Multitarget Tracking in a Multisensor Multiplatform Environment

A. Gad, M. Farooq, J. Serdula, and D. Peters
Department of Electrical and Computer Engineering,
Royal Military College of Canada,
Kingston, Ontario, Canada, K7K 7B4,
Tel No. 613-541-6000 Ext. 6032 Fax No. 613-544-8107
e-mail: farooq@rmc.ca

ABSTRACT

Due to the current advances in technology, it is both possible as well as feasible to track multiple targets in a network centric environment. To this end, the development and the design of a network centric environment must be based on solid understanding of the theoretical foundations and should yield required performance in a control simulation. The paper provides an overview of various issues involved in a network centric sensor data fusion environment. Besides discussing the conventional techniques to resolve the sensor integration, registration, association, and fusion issues, non-conventional approaches, such as Fuzzy Logic and Viterbi based methods are also be explored in this paper. In addition, the design of a versatile simulation environment based on a multi-tiered fusion architecture to evaluate the sensor integration techniques is presented.

Key Words: Target Tracking, Sensor Fusion Architectures, Multiplatform Data Fusion.

1. INTRODUCTION

Target tracking is an integral part of surveillance systems employing one or more sensors to interpret the environment that include both targets and false alarms. Typical sensor systems, such as radar, infrared (IR), laser radar (LADAR), and sonar, report measurements from diverse sources, targets of interest and background noise sources such as clutter and false alarms. The tracking objective is to collect sensory data from the surveillance volume containing one or more potential targets of interest and then partition the sensory data into sets of observations measured from the same target. The tracking algorithm is composed of three steps between time scans: prediction, data association, and state update or filtering.

Sensor integration and registration is a prerequisite to exploiting the inherent advantages of multi-sensor systems over single sensor systems. Using a single sensor, we can monitor objects with a precision and accuracy that depend on the sensor characteristics. By using multiple sensors to observe a target, we can obtain multiple viewpoints, extended coverage both spatially and temporally, reduce the ambiguity and obtain a more precise estimate of object kinematics than that which is possible through the best individual sensor. Engineers can replace a single very expensive sensor with many cheaper sensors in a tracking scenario or employ a variety of sensors to construct a comprehensive view of the environment. This certainly is the case with a netted sensory (network centric) system. For example, a single sensor may have a blind azimuth (screening angle) which an adjacent sensor may cover. In those areas where sensor coverage overlaps, the quality of object recognition and tracking is improved by the additional data provided from overlapping sensors which not only improves our estimate of object kinematics, but also helps with its detection when the environment is changing. From the military point of view, multiple sensors provide diverse information, which can be used by the decision-makers to derive an appropriate response to perceived threats. As the number of threats being monitored increases, the difficulty in maintaining an accurate picture of the environment grows exponentially. As such, the need to develop state-of–the–art techniques capable of functioning in a cluttered, dynamic environment containing the objects of interest is of fundamental importance to enhancing the survivability and usefulness of a multi-sensory system.

The basic principles of Multitarget Tracking (MTT) have been formulated in the early papers by Wax [1] and Sittler [2] but these papers were written before the widespread application of the Kalman filtering techniques [3]. Bar-Shalom [4] and Singer [5] can be credited of modern MTT schemes that combine the data association techniques and Kalman filtering theory. Starting with Farina and Studer [6], a number of books, including [7-15], have been written to address the numerous problems involved in tracking multiple targets with one or more sensors.

The development and design of a network centric environment must be based on solid understanding of the theoretical foundations and should yield required performance in a control simulation. To this end, the paper provides an overview of the integration, registration, association, and fusion issues in a network centric environment.

Besides discussing the conventional techniques to resolve the sensor integration, registration, association, and fusion issues, non-conventional approaches, such as Fuzzy Logic and Viterbi based methods are also explored in this paper. In addition, the design of a versatile simulation environment based on a multi-tiered fusion architecture to evaluate the sensor fusion techniques is presented.

2. DATA ASSOCIATION TECHNIQUES

Data association is a technique for correlating observations from multiple sensors about a target (track) in a surveillance volume. Because of the uncertainty in the origin of each measurement due to noise or clutter, the performance of the tracking system depends on the data association process. Conventionally, several tracking algorithms have been proposed ranging from the simpler nearest neighbor standard filter (NNSF) [16] to the very complex multiple hypothesis tracker (MHT) [17]. The simpler techniques yield poor performance in presence of clutter. The more complex MHT provides acceptable performance but requires extensive computational resources due to the storage of a large number of hypotheses. Due to these difficulties, recursive algorithms have been developed based on the probabilistic data association (PDA) method which uses a weighted average of all the measurements falling inside the track's validation gate [4] to estimate the target states. The PDA is considered to be the best compromise between performance and complexity; however, in a low signal-to-noise ratio (SNR) environment, the PDA does not yield acceptable performance. This is due to the fact that at low SNR the target originated measurements may fall outside the validation gate and the PDA tracker may not able to estimate the target states due to the limited size of the validation gate. Recently, knowledge-based techniques have been employed to solve the data association problem in low SNR. The knowledge-based techniques include fuzzy logic [18-20], neural network [21-23], and the Viterbi technique [24-27].

2.1 The Nearest-Neighbor Standard Filter (NNSF)

In the NNSF, the validated measurement nearest to the predicted measurement is used to update the target state [16]. The distance measure to be minimized is the weighted norm of the innovation. It is the simplest method for data association which maintains the single most likely hypothesis. Sometimes, the nearest neighbor is not the measurement originating from the target. Therefore, the NNSF will sometimes use false measurements while assuming that these are target originated measurements or an observation falls in more than one gate (i.e., belongs to more than one track or target) and hence yielding erroneous target estimates.

2.2 The Optimal Bayesian Filter (OBF)

This approach is considered to be, theoretically, the best Bayesian filter [9]. It is assumed that there is only one target of interest and there are an arbitrary number of observations due to clutter or false alarms. In this method, the state is decomposed according to the total probability theorem in terms of measurements from the initial to the present time, rather than in terms of only the latest set of measurements as in the PDA and JPDA. In this technique, the memory and computation requirements increase with time, therefore, the suboptimal algorithms, which have lower computational requirements, are more practical than the optimal algorithm.

2.3 Multiple Hypothesis Tracking (MHT)

The MHT tracking algorithm was originally developed by Reid [17] in the context of multitarget tracking. This algorithm allows multiple hypotheses to be propagated in time with certain hypotheses emerging as likely and others as unlikely as data are received over time. The algorithm manages the hypotheses by propagating them over time, deleting those that are unlikely, combining those that are similar, and retaining those that remain. The metric for ranking the hypotheses is simply a probability defined over all existing hypotheses, with the understanding that the optimal Bayesian inference must be sacrificed by deleting hypotheses with small but non zero probability.

There are two basic approaches to MHT. The first is Reid's algorithm [17] where the hypotheses are continually maintained and updated as measurements are received. This is the measurement-oriented approach and is detailed in references [15,17]. The second is the track-oriented approach where tracks are initiated, updated, and scored before being formed into hypotheses. The scoring process consists of comparing the likelihood that the track represents a true target versus the likelihood that it is a collection of false alarms. Thus, unlikely tracks can be deleted before the next stage in which tracks are formed into hypotheses.

The measurement-oriented MHT technique deals with the association of sequences of measurements and the evaluation of the probability of each association hypothesis [17] which yields the probability of each established track or a new track giving rise to a certain measurement sequence. The latter feature allows consideration of track initiation for new targets within the framework of the algorithm. Unless one utilizes pruning techniques, the algorithm is computationally very expensive.

2.4 Probabilistic Data Association (PDA)

The PDA is a technique of target tracking in a cluttered environment [8]. The PDA filter assumes that there is only one target of interest whose track has already been initialized. The basic assumption of the PDA filter is that the state is assumed to be normally distributed according to the latest estimate and covariance matrix. The PDA uses a weighted average of all the measurements falling inside the validation gate of a target. The estimate is calculated as follows:

$$\hat{x}(k+1|k+1) = \sum_{i=0}^{m_k} \beta_i(k+1)\hat{x}_i(k+1|k+1) \tag{1}$$

where $\beta_i(k)$ is the association probability of the measurement z_i, $\hat{x}_i(k+1|k+1)$ is the estimate associate with the i^{th} measurement, and $\hat{x}(k+1|k+1)$ is the overall estimate. The association probabilities based on the parametric model are [8]:

$$\beta_i(k) = \begin{cases} \dfrac{c^{-1} V_k^{-m_k+1} P_D N[\nu_i(k); 0, S_i(k)]}{P_D P_G m_k + (1-P_D P_G)\lambda V_k}, & i = 1, \ldots, m_k \\ \dfrac{c^{-1} V_k^{-m_k} (1-P_D P_G)\lambda V_k}{P_D P_G m_k + (1-P_D P_G)\lambda V_k}, & i = 0 \end{cases} \tag{2}$$

Based on the nonparametric model, the association probabilities are:

$$\beta_i(k) = \begin{cases} c^{-1} m_k^{-1} V_k^{-m_k+1} P_D N[\nu_i(k); 0, S_i(k)], & i = 1, \ldots, m_k \\ c^{-1} V_k^{-m_k} (1-P_D P_G), & i = 0 \end{cases} \tag{3}$$

where P_D is the probability of detection, P_G is the gate probability, m_k is the number of measurements inside the validation gate, V_k is validation region, N [.;.,.] is the Gaussian noise process, ν_i the innovation, and S_i is the innovation covariance.

2.5 Joint Probabilistic Data Association (JPDA)

The JPDA is an extension of the PDA to the case where there are a known number of targets in clutter [13]. When there are several targets in the same region, a measurement from one target can fall in the validation gate of a neighboring target. This behavior can happen many times during the tracking process, resulting in persistent interference. Since the PDA models all the incorrect measurements as random interference with independent uniform spatial distributions, its performance can degrade significantly when the existence of neighboring targets gives rise to interference that is not correctly modeled. The JPDA algorithm computes the probabilities of association only for the latest set of measurements of various targets. The key to the JPDA algorithm is the evaluation of the conditional probabilities of the joint association events pertaining to the current time. To reduce the computational load of the algorithm, various pruning schemes such as the depth first search have been explored in the literature [28].

2.6 Fuzzy Data Association (FDA)

The conventional tracking techniques apply the “all-or-none” criterion to the tracking problem. In the target detection case, the signal detection is accomplished by comparing the target signal against a threshold. A detection is declared if the SNR exceeds a certain threshold. If the SNR is below the threshold, the detection algorithm will classify it as a non-target. Similarly, in the data association problem a validation gate is created around the predicted target position. If the measurement falls within the validation gate, it is considered as a target; otherwise, it is considered as a non-target or false alarm. At lower SNRs, the decision has to be made at the fuzzy boundaries. In this case, the bivalent logic employed by the conventional tracking techniques fails [18-20]. The FDA tracker has been exercised against various target profiles with different clutter densities. Simulations [18,19] have revealed that the algorithm yields acceptable results for the data at low SNR.

2.7 Viterbi Data Association (VDA)

The VDA is a recursive algorithm, which provides a solution to the discrete linear optimization problem. The VDA is based on a trellis in which, from a given sequence of symbols, the most-likely state transition sequence in a state diagram is determined. The algorithm is based on the Markov Process model. The shortest (optimum) path, based on the likelihood function, across the trellis yields the desired target track. The VDA has been applied to many different areas in decoding, such as text recognition, as well as estimation and detection problems in digital communications. Recently it has also found applications in target detection and tracking [24-27]. An observation based VDA algorithm shows a good tracking performance while having low computation complexity [24, 25].

2.8 Remarks

The integer programming algorithm, introduced by Morefield [29], which reveals that the multitarget tracking data association can be expressed as a discrete optimization problem for which mathematical programming methods are applicable. This approach solves the data association problem using the method of 0-1 integer programming.

The Auction assignment algorithm [30] seeks to maximize the gain. Thus, the elements in the observation-to-track assignment matrix are best chosen to be the score gains associated with the allowed assignments (that pass gate tests). The auction algorithm is composed of two phases: the bidding phase and the assignment phase. The bidding phase consists of finding the “best” track for each unassociated observation and bidding for it. The assignment phase assigns a track to each observation and removes a previous assignment if necessary. As in real auctions, the algorithm converges more quickly with larger bidding steps but larger bidding steps may not achieve the optimal assignment.

The Jonker-Volgenant-Castanon's algorithm (JVC) is the shortest augmenting path based 2-D assignment algorithm [31]. The computation complexity of the JVC is $O(n^3)$. The three basic steps of the JVC algorithm are: the initialization, the augmentation, and the dual solution update.

The Probabilistic Multiple Hypothesis Tracking (PMHT) algorithm [32] uses the Expectation-Maximization (EM) algorithm and a modified probabilistic model to develop a "soft" association tracker. The PDA and the MHT algorithms assume that a target can generate at most one measurement per scan. The PMHT sacrifices this constraint, and considers the measurement/target association process as independent across measurements. By doing so, it is able to render a fully-optimal (under a modified assumption) tracker. The associations become soft, governed by their posterior probabilities, while the integer-programming problem of target tracking becomes continuous and amenable to an iterative "hill-climbing" method via the EM algorithm.

In the multidimensional assignment algorithm [33], the measurements in the last (S - 1) scans are associated with the list of tracks, denoted as S-D Assignment, and has been shown to be a feasible alternative to MHT. The S-D assignment can be viewed as an intelligent MHT within a window of length (S-1). Unfortunately, for $S > 2$, the assignment problem is NP-hard even under the assumptions of zero false alarm and unity detection probabilities.

3. DATA FUSION ARCHITECTURES

In the surveillance environment, multiple observations and existing knowledge are employed using data fusion. Data fusion is a diverse field that can employ methods of mathematics, probability, operational research, industrial engineering, mathematics of computing, statistics, communication and decision theory, fuzzy logic, uncertainty management, estimation theory, image processing, digital signal processing, computer science and artificial intelligence in its functions. In this section, we will review the existing data fusion models [34]. During 1980, the intelligence cycle model, the Joint Directors of Laboratories (JDL) model, and the Boyd control loop (also called "Observe, Orient, Decide, and Act" (OODA) model) were introduced. In 1990, the Dasarathy model and the Waterfall model were developed. Recently, the Omnibus model has been proposed. These models identify the processes, functions, and techniques applicable to data fusion as information flows from the sources to the human operator.

3.1 The Intelligence Cycle

The intelligence process [35] can be described as a cycle that can be used for modeling the data fusion process. The intelligence cycle comprises four phases; collection, collation, evaluation, and dissemination. In the collection phase, raw intelligence data are obtained. The sources are electronic sensors or human derived sources. The data is presented in the form of an intelligence report which has a high abstraction level. In the collation phase, the associated intelligence reports are analyzed, compared, and correlated. In the evaluation phase, the collated intelligence reports are fused and analyzed. In the dissemination phase, the fused intelligence is distributed to military commanders who use the information to produce the required decisions.

3.2 The JDL Model

The JDL model has been proposed by the US Joint Directors of Laboratories Data Fusion Sub-Group in 1985 [36]. The JDL model is divided into five levels. At level 0, the pre-detection activities such as pixel or signal processing, spatial or temporal registration is present. Level 1 is concerned with estimation and prediction of target locations, behavior or identity. Level 2 investigates the relations among entities such as force structure and communication roles. Level 3 delineates sets of possible courses of action and the effect on the current situation. Level 4 is an element of Resource Management used to close the loop by re-tasking resources to support the objectives of the mission.

The JDL model is not intended to prescribe a strict ordering on the data fusion levels. This was indicated diagrammatically by the use of an information bus rather than a flow structure. Nevertheless, data fusion system designers have consistently assumed this ordering. Clearly, there is a need from users to have an ordering while the authors of the JDL model rightly defend the need for a model which admits systems with different hierarchies at different levels.

3.3 The Boyd Control Loop

The Boyd control loop (or OODA) [37] is divided into 4 phases. The observe phase is comparable to the JDL Level 0 and part of the collection phase of the intelligence cycle. The orient phase includes the functions of JDL Levels 1, 2 and 3. It also includes the structured elements of collection and the collation phases of the intelligence cycle. The decide phase includes JDL Level 4 and the dissemination activities of the intelligence cycle. The act phase has no direct analogue in the JDL model and is the only model that explicitly closes the loop by taking into account the effect of decisions in the real world.

3.4 The Waterfall Model

The Waterfall [38] focuses on the processing functions at the lower levels. The sensing and signal processing levels correspond to JDL level 0. The feature extraction and pattern processing levels correspond to JDL level 1. The situation assessment level corresponds to JDL level 2. The decision making level corresponds to JDL level 3. The major limitation of the Waterfall model is that the feedback is not explicitly depicted.

3.5 The Dasarathy Model

The Dasarathy model [39] is based on fusion functions rather than tasks and may therefore be incorporated in each of the fusion activities. Many researchers have identified the three main levels of abstraction during the data fusion process as decisions (symbols or belief values), features (intermediate-level information), and data (more specifically sensor data). As was pointed out by Dasarathy, fusion occurs both within these levels and as a means of transforming between them.

3.6 The Omnibus Model

The Omnibus model [40] overcomes some of the main limitations of the previous models while capitalizing on their advantages. In the Omnibus model, feedback is explicit and the previously neglected concept of loops within loops is acknowledged. The cyclic nature of the data fusion process is made explicit by retaining the general structure of the Boyd loop. The fidelity of representation expressed by the Waterfall model is then easily incorporated into each of the four main process tasks. The levels in the process where fusion may take place are explicitly indicated.

4. DATA FUSION TECHNIQUES

Many benefits can be derived from the multisensor data fusion in multitarget surveillance systems. The data from each sensor can be used to complement the data from the other sensors to obtain broader coverage and more accurate target state estimates and ID decisions. This way we can eliminate the false tracks and the countermeasures. The tracking accuracy can also be improved using similar sensor types such as distributed infrared sensors or radars for position estimates. The actual deployment of the automated multiple sensor systems is very difficult since we have to accurately choose the proper tracking architecture to get a more accurate surveillance picture than what we can get using the manual integration of data from the individual sensors. The proper tracking architecture must consider important issues such as time alignment and synchronization of tracks and measurements, the resolution of the sensors, data association using dissimilar data, and the registration problem. The multisensor data fusion has been widely used in the last decade in the military application. The military defense applications include the air-to-air and surface-to-air, strategic warning and defense, battlefield intelligence, and maritime surveillance. Non-military applications include civilian air traffic control, monitoring of manufacturing processes, robotics, condition-based maintenance of complex machinery, and medicine.

For the air-to-air and surface-to-air defense, it is necessary to detect, track and identify aircraft at proper ranges so that the defense weapons would have enough time to respond to the threats. In the strategic warning and defense scenarios, the aim is to detect the strategic actions, to be able to identify and track ballistic missiles and warheads, and to obtain the information about the enemy's military activities such as the enemy's force distribution, movements, and intention. In the battlefield intelligence, the aim is to identify ground targets to get a better idea about the enemy's forces, tactics, and strategies. This system utilizes the enemy's order of battle and creates the enemy database. This database should include the identification, locations, and characteristics of the enemy's military units. This would help one to determine the enemy's intent and situation and, subsequently, evaluate the seriousness of a given threat.

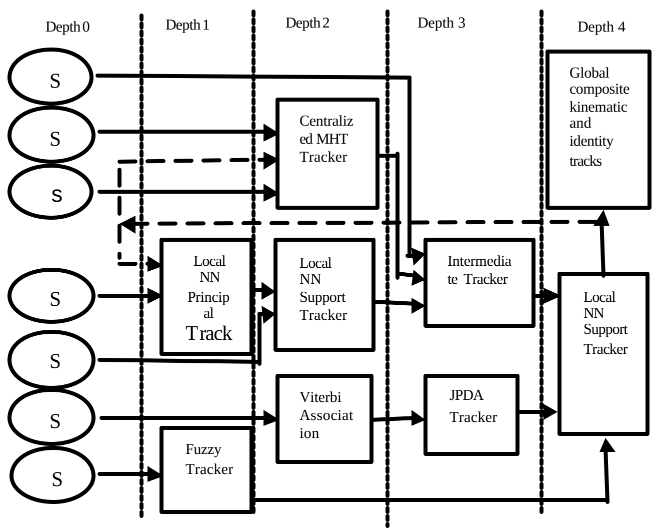

Fig. 1 Multi-tiered generalized architecture [42]

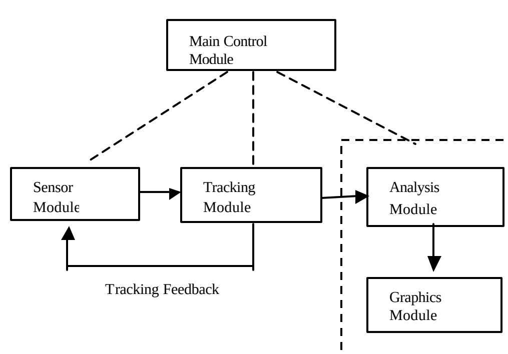

Fig. 2 CASE-ATTI testbed global structure [42]

There are many data fusion algorithms [41], e.g., centralized estimation fusion (CEF), central level tracking topology, centralized measurement fusion (CMF), generic decentralized fusion (GDF), decentralized information type fusion (DIF), static information fusion (SIF), sequential fusion (SF), sensor level tracking topology, and decentralized hybrid Multisensor Multitarget Tracker (MSMT). In order to take the advantage of the centralized and the decentralized fusion techniques, a Multi-tiered generalized fusion architecture [42] has been utilized to develop a testbed that includes dissimilar sensors and various data association and tracking schemes. The testbed called CASE-ATTI (Concept Analysis Simulation Environment - Automatic Target Tracking and Identification) has been developed in the department of Electrical and Computer Engineering at the Royal Military College of Canada (RMC) for the Defence Research Development Canada–Valcartier (DRDC-Valcartier). The testbed, as shown in figure 2, has been developed in a modular form using object oriented C++. The architecture allows testing and evaluation of each module independently, thus making the overall testbed fault tolerant and robust. Moreover, the testbed is platform independent, i.e., it can be ported to any workstation.

5. MULTIPLATFORM FUSION

Multiplatform multisensor (MPMS) fusion refers to fusing data from sensors which are physically located at different platforms. Sensory data are communicated between platforms through datalinks. MPMS fusion has become an issue worthy of attention on account of increased computation capability, deeming MPMS multitarget tracking fusion possible [43]. Perhaps the requirement for MPMSfusion which receives the most attention is the communication bandwidth required to communicate data either between platforms (distributed fusion) or from a platform to the central processing centre (centralized fusion). Hong et al. [43] reduce the communication requirements by compressing the data using the wavelet transform whenever the target is not maneuvering. This is called adaptive-rate data communication and results in an increase in mean-square error of less than one percent.

Durrant-Whyte et al. [44] describe the architectures of decentralized multi-platform systems with explicit distinctions made between hardware components: sensors, data processors, and communication modules. The author divides his architecture into four components: the world module, the sensor module, the estimation module, and the communications module. The details of various modules can be found in reference [44]. The various algorithms are implemented in decentralized fusion architecture.

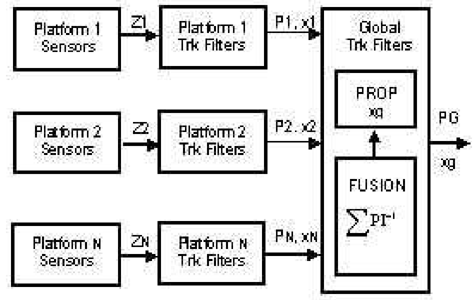

Fig. 3 Ad Hoc Fusion Filter

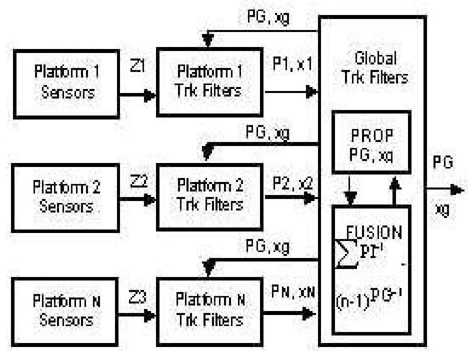

Fig. 4 Optimal Hierarchical Estimator

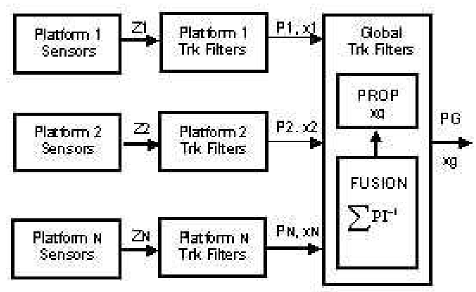

Fig. 5 Federated No-Reset Filter

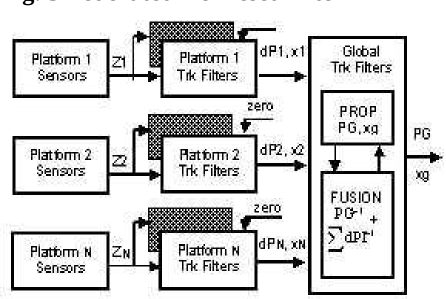

Fig. 6 Federated Zero-Reset Filter

Stromberg et al. [45] compare the relationship between tasks (consumers) and servers (producers) on each platform. Tasks "buy" processing time from sensor agents while sensors sell their services to tasks that consume it. When the combined number of sensors and tasks is large, one of the most important issues is the distribution of tasks among sensors, i.e., which sensor to associate with which task and at which time. This problem is known as task allocation of processors in software engineering. Two scheduling mechanisms are the best-first method, in which the most important task is scheduled first, and the brick method, in which slots of individually planned actions are allocated when the action is planned. The brick method utilizes a more efficient scheduling scheme but will require a complete re-scheduling each time an important but late request for action arrives.

Four candidate architectures for multiplatform track fusion are described in Carlson [46], namely: the ad hoc method, the optimal hierarchical estimator (OHE) method, the federated no-reset (FNR) method and the federated zero-reset (FZR) method. These four methods are illustrated in Figures 3 to 6, respectively. Carlson places the majority of his emphasis on the FZR. The ad hoc method reuses old information thus overweighing old information and under weighing new information. The other three methods discard old information after its incorporation into the global track filter, although each method discards the old information at different stages. This way, only the information gained since the last fusion cycle is transmitted. In the OHE method, which is described in detailed in [47], there is only one master global track filter (GTF). This master GTF subtracts the old information from successive filters instead of re-calculating the information to be discarded for each platform. All platform track filters (PTFs) are required to send their solutions to the GTF at the same time and the GTF must send its solutions back to the PTFs before processing is resumed. This requirement for two-way communication increases the bandwidth requirements. Overall, Carlson prefers the FZR method and concludes the paper with a list of advantages and disadvantages of the FZR over the other methods. The majority of data fusion algorithms assume that noise from multiple sensors is independent; they do not take into account the fact that the noise from two sensors measuring the same target track may be correlated [48,49].

5. CONCLUSIONS

A brief overview of integration, registration, association, and fusion techniques in a network centric environment have been presented in this paper. Besides discussing the conventional techniques, non-conventional approaches such as fuzzy logic and Viterbi algorithms have been also discussed. A state-of-the-art simulation environment exploiting a multi-tiered architecture was also outlined. The testbed is constantly evolving by incorporating the most effective and efficient tracking and fusion techniques presented in the literature. To assess the feasibility of the testbed, it has been exercised against a number of scenario involving realistic situations. The results are analyzed to fine-tune the overall simulation environment. Multiple copies of the testbed will be utilized to emulate the multiplatform network centric fusion system and its performance will be assessed against various scenarios.

6. REFERENCES

[1] N. Wax, “Signal-to-Noise Improvement and the Statistics of Tracking Populations”, J. of Applied Physics, pp. 586-595, May 1955.

[2] R. Sittler, “An Optimal Data Association Problem in Surveillance Theory”, IEEE Tran on Military Electronics, pp. 125-139, Apr. 1964.

[3] N. Nahi, “Estimation Theory and Application”, New York: John Wiley & Sons, 1969.

[4] Y. Bar-Shalom, and E. Tse, “Tracking in a Cluttered Environment with Probabilistic Data Association”, Automatica, , pp. 451-460, 1975.

[5] R. Singer, and J. Stein, “An Optimal Tracking Filter for Processing Sensor Data of Imprecisely Determined Origin in Surveillance Systems”, Proc. 1971 IEEE CDC, FL, pp. 171-175, 1971.

[6] A. Farina and F. Studer, “Radar Data Processing”, Vols. I and II, Letchworth, Hertfordshire, UK: J. Wiley and Sons 1985.

[7] S. Blackman and R. Popoli, “Design and Analysis of Modern Tracking Systems”, Artech House, 1999.

[8] S. Blackman, “Multiple Target Tracking with Radar Applications”, Artech House, 1986.

[9] Y. Bar-Shalom and T. Fortmann, “Tracking and Data Association”, Academic Press, 1988.

[10] E. Waltz and J. Llinas, “Multisensor Data Fusion”, Artech House, 1990.

[11] D. Hall, “Mathematical Techniques in Multisensor Data Fusion”, Artech House, 1992.

[12] Y. Bar-Shalom and X.-R. Li, “Estimation and Tracking: Principles, Techniques and Software”, Norwood, MA: Artech House, 1993.

[13] L. Klein, “Sensor and Data Fusion Concepts and Applications”, Bellingham, WA: SPIE Optical Engineering Press, 1993.

[14] Y. Bar-Shalom and X.-R. Li, “Multitarget-Multisensor Tracking: Principles and Techniques”, Storrs, CT: YBS Pub., 1995.

[15] Y. Bar-Shalom and W. Blair, “Multitarget-Multisensor Tracking: Applications and Advances – Volume III”, Norwood, MA: Artech House, 2000.

[16] A. Farina and S. Pardini, “Track-While-Scan Algorithm in a Clutter Environment”, IEEE Trans. on AES, pp. 769-779, Sept. 1978.

[17] D. Reid, “An Algorithm for Tracking Multiple Targets”, IEEE Trans. On Automatic Control, AC-24, pp. 843-854, Dec. 1979.

[18] A. Gad and M. Farooq, "Tracking Highly Maneuvering Targets in Clutter using Interacting Multiple Model Fuzzy Logic Based Tracker", SPIE, vol. 4729, April 2002.
[19] T. Quach and M. Farooq, "A Fuzzy Logic-Based Target Tracking Algorithm", SPIE, Vol. 3350, Orlando, FL, pp. 476-487, 1998.
[20] C. Moore, C. Harris, and E. Rogers "Utilizing fuzzy models in the design of estimators and predictors: An agile target tracking example", IEEE Conf. on Fuzzy Systems, pp. 679-684, 1993.
[21] T. Robb and M. Farooq, "Application of Neural Networks to Multi-Target Tracking", SPIE, vol. 4052, Orlando, FL, USA, pp. 14-25, April 2000.
[22] L. Chin, "Application of Neural Networks in Target Tracking Data fusion", IEEE Trans. on AES, Vol. 30, No. 1, pp. 281-287, Jan. 1994.
[23] J. Steck and S. Balakrishnan, " Use of Hopfield Neural Networks in Optimal Guidance", IEEE Trans. on AES, pp. 287-293, Jan. 1994.
[24] A. Gad and M. Farooq, "Viterbi-based Data Association Techniques for Target Tracking", Proceeding of SPIE, vol. 5096, April 2003.
[25] A. Gad and M. Farooq, "Single Target Tracking in Clutter: Performance Comparison between PDA and VDA", the 6th international Conf. on Information Fusion, Cairns, Australia, July 2003.
[26] T. Quach and M. Farooq, "Maximum Likelihood Track Formation with the Viterbi Algorithm", Proc. of the 33rd Conf. on Decision and Control, pp. 271-276, Dec. 1994.
[27] B. La Scala and G. Pulford, "A Viterbi Algorithm for Data Association", 35th Conf. on Decision and Control, Kobe, Dec. 1996.
[28] B. Zhou, "Multi-target Tracking in Clutter: Algorithms for Data Association and State Estimation", Ph.D. Dissertation, Dept. of Elec. and Comp. Eng., Pennsylvania State University, PA, 1992.
[29] C. Morefield, "Application of 0-1 Integer Programming to Multitarget Tracking Problems", IEEE Trans. Automatic Control, Vol. 22, No. 3, pp. 302- 312, June 1977.
[30] D. Bertsekas, "The Auction Algorithm: A Distributed Relaxation Method for the Assignment Problem", Annals of Op. Res. Special Issue on Parallel Optimization, Vol. 14, pp. 105-123, 1988.
[31] R. Jonker and A. Volgenant, "A Shortest Augmenting Path Algorithm for Dense and Sparse Linear Assignment Problems", J. Computing, vol. 38, pp. 325-340, 1987.
[32] R. Streit and T. Lugiubuhl, "Maximum Likelihood Method for Probabilistic Multi-Hypothesis Tracking", Proceeding of SPIE, Vol. 2235, pp. 394-405, Apr. 1994.
[33] S. Deb, K. Pattipati, and Y. Bar-Shalom, "A Generalized S-D Assignment for Multisensor-Multitarget State Estimation", IEEE Trans. on AES, Vol. 33, No. 2, pp. 523-538, April 1997.
[34] A. Gad and M. Farooq, "Data Fusion Architecture for Maritime Surveillance", The 5th international Conf. on Information Fusion, Annapolis, Maryland, pp. 448-455, July 2002.
[35] A. Shulsky, "Silent Warfare: Understanding the World of Intelligence", Brassey's, 1993.
[36] F. White, "A Model for Data Fusion", Proc. of the 1st Int. Symposium on Sensor Fusion, 1988.
[37] J. Boyd, "A Discourse on Winning and Losing", Maxwell AFB Lecture, 1987.
[38] M. Bedworth, "Probability Moderation for Multilevel Information Processing", DRA Technical Report DRA / CIS(SEI) / 651 / 8 / M94.AS03BPO32 / 1, 1994.
[39] B. Dasarathy, "Sensor Fusion Potential Exploitation - Innovative Architectures and Illustrative Applications", IEEE Proceeding, Vol. 85, No. 1, pp. 24-38, 1997.
[40] M. Bedworth and J. O'Brien, "The Omnibus Model: A New Model of Data Fusion?", Proceeding IEEE AES Systems Magazine, pp. 30-36, April 2000.
[41] S. Bruder and M. Farooq, "Sensor Fusion Techniques and Hyprid Multisensor Multi-target Tracker", EE Technical Report No. 90/3, Elec. & Comp. Eng, RMC, Kingston, Canada.
[42] R. Johnson and M. Farooq, "CASE-ATTI Multiple Sensor Multiple Target Tracking Module", EE Technical Report No. 95/3, Elec. & Comp. Eng, RMC, Kingston, Canada.
[43] L. Hong, Z. Ding, and R. Wood, "Development of multirate model and multirate interacting multiple model algorithm for multiplatform multisensor tracking", Optical Eng., vol. 37, 453-467, 1998.
[44] H. Durrant-Whyte, R. Deaves, and P. Greenway, "Decentralized Multiplatform Data Fusion", Proceeding of SPIE, vol. 3393, pp. 63-71, 1988.
[45] D. Stromberg, B. Andersson, and F. Lantz, "On Platform-Based Sensor Management", Information Fusion Conference, pp. 600-607, 2002.
[46] N. Carlson, "Federated Filter for Multiplatform Track Fusion", Proceeding of SPIE, vol. 3809, pp. 320-331, 1999.
[47] C. Chong, S. Mori, and K. Chang, "Distributed Multitarget Multisensor Tracking", Chapter 8, Multitarget-Multisensor Tracking, Artech House, 1990.
[48] Y. Bar-Shalom and L. Campo, "The Effect of the Common Process Noise on the Two-Sensor Fused Track Covariance", IEEE Transactions on AES, vol. 22, no. 6, pp. 803-805, 1986.
[49] Y. Bar-Shalom, "On the Track-to-Track Correlation Problem", IEEE Transactions on AC, vol. 26, no. 2, pp. 571-572, 1981.