A Fuzzy Logic-Based Multisensor Data Fusion for Maritime Surveillance – Real Data Testing

Ahmed S. Gad
R & D Branch Head, Egyptian Navy
ahmed.gad@ieee.org

Abstract

Multisensor data fusion is the most important technique employed to support Maritime Surveillance thus improving the quality of target tracking system. One of the major problems is that the surveillance area is generally large, hence making it difficult to arrive at a feasible data fusion architecture. The latter arises due to timing, accuracy, and different types of sensors and sensor platforms. In this paper, an efficient fuzzy logic-based data fusion technique is employed to support the maritime surveillance process. A real data set is used to evaluate the performance of the proposed data fusion algorithm which interacts with data fusion processes at different information levels. The results have proven that the proposed technique has an acceptable performance and computation complexity which is vital in real-time applications.

1. INTRODUCTION

The multisensor data fusion problem requires the development of methods for the combination of the data from multiple sensors. In a multisensor tracking system we must first define the level at which sensor data should be fused. There are three ways to fuse the data: at the sensor-level, the central-level, or the hybrid level. Moreover, the sensors could be similar or dissimilar in purpose, use, and the nature of the measured data, [1]-[3].

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.

For economical purposes or due to the restriction or the lack of high technology, engineers can replace a single very expensive sensor with many cheaper sensors in a multitarget tracking scenario or employ a variety of sensors to construct a comprehensive view of the environment, [1], [2]. 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 the target estimate, 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.

Data from different sensors are combined using signal processing, pattern and image recognition, artificial intelligence, and information theory. Sensor can provide both the kinematic (positional information) as well as the non kinematic data (identity, radar cross-section area, IFF, etc.).

In this paper, efficient fuzzy logic-based data fusion technique is employed to support the maritime surveillance process. A real data set is used to evaluate the performance of the proposed data fusion algorithm which interacts with data fusion processes at different information levels. The real data testing includes three radars located in a maritime surveillance area of interest. The results have proven that the proposed technique has an acceptable performance and computation complexity which is vital in real-time applications.

2. Multisensor data fusion techniques

The sensor fusion problem requires the development of methods to combine the data from multiple sensors for tracking and identification. These sensors could be radars, sonar, or Electronic Support Measure (ESM). The use of multiple sensors requires the fusion of different types of data such as sensor reports containing measured attributes (target type and feature), [4]-[9]. In a multisensor tracking system we must first define the level at which sensor data will be fused into tracks. There are three ways to combine the data: sensor-level, central-level, or combined data fusion, [10], [16].

The sensor-level fusion is shown in figure 1. Each sensor will maintain its own track file. Then, the sensor-level track files will be updated using communication links among the sensors and between the sensors and the central track file. The sensor-level tracks must be combined into a central track file. Thus, each sensor will have separate track files and a central track file will be formed as a composite of these files. The advantages of using sensor-level fusion are the reduced data-bus loading, the reduced computational loading, and the higher survivability due to distributed tracking capabilities. The disadvantages are due to the fact that the central-level tracks are updated with sensor-level track data, instead of sensor report data. If a central-level track is updated with a sensor-level track, the usual assumption of error independence from one update period to another is not valid.

The second alternative for combining the sensor data is the central-level fusion shown in figure 2. In this approach, all the report data are sent directly to a central processor where a master track file is maintained. The advantage of this approach is the improved tracking accuracy because the target track is performed using the observations from more than one sensor and thus resulting in fewer miscorrelations. Another advantage is the improvement of track confirmation and continuity. The disadvantage of using central-level fusion is when one sensor becomes faulty it will highly affect the central-level tracking performance, [4]-[9].

There are several other approaches which are intermediate between sensor-level and central-level tracking which is called hybrid or combined fusion. One method averages all the measurements from a given target for a certain time interval and uses this average to update the central track. Another method forms a central-level track from one of the sensors and then allows selected measurements from all sensors to update that central track as shown in figure 3, [4]-[9].

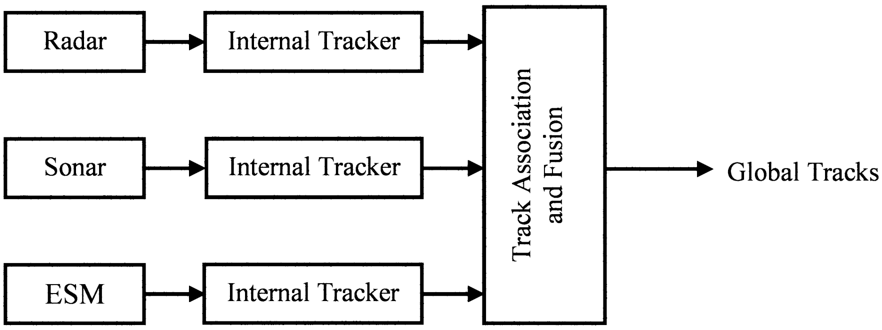

Figure 1. Decentralized sensor-level data fusion block diagram

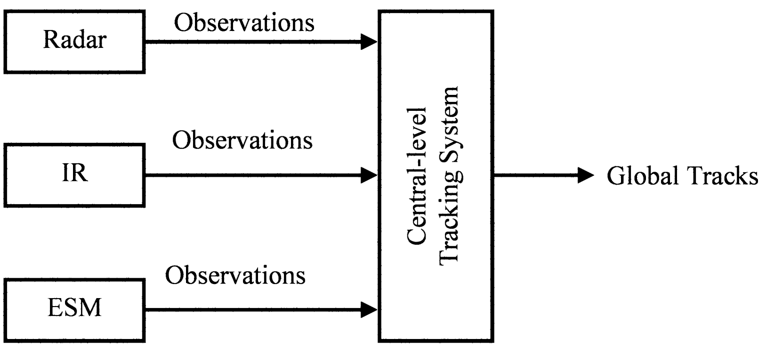

Figure 2. Central-level data fusion block diagram

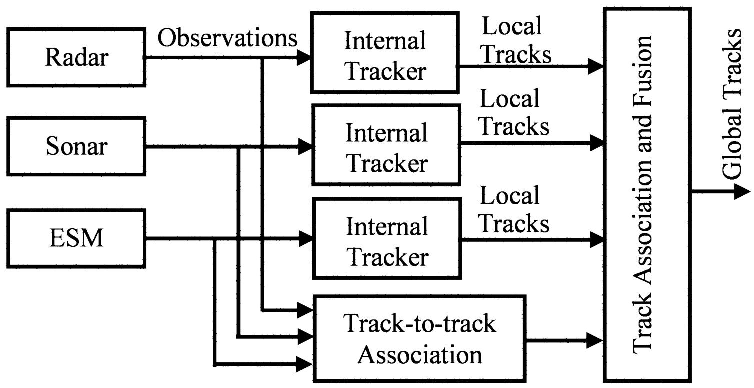

Figure 3. Combined position fusion block diagram

3. Fuzzy logic-based multisensor data fusion algorithm

Fuzzy logic is a design methodology that can be used to solve real world problems. It has the advantage of lower costs, superior features, and better performance. Fuzzy logic makes it possible to describe complex systems using the experience and knowledge of the experts in English-like rules, which are easy to learn and use, even by non-experts. The fuzzy technique does not require system modeling or complex mathematical equations. The design methodology is to first understand and characterize the system behavior by using our basic knowledge and experience and then design the algorithm using the fuzzy rules that describe the relationship between its input and output. This is done by debugging the design through simulations. If the performance is not satisfactory, then the rules are either modified or added to the existing fuzzy algorithm.

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. 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 (or tracks) measured from the same target. The sensor-level fusion is used in the proposed algorithm employing composite kinematic/Identification (ID) tracking scheme along with fuzzy logic. The proposed multisensor data fusion algorithm is shown in figure 4.

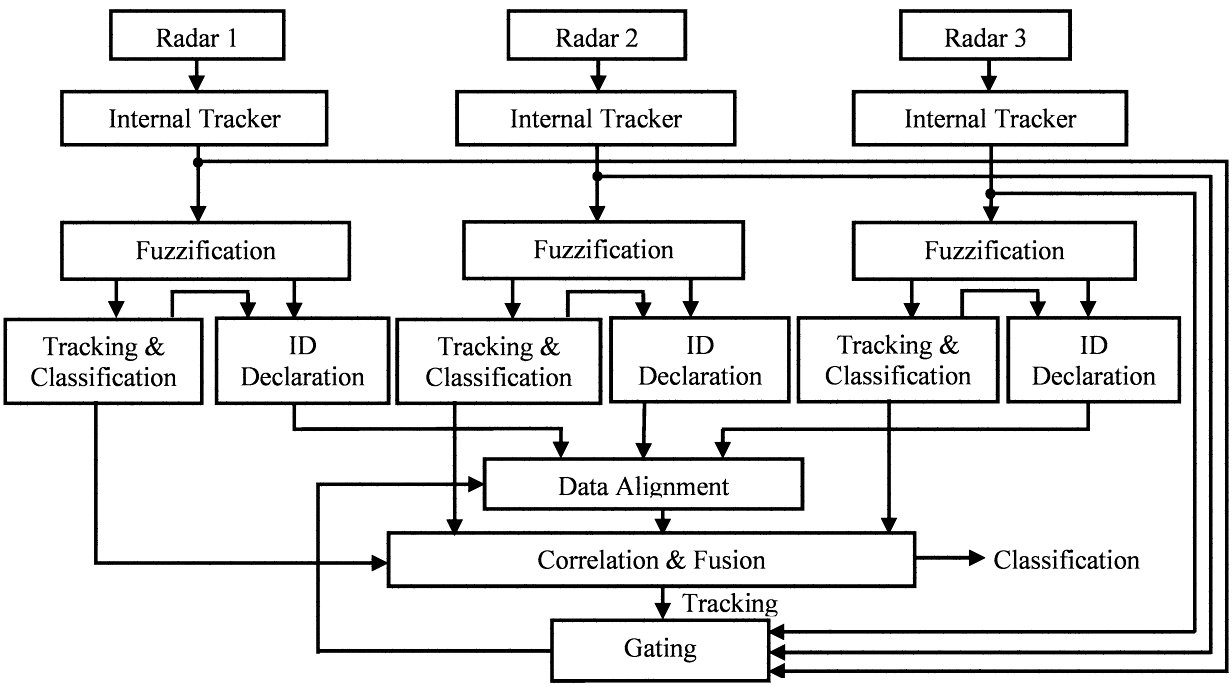

Figure 4. Fuzzy logic-based multisensor data fusion module

The data fusion algorithm accepts target list from each radar tracker then start the fuzzification process. The fuzzifier maps crisp input numbers into fuzzy input sets that can be used to activate rules which are in terms of linguistic variables with fuzzy sets associated with the latter. The fuzzification interface transforms each data received from the trackers into fuzzy variables. The number of fuzzy sets defined in the input discourse and their specific membership functions define the fuzzification interface design. The algorithm uses four membership functions; speed difference (ΔS), distance (D), course difference (ΔC), and correlation degree (F). The ID information is either manual (human input) or automatic Identification of Friend or Foe (IFF) and not involved in the fuzzification process. The speed difference, distance, course difference, and correlation degree membership functions are shown in figures 5, 6, 7, and 8, respectively.

An inference engine maps fuzzy input sets into fuzzy output sets. It handles the way in which rules are combined and emulates the expert's in interpreting and applying knowledge about the best association method. It uses the fuzzy rules in the rule-base to produce fuzzy conclusions, simulates human decision making procedure, and employs the fuzzy knowledge-base and fuzzy input to generate fuzzy decisions (outputs). There are two common methods to perform fuzzy logic inferences: the max-min and the max-product methods. In the max-min method, the final output membership function for each output is the union of the fuzzy sets assigned to that output, and the degree for the membership values are clipped at the degree of the membership for the corresponding premise. In the max-product method, the final output membership function for each output is the union of the fuzzy sets assigned to that output in a conclusion, and their degree of membership values are scaled to peak at the degree of membership for the corresponding premise.

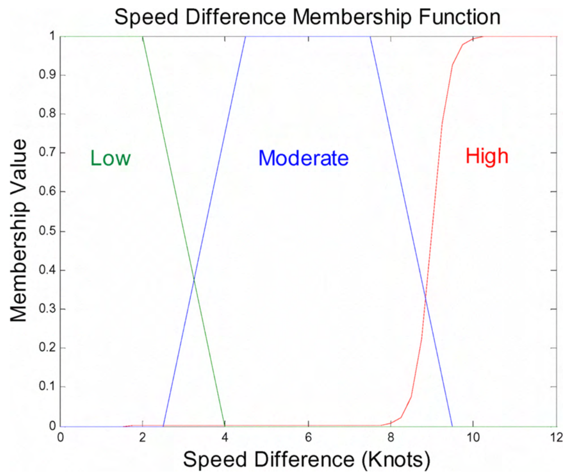

Figure 5. Speed difference membership function (ΔS)

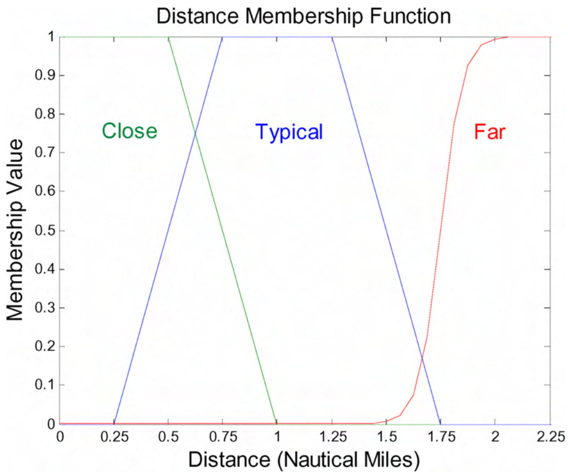

Figure 6. Distance membership function (D)

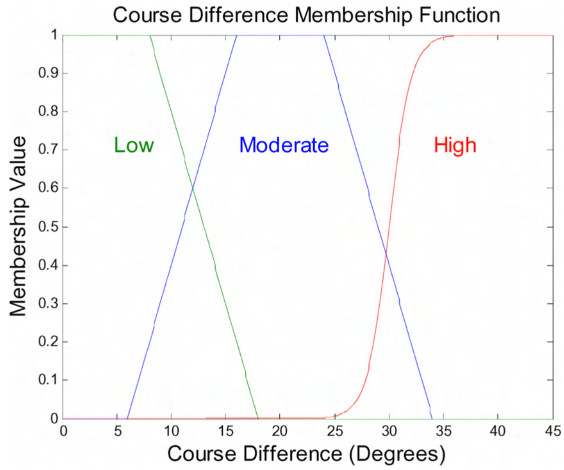

Figure 7. Course difference membership function (ΔC)

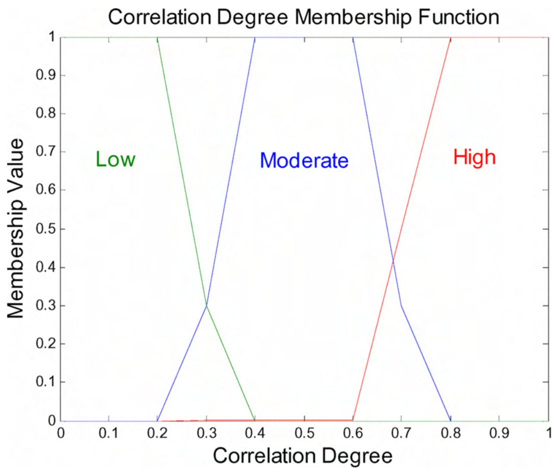

Figure 8. Correlation degree membership function (F)

In the present work, the Min-Max rule of implication is more appropriate, and thus we will use it in the fuzzy correlator. In the Min-Max rule of inference, the consequent fuzzy variable is restricted to the minimum of the predicate truth. The output fuzzy variable for the whole set of propositions is the maximum of the consequent fuzzy variable over the set of propositions. Let x_i be a point in the variable domain and $\mu_A(x_i)$ be the membership value in the fuzzy set A. The Min-Max rule of inference can be described by the following two steps:

1) Determine the consequent fuzzy set (cfs) for each proposition by restricting the consequent set to the minimum level of all the predicate fuzzy sets (pt):

$$\mu_{cfs}(x_i) = MIN(\mu_{pt}(x_i), \mu_{cfs}(x_i)) \quad (1)$$

2) Determine the solution fuzzy set (sfs) from the set of consequent fuzzy sets (cfs) calculated in step (i) by taking the maximum of the consequent fuzzy sets:

$$\mu_{sfs}(x_i) = MAX(\mu_{cfs}(x_i), \mu_{sfs}(x_i)) \quad (2)$$

In a data fusion system, the domains of the system variables to be considered are the speed difference domain, the distance domain and the course difference domain. In the speed difference domain, we have three fuzzy sets, namely; low, moderate and high ΔS. In the distance domain, we have; close, typical and far D. In the course difference domain, we have; low, moderate and high ΔC. In the correlation degree domain, we have; low, moderate and high F. It is noteworthy that each of these system variables is in fact a fuzzy set. The set membership is not a bivalent but a continuous function on the real interval [0, 1].

It was found practically that radars measure target's course erroneously due to the limited tracking capabilities of the coastal (navigational) radars. Hence the measured range and bearing can be used along with the time difference to calculate the targets' course and speed; the above mentioned parameters are calculated at each time instant for all track lists before the fuzzy correlation test is applied. Due to the inaccurate course measurement, ΔC fuzzy membership function is only used if the target course was calculated by the proposed data fusion module. The proposed fuzzy rule-base is summarized in table 1.

Table 1. Correlation degree (F) fuzzy rules

			ΔS		
		ΔC	*Low*	*Moderate*	*High*
D	*Close*	*Low*	High	High	Moderate
		Moderate	High	Moderate	Low
		High	Moderate	Low	Low

	Typical	*Low*	High	Moderate	Moderate
		Moderate	Moderate	Moderate	Low
		High	Moderate	Moderate	Low
	Far	*Low*	Moderate	Moderate	Low
		Moderate	Moderate	Low	Low
		High	Moderate	Low	Low

Defuzzification is the final phase of fuzzy reasoning. The evaluation of the model propositions is handled through an aggregation process that produces the final regions for each solution variable. The region is then decomposed using one of the defuzzification methods. The composite-moments method, also called the centroid or the center of gravity method, is used in the proposed data fusion module. The centroid method finds the balance point of the solution fuzzy region by calculating the weighted mean of the fuzzy region. Mathematically, for fuzzy solution region A, this procedure is formulated as:

$$\Re = \frac{\sum_{i=0}^{n} d_i \,.\, \mu_A(d_i)}{\sum_{i=0}^{n} \mu_A(d_i)} \qquad (3)$$

where $\Re$ is an element from domain of fuzzy set, d_i is the ith domain value, and $\mu_A(d_i)$ is the truth membership value for that domain point.

In the centroid defuzzification method, a point representing the fuzzy set's center of gravity is found. The centroid defuzzification is the most widely used technique because it has several desirable properties:

1) Defuzzified values tend to move smoothly around the output fuzzy region; that is, changes in the fuzzy set topology from one model to the next usually result in smooth changes in the expected values.
2) It is relatively easy to calculate.
3) It can be applied to both fuzzy and singleton output set geometries.

The correlation decision in the proposed data fusion module is based on a lower limit for succeeded correlation. The decision limit is chosen to be 75 % correlation coefficient as the lower limit for success. The resultant correlated track was calculated using succeeded track samples at each time index. The track parameters are calculated as the weighted sum of the succeeded samples. The weights are obviously the corresponding correlation coefficients for each track calculated using the above mentioned center of gravity method.

4. Real data testing

In this section, three distributed radars (Radar 1, Radar 2, and Radar 3) are used to track a single target in a network centric environment using the fuzzy logic-based multisensor data fusion algorithm proposed and detailed in section III. The radars are dissimilar 2-D navigational radars distributed over about 100 miles. The average maximum radars' range is 40 miles. A fast boat was used for the evaluation and testing of the proposed fuzzy logic-based data fusion module. The fast boat was used as a case-study target where its path was planned beforehand such that it should be tracked by at least two radars during the navigation path. The average speed of the fast boat was approximately 20 knots. The other targets happen to be in the planned area were rejected from the source, i.e., the three radars have only tracked and sent one target (the fast boat).

Since the real data testing is expensive, the data was received from the four radars and recorded at the fusion center then introduced to the data fusion module where the data was correlated and fused. The analysis of the results can be shown in figure 9 through 11. Figure 9 shows the location and coverage of the radars (R1, R2, and R3). Figure 10 shows the fast boat (target) track as recorded from the boat global positioning sensor (GPS) and collected at the fusion center on time using wireless communication radios. This track will be used in the analysis as the target reference position assuming that satellite errors in calculating the position is minimal and time and coordinates alignment between radars is performed accurately.

Table 2 shows a sample of the real data results for radar number 2. The speed and course differences in the table were calculated using the information of target's successive positions and the time interval. Fortunately, all data in the selected sample pass the correlation test. The correlation coefficients are higher than the decision lower limit. The resultant correlated track was calculated using the weighted sum of the success samples and the weights obviously are the correlation coefficients.

Figure 11 shows the three tracks collected simultaneously from the three radars and the resultant correlated track. The figure reveals that the correlated tracks is more accurate and smooth than any other single track form the radars. The correlated track is compared to the reference target track and shows absolutely negligible errors. The result depicts the superiority of the proposed technique over the classical techniques in terms of simplicity, complexity, and cost.

The behavior of the three radars is dependent on the target location, i.e., the errors are minimal when the target in front of the radar location and increases as the target goes far. It is evident from results that the accuracies of radars are not the same depending on the calibration, age, and technology (tracking scheme) for each radar.

Note that, not all track samples are correlated from the three radars at all time indices due to existing errors. Also, the target cannot be tracked by the three radars at all time indices due to the limited radar coverage. The proposed tracking and classification module handles the data discontinuity from the radars and assist in the correlation and fusion process so that the track-to-track fusion process takes into consideration the identification and classification as primary keys.

Table 3 shows the probability of detection and correlation for the three radars. The probability of detection here means the probability of the target falls within the radar coverage area. The probability of correlation is calculated as the ratio of the number of correlated track samples and the overall number of target samples while falling in the coverage area of the radar.

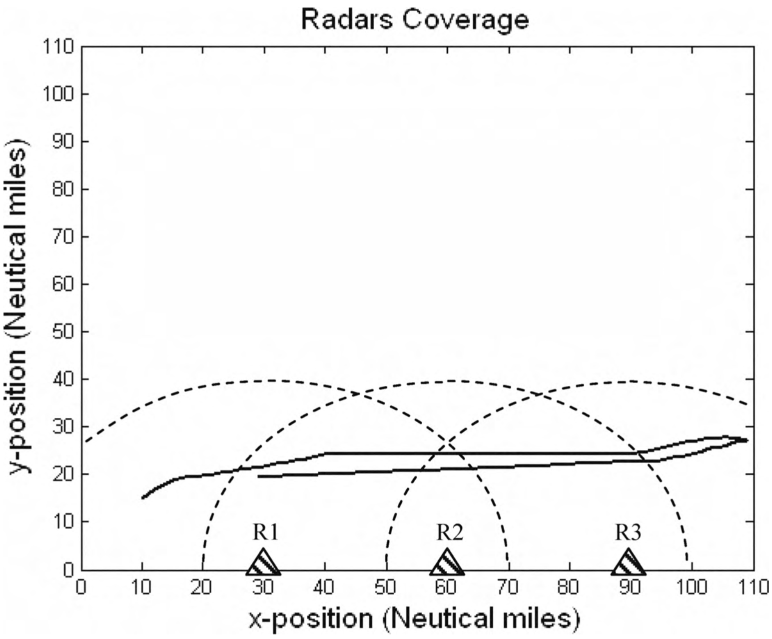

Figure 9. The three radars coverage relative to the target track

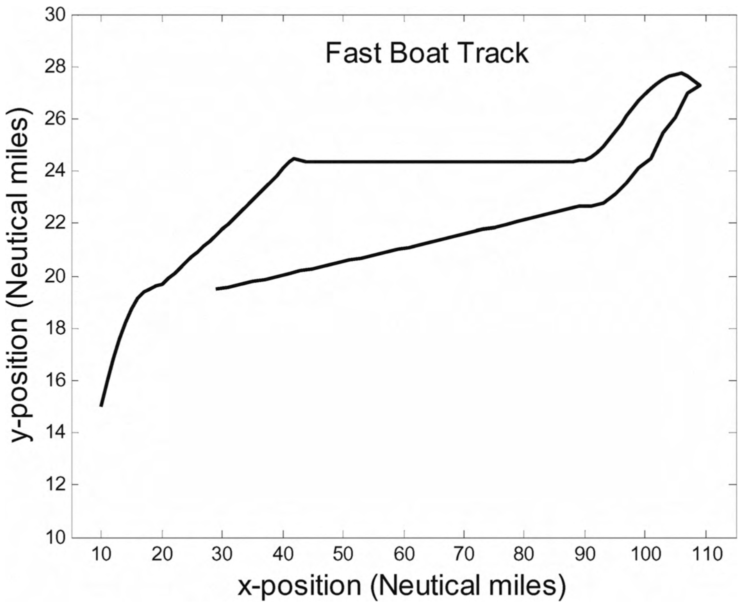

Figure 10. The fast boat track received by fusion center

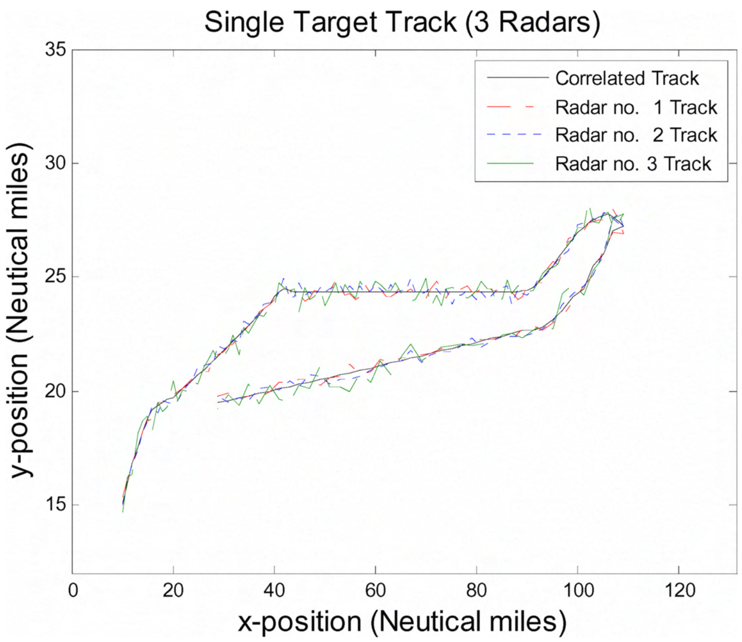

Figure 11. Radars' tracks vs correlated track

Table 2. Sample of real data results (radar number 2)

Time index	ΔS	D	ΔC	F (%)
51	1.3865864	0.1331630	6.0208350	94.23 %
52	2.3333083	1.9766035	19.976711	83.16 %

53	1.0268774	0.3617085	10.688885	90.76 %
54	1.5557581	0.2441399	8.5545368	93.46 %
55	1.1572458	0.1158630	4.2087847	96.15 %
56	1.1162364	0.0932534	5.3620936	96.33 %
57	2.4263866	1.7740173	16.020117	85.46 %
58	1.4956162	0.1844793	2.9949045	95.45 %
59	1.0305490	0.1577583	1.0063926	98.76 %
60	1.5078351	0.0256075	3.5970064	95.55 %

Table 3. Detection and correlation probability

Probability / Radars	Probability of Target Detection	Probability of Correlated Track
Radar no. 1	53 %	98 %
Radar no. 2	92 %	90 %
Radar no. 3	66 %	84 %

5. Conclusions

In the maritime surveillance, multiple observations and existing knowledge are employed using data fusion. Multisensor data fusion is one of the effective approaches for solving different sets of problems having common characteristics. It uses the data from multiple sensors to perform inferences that may not be possible from a single sensor alone. A fuzzy logic-based data fusion technique has been exercised against realistic real time scenario. It has been observed that the algorithm can handle multiple dissimilar sensor data, which are encountered in the real situations. On the basis of the results, it is evident that the proposed data fusion algorithm is an excellent alternative to the probabilistic based data fusion schemes when dealing with a large scale maritime surveillance area due to the design and implementation simplicity, the reduced computation complexity and the ability of dealing with multiple targets at low signal-to-noise ratio environments, [12]-[16].

The large-scale maritime surveillance system involves the multiprocessing between distributed data, external interfaces to real-time sensors, mobile platform constraints, and reliability requirements. It also involves data fusion systems which include the fusion algorithm selection, proper timing to fuse data, and man-in-the-loop role. Future work is directed towards adding two issues to the fusion testbed. Firstly, man-in-the-loop which assess in the decision-making process based on the situation and threat assessment measures. Secondly, the model selection module which will allow the choice of the suitable association technique based on the maritime situation measures.

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