pulse length provides a higher Signal-to-Noise Ratio (SNR) at the cost of more radar energy, the proper coordination of the waveform selection with the tracking algorithm is an important “real-world” issue. For example, a higher target SNR results in fewer FAs at the costs of more radar energy. For this benchmark the “best” tracking algorithm is the one that minimizes a weighted average of the radar energy and radar time, while satisfying a constraint of 4% on the maximum number of lost tracks.

The results of the second tracking benchmark are summarized in Figure 2, where the average revisit period and average power are given versus the computational cost of implementing the algorithms. In Figure 2, the computational cost is given in units of the computational cost of implementing a Kalman filter. The adaptive Kalman filter was found to provide an average revisit period of 1.2s, while the IMMPDAF [25] provided an average revisit period of about 2.5s. The IMMPDAF was also found to provide a 50% reduction in the radar power required by the adaptive Kalman filter. Thus, the IMMPDAF was found to provide significant reductions in radar time and energy for a computational cost of 9 Kalman filters instead of the computational cost of the adaptive Kalman of 1.5 Kalman filters. The IMM/MHT [6] was found to provide an average revisit period of 2.55s, which is a marginal improvement of the average revisit period of the IMMPDAF. The IMM/MHT [6] was found to provide a 50% reduction in the radar power required by the IMMPDAF.

Since the IMM/MHT required a computational cost of implementation of approximately 45 Kalman filters, the IMMPDAF is the better choice for radar systems where radar time is critical and the IMM/MHT is the better choice when radar energy is critical. Since both radar time and energy jointly impact the tracking performance of the radar, the actually performance measures of the second benchmark are formulated as a combination of radar time and energy [9].

Figure 1: Results of tracking benchmark I: average revisit period
6 Summary

The objective of the proposed research is to develop a state-of-the-art detection, tracking and fusion testbed with advanced algorithms for hybrid distributed sensors based surveillance of air, littoral and sea targets. The gathered information or sensor reports are processed in one or more fusion centres and at different fusion levels. In this project we plan to develop algorithms that solve some critical problems in a network-centric surveillance scenario. The proposed work will develop 1) different architectures for fusion of data from hybrid distributed sensors and ways to quantify their performances; 2) algorithms for preprocessing multisensor data; 3) robust multitarget trackers; 4) association techniques for combining raw sensor data, tracks and target features in distributed and hierarchical architectures; 5) a simulation environment to implement and evaluate the new algorithms developed in this project. There is a tremendous synergy to be derived from the fusion of information. However, the challenge here is to assign each detected target a single track. The more sensors, the more confusion about association and track management. To palliate to this problem, The U.S Navy CEC (Cooperative Engagement Capability) system was developed under the assumption of complete data sharing between the platforms (very expensive approach and prone to jamming). Our research will explore different fusion architectures and study their performances in terms of track precision, continuity and timeliness under the constraints of communication bandwidth and will identify an affordable solution that fits the needs of the Canadian Navy.

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References


