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INFORMATION FUSION IN UNDERWATER SONAR SIMULATION

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ABSTRACT

This paper discusses information fusion methodologies, selection of one of these methodologies, and application of these fusion methodologies to underwater sonar simulation. Bayesian Inference and Dempster-Shafer are the two methods that have been studied in detail. In conclusion, the Dempster-Shafer approach was selected as the preferred method. Dempster-Shafer's main advantage is that it does not need conditional likelihoods. Also, Dempster-Shafer does not have computational complexity problems when multiple hypotheses and multiple conditional dependent events are examined. This method was applied to the multisensor information fusion problem in a simulation which includes a passive sonar, an active sonar, and a radar. The simulation is conducted on a geographical information system.

1 INTRODUCTION

In the past researchers' main problem was to obtain the information itself. However, the amount of available information has increased so dramatically over the last few decades, now the new problem is joining information from different sources and obtaining a single vision of the facts. This is exactly the problem of multisensor data fusion for underwater sonars. Since different sensors have different capabilities for detecting underwater entities, each sensor gives partial or deviated information of the whole object. Only after systematic information fusion, navy ships can identify the entities and decide their subsequent actions.

There are different information fusion methods but the benefits depend on the objective or the level in which the fusion will be applied. Hall and Llinas (1997) divide the information fusion to the following steps:

a) Determining the target's position and velocity from a noisy time-series of measurements. Kalman filter and its variants are proposed at this stage.
b) Establishing target identity: A transformation must be made between observed target attributes and the labeled identity. Techniques such as clustering algorithms (feature-level fusion), neural networks (feature-level fusion), template methods (feature-level fusion), Bayesian inference (decision-level fusion), Dempster – Shafer (decision-level fusion), and weighted decision (decision-level fusion) are used at this stage.
c) Interpreting the target's intent: Rule-based reasoning systems (knowledge-based methods), and fuzzy logic.
d) Quantifying the effectiveness of data fusion system: Monte Carlo simulations, and covariance error analysis techniques.

The focus of this paper is decision-level fusion using Bayesian and Dempster-Shafer inference. Section 2 summarizes previous work from our research team on modeling the effectiveness of underwater sonar, a project funded by the Office of Naval Research. Bayesian Inference and Dempster-Shafer methods are discussed in section 3. A brief literature review of the results obtained from other authors using similar methods for the information fusion problem is also shown. We also discuss the implementation of the methods in the information fusion problem in a simulation model that represents the navy surveillance. The implementation of the enhanced simulation model is shown in section 4. The conclusions and future extensions are discussed in section 5.

2 PREVIOUS WORK

A simulation environment has been created which uses a hybrid simulation modeling environment (agents, discrete-event, and system dynamics) integrated to a Geographical Information System (GIS) engine, ArcGIS. This environment simulates a Navy ship which tows an array of sensors; some passive and some active. Sensors are used to detect and classify all objects within a given detection range. Sensors include radar, sonar, infrared and optic sensors. Ships also carry integrated surface picture capabilities to reduce the false alert rate.

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The hybrid simulation modeling system was built using AnyLogic™, a simulation software developed by XJ Technologies (XJ Technologies 2008). AnyLogic™ was selected, among other reasons, because it is based on Java, an object-oriented programming (OOP) language. OOP is desirable as it allows reusability, extensibility, and maintainability of the previously built model (Akin, Zhu, Bull, Rabelo and Sepúlveda 2008). On the other hand, ArcGIS Engine (ESRI 2008) was used to provide GIS services (maps and querying capabilities) to the simulation model and to dynamically display the simulation outputs (Zhu, Sala-Diakanda, Rabelo, Sepúlveda, and Bull 2007). As the simulation runs, its objects (the different ships and animals) routinely request geographic information with respect to their positions. Depending on the information provided, such as proximity to land, other ships, or water depth, the simulation model may modify the attributes (such as their course) of some objects. ArcGIS Engine then uses this information to dynamically update the display of the simulation (Figure 1).

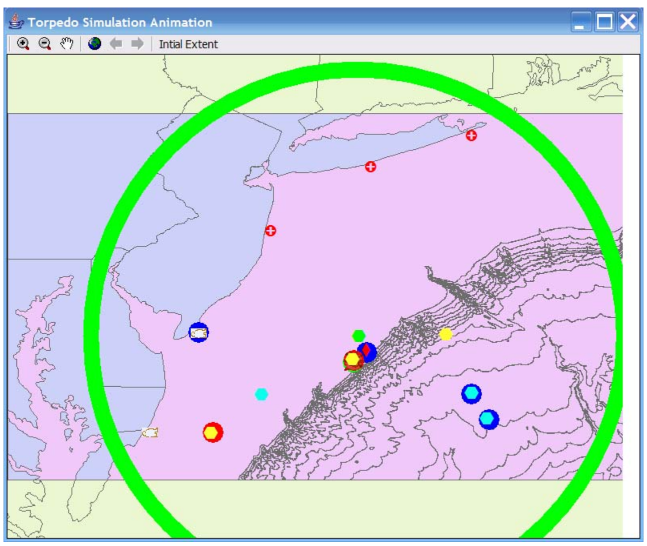

Figure 1: Simulation scenario using the different geographical databases for the coast and inland ports of Northeast United States, Zhu et al. (2007) p 1384.

The goal of this simulation environment is to assess the decision-making effectiveness of the sensor system as a whole. Therefore, the implementation of information fusion methods to obtain a higher performance classification system as a result of the different sources of sensor data is an evolutionary step for this simulation environment.

2.1 Advantages of GIS based simulation

The main advantage of a GIS based simulation is that it better mimics the real simulation environment. For instance on a 2D environment if you map a 300 nautical mile by 500 nautical mile rectangle area, it would be an exact rectangle. However, it is not possible to come up with a perfect rectangle on the earth since the shape of the earth is not flat. Figure 2 shows an example area to the north-east of Hawaii. Even though the sides of the area are exactly 500nm and 300nm the shape is not a 2D rectangle. If you would check the diagonals you will see that one of them is 593.4nm the other is 573.4nm. If this was a 2D rectangle both diagonals would have been 583 nm. Therefore using GIS based simulations will result in more accurate results.

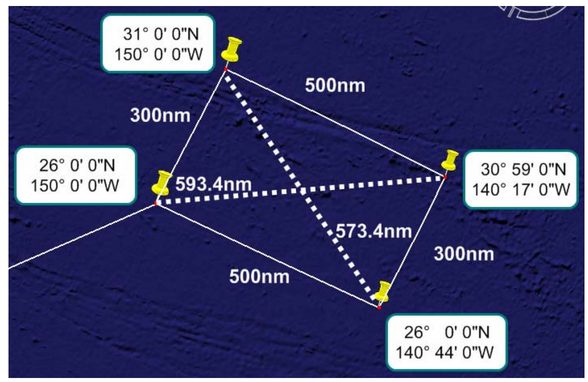

Figure 2: Distances on real GIS

Another advantage of using GIS based simulations is the possibility to create realistic logs of the action which takes place in the simulation. Therefore once the simulation is complete we could feed the log into SIMDIS (Simdis 2008) and get a 3D representation of the simulation.

3 INFORMATION FUSION METHODS

The literature offers several methods for information fusion, for determining the target's position and velocity, and also for establishing the target's identity. To determine the position and velocity, sequential estimation techniques and Kalman filter are used. These methods seek an equation that estimates an a-posteriori state as a linear combination of a-priori states.

Once the position and velocity is determined, we need to solve the association problem for which we have Clustering Algorithms, Heuristic Methods, Artificial Neural Networks, Bayesian Inference, and Dempster-Shafer methods. Clustering Algorithms is a set of algorithms that require the definition of an association measure to define closeness between two observed feature vectors (Hall 1992). These are feature-level fusion techniques that allow separation of the data into identifiable groups. Although these techniques are used by several authors in our case clustering the information obtained from different sonars does not give a relevant result in the process to identify entities.

Heuristic method for identity detection considers Voting, Scoring model (weighted), Ordinal ranking, Q-sort, and

Pairwise ranking. However, to build these heuristics one needs to gather a large amount of historical data to create the suitable weight for each sensor and most of the time these heuristics need specific parameters which do not allow the standardization of the procedures for different scenarios in the simulation (Hall 1992; Hall and Nauda 1990; Ku and Choi 2000; Steinmetz et al. 1996,).

According to Hall and McMullen (2004), an artificial neural network is an interconnected group of artificial neurons that uses a mathematical or computational model for processing information. In general, data vectors are input of the network and the neural network performs a nonlinear transformation, given an output vector. Neural networks need examples and historical data to be trained. In our case, we do not have historical and benchmark data.

Bayesian inference is a theory for the mathematical representation of uncertainty which focus on aleatory uncertainty (which results from random behavior). The method is based on the establishment of a hypothesis of which the likelihoods are updated according to incoming new additional evidence. This method allows us to identify the entity when we have new information through time. Bayesian inference is further explained in section 3.1.

The other method we studied was Dempster-Shafer (D-S), another theory for the mathematical representation of uncertainty, which focus on epistemic uncertainty (results from lack of knowledge), also called subjective uncertainty or ignorance. The focus of D-S theory is to determine a set of intervals (lower bound, called "belief" or "support," to upper bound, called "plausibility") and assign a probability mass to each interval in the set. Thus, D-S allows building interval probabilities and uncertainty intervals to determine the likelihood of hypotheses based on multiple evidences. This method is explained in section 3.2.

3.1 Bayesian inference

Bayesian Inference method updates the likelihood of a hypothesis given a previous likelihood estimate and additional evidence such as new observations.

In order to apply this method we need to identify:

- Mutually exclusive and exhaustive hypotheses that can explain an event E that has just occurred. These hypothesis are represented by $H_1, H_2, H_3, \ldots, H_j$
- A-priori probability of hypothesis H_i being true, $P(H_i)$
- The conditional probability of observing evidence E, given that H_i is true, $P(E/H_i)$
- The sum of all the a-priori probability must be one, $\sum_i P(\mathrm{H}_i) = 1$

Then, the a posteriori probability of hypothesis H_i being true given the evidence E has been observed is given by

$$P(H_i / E) = \frac{P(E/H_i)}{\sum P(E/H_i) P(H_i)}$$

Hall and McMullen (2004) indicate that the ability to use subjective probabilities for a priori probabilities for hypotheses, and for the probability of evidence given a hypothesis, allow implementation of Bayesian inference process for multisensor fusion since probability density functions are not required.

3.2 Dempster-Shafer method

The Dempster–Shafer method uses probability intervals and uncertainty intervals to determine the likelihood of hypotheses based on multiple evidences. This method can be used on propositions that may contain overlapping or conflicting hypotheses.

In order to apply D-S method it is necessary to define:

- An elemental set of propositions called the frame of discernment. This set is composed by n mutually exclusive and exhaustive set of propositions in regard to a subject area, such as $\theta = \{A_1, A_2, A_3, .. A_n\}$
- A set that includes 2^{n-1} general propositions by boolean combinations of the θ set. This set is called 2^θ and it is defined as

  $2^\theta = \{ X_1=\{A_1 \vee A_2\}, X_2=\{ A_1 \vee A_3\}, \ldots, X_m=\{ A_1 \vee A_2 \vee A_3 \vee \ldots \vee A_n\}$
- One important general proposition inside of 2^θ is the boolean disjunction of all of the elementary propositions ($\bar{X} = A_1 \vee A_2 \vee A_3 \vee \ldots \vee A_n$) which is equivalent to a general level of uncertainty or to saying that "we don't know." In particular, if $m(\bar{X}) = 1$, the sensor is unable to distinguish among any elementary proposition.
- The probability mass, m(X), is a concept developed in D-S to represent assigned evidence. A sensor may assign probability masses to an elementary proposition or to a general proposition in the set 2^θ, such as $m(A_1)$, $m(A_2)$, or m(X). m(X) represents the proportion of all relevant and available evidence that supports the claim that the actual state belong to X but not to a particular subset of X
- Each probability mass must be less than or equal to one and their sum over all of the elements must be one.

  Each $m(X) \leq 1$ and $\sum_{i=1}^{n} \mathrm{m}(Xi) = 1$
- The probability of a proposition A_i is given by the sum of $m(A_i)$ for the element of θ that contains A_i exactly,

and m(X) for those general propositions in 2^θ that contain A_i as an element.

$$\Pr obability\{A_i\} = \sum_{A_i \in \theta, 2^\theta} m(\theta, 2^\theta)$$

Then the Dempster-Shafer approach gives evidential intervals for each A_i or X_i, denoted by [Spt (A_i), Pls (A_i)] or [Spt (X_i), Pls (X_i)] respectively. Where supportability (Spt) assigns probability masses to an elementary proposition or to a general proposition in the set 2^θ (the sum of the masses of all subsets of A_i)

$$Spt[A_i] = \sum_{A_i \in \theta, 2^\theta} m(\theta, 2^\theta)$$

The plausibility of a proposition A_i, is defined as the lack of evidence supporting its negation (~A). It is the sum of all the masses of all sets that intersect A_i.

Pls (A_i) = 1- Spt (~A_i)

Then, Spt (A_i) ≤Pr(A_i) ≤ Pls (A_i)

Liu, Tan, and Yang (2003) show the Dempster combination rule to fuse information from two resources as

$$m(A) = m_1 \oplus m_2 = K \sum_{B_i \cap C_j \neq A} m_1(B_i) m_2(C_j)$$

where

$$K^{-1} = \sum_{B_i \cap C_j \neq \Phi} m_1(B_i) m_2(C_j)$$

In this rule, $m_1 \oplus m_2$ is the orthogonal sum operator; K is a measure of the amount of conflict between the two mass sets; and (1-K) is a normalization factor used to ignore conflict.

Bayesian Inference and the Dempster-Shafer method produce identical results when all of the hypotheses considered are mutually exclusive and the set of hypothesis is exhaustive.

4 IMPLEMENTATION

In our previous work (Sepúlveda et al. 2006; Zhu et al. 2007; Akin et al. 2008) we developed a framework to evaluate the effectiveness of an underwater sonar system to detect and differentiate entities. However, the sensor fusion part was not fully implemented previously. Thus, this paper focuses on the multisensor data fusion analyzing and comparing different sensor fusion algorithms. In the next subsections we will discuss the implementation of multisensor data fusion algorithms in our scenario.

4.1 Description of the scenario

In the modern era of ocean combat, one of the main tasks is to identify possible torpedo attacks. There are many different entities in the sea, such as animals and ships. A navy ship patrols around the ocean with a set of sensors monitoring its environment. These sensors need to detect all different objects and differentiate these entities from torpedoes.

A typical scenario in this paper is that a navy ship gathers information from different sensors. Based on their data inputs, we need to fuse them together to identify potential suspects. The simulation models the sensor fusion process and then calculates the efficiencies of different fusion algorithms.

4.2 Incorporation to the simulation model

A navy ship has a set of sensors including passive sonars, an active sonar, and a radar. Different sensors have different detection capabilities. A data fusion structure needs to be implemented to fuse data together to identify and classify suspects. There are two important aspects in this process: target tracking and sensor fusion.

4.2.1 Tracking structure

The tracking process deals with the association of the current detection with previous historical data. There are three steps in this process: alignment, association, and updating.

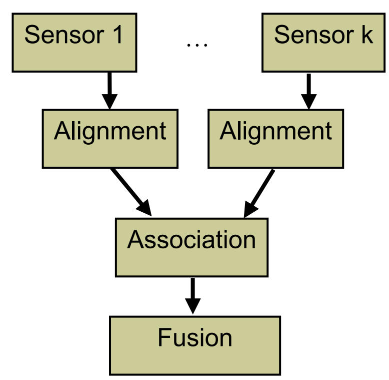

Figure 3: Tracking structure

Alignment deals with the spatial registration or temporal prediction of the target tracks based on the inputs of different sensors. The first step in this process is to convert the data from different sensors to a common coordinate system.

In association, we organize the data from different sensors into different sets by predicting whether they were originated from the same targets. Based on different tracking models (whale, navy ship, enemy ship), we can compute the extrapolated tracks. By comparing extrapolated tracks, the current positions and possible errors, we can associate the data input. In this paper we implement the Joint Probabilistic Data Association (JPDA) algorithm (Bar-Shalom, Fortmann, Scheffe 1980). JPDA applies a Bayesian estimate of the correspondence between features detected by sensors and targets to be tracked. It computes the probabilities of association of the set of measurements to various targets at time t.

After association, we update the states for each tracked entity. We will discuss the updating process in the next subsection.

4.2.2 Data fusion structure

Basically there are two different data fusion issues: spatial fusion and temporal fusion. Spatial fusion fuse data gathered from different sensors at the same time. Temporal fusion deals with the fusion of historical data with current inputs from different sensors. Many different fusion architectures available have been discussed in the literature, such as centralized, hierarchical, and distributed. In our model we design a hierarchical fusion architecture which can fuse data from different sensors both spatially and temporally (Liggins et al.1997).

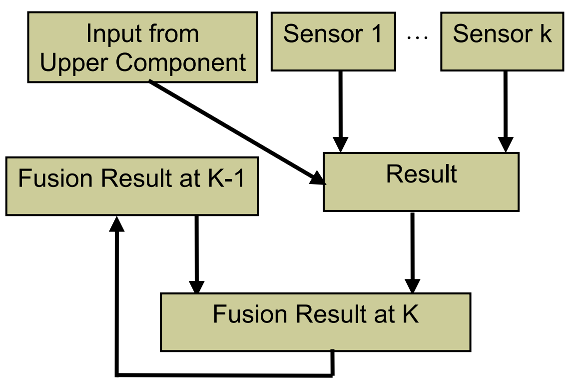

Figure 4: Spatial-temporal sensor fusion structure

Figure 4 shows the spatial-temporal sensor fusion architecture at modular level. *Input from Upper Component* is the data input from upper modules. *Sensor 1* and *Sensor 2* here are sensors which belong to this module. *Result* is the sensor fusion result from the data inputs mentioned above. *Fusion Result at K-1* is the previous final sensor fusion at time *K-1*. *Fusion Result at K* is the final fusion result at this moment, which will be used to update the data stored in *Fusion Result at K-1* and will be used as the *Input from Upper Component* of the next module.

Figure 5 shows the procedural structure of the fusion system. There are three different modules in the system which procedurally fuse data from different types of sensors.

- *Passive Sonar Data Fusion*

Passive sonar listens to the environment and receives information passively. Once it detects any signal, it will trigger the sensor fusion process. The module fuses data from different sensors (or different measurements). Once it reaches a threshold, if the object is classified as a threat, the module will trigger the *active sonar data fusion* and its related active sonar.

- *Active Sonar Data Fusion*

Active sonar scans the environment by pinging and then analyzing rebounding signals. *Active sonar fusion* fuses data from different active sonars. Once it reaches a threshold, if the object is confirmed as a threat, *radar sonar data fusion* will be triggered.

- *Radar Sonar Data Fusion*

This module is more about confirming whether an object is detectable as above or under water. Radar scans the environment and then analyzes the rebounding signals. Data inputs from different radars and previous module will be fused here. If a threshold is reached, the countermeasures system will be alerted.

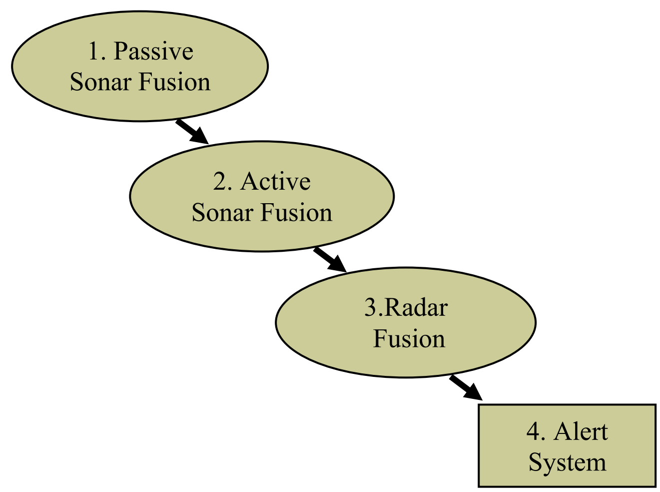

Figure 5: Procedural sensor fusion structure

4.3 Algorithm comparison

This section describes a simulation experiment devised to compare the behavior of the Bayesian and D-S algorithms for an underwater sonar system.

Figure 6 describes the pattern (distributions) of the noise made by different simulated objects. For the experiment, it was assumed that the noise patterns are uniform for almost all ships except by “old” enemy ships and that the noise caused by sea animals is uniformly distributed. Table 1 and Table 2 show probability distributions over sound ranges.

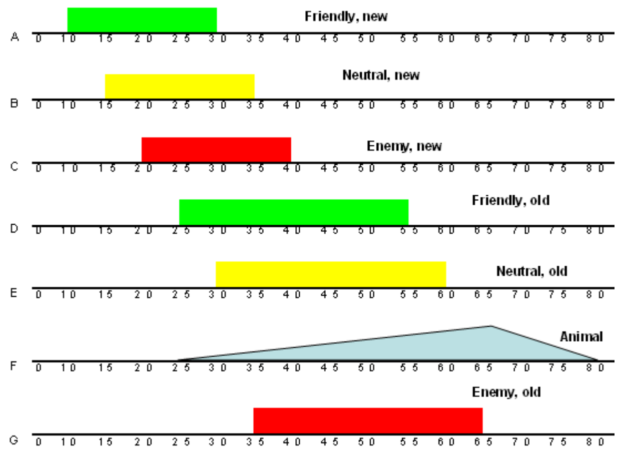

Figure 6: Noise Patterns (distribution)

Table 1: Probability Distributions over Sound Ranges for Passive Sonar

L.B.	U. B.	A	B	C	D	E	F	G
[13	,18]	1	0	0	0	0	0	0
(18	,23]	0.5000	0.5000	0	0	0	0	0
(23	,27]	0.3333	0.3333	0.3333	0	0	0	0
(27	,30]	0	0.5000	0.5000	0	0	0	0
(30	,32]	0	0.3704	0.3704	0.2593	0	0	0
(32	,34]	0	0	0.5882	0.4118	0	0	0
(34	,35]	0	0	0.5840	0.4088	0	0.0071	0
(37	,40]	0	0	0	0.4538	0.4538	0.0923	0.0000
(40	,50]	0	0	0	0.2955	0.2955	0.1134	0.2955
(50	,55]	0	0	0	0	0.3780	0.2439	0.3780
(55	,60]	0	0	0	0	0	0.4504	0.5496
(60	,71]	0	0	0	0	0	1.0000	0

- L.B.: Lower bound
- U.B.: Upper bound

Table 2: Probability Distributions over Sound Ranges for Active Sonar

L.B.	U. B.	A	B	C	D	E	F	G
[10	,15]	1	0	0	0	0	0	0
(15	,20]	0.5000	0.5000	0	0	0	0	0
(20	,25]	0.3333	0.3333	0.3333	0	0	0	0
(25	,30]	0.2694	0.2694	0.2694	0.1796	0	0.0123	0
(30	,35]	0	0.2882	0.2882	0.1921	0.1921	0.0393	0
(35	,40]	0	0	0.3099	0.2066	0.2066	0.0704	0.2066
(40	,45]	0	0	0	0.2876	0.2876	0.1373	0.2876
(45	,50]	0	0	0	0.2767	0.2767	0.1698	0.2767
(50	,55]	0	0	0	0.2667	0.2667	0.2000	0.2667
(55	,60]	0	0	0	0	0.3465	0.3071	0.3465
(60	,65]	0	0	0	0	0	0.5056	0.4944
(65	,80]	0	0	0	0	0	1	0

4.3.1 The Experiment

In the simulation, an object (ship or animal) is created and generates noises in the appropriate range level. For example an old neutral ship generates a noise of 52 units. The passive sonar detects the noise and tries to classify the object, first using Bayesian and then using the D-S algorithm.

For Bayesian, the simulation starts with the same a-priori probability (1/7) for each object. The a-posteriori probability for each object is then calculated based on the prediction by the sensor (table 1).

For D-S, the simulation starts with probabilities of the first prediction of the sensor. In other words, there are no a-priori probabilities.

The simulated object then generates another noise in the appropriate noise level and the passive sonar fuses this new information with the previous assessment. In other words, Bayesian uses a-priori probabilities from the previous iteration and calculates a new set of values for the a-posteriori probabilities. D-S, on the other hand, uses the Dempster combination rule to fuse the current observation with the previous one and determine new lower (support or belief) and upper limits (plausibility) for the probabilities. This is repeated over and over until a decision threshold is reached. We set, arbitrarily, a value of 75% as the cut-off value for a decision (for the a-posteriori probability or the support level, as appropriate). We record the number of iterations needed by each algorithm to reach a classification decision and more importantly, the active sonar will be triggered.

Active sonar differs from passive sonar in the way that the active sonar sends out signals to detect objects instead of listening to the noise passively (see table 2). When there is a bounced signal, the active sonar analyzes it. Active sonar is comparatively more precise. The sensor fusion rules are the same. A value of 90% is set as the cut-off value for a decision. The number of iterations to reach a classification decision will be recorded and the radar will be triggered.

Radar differs from active sonar and passive sonar in the way that it can only detect objects above water. Thus, the radar can only classify the objects above the water. Cut-off value for a decision here is 95%. Related data will be saved and a signal will be sent to the ship. For objects under water, radar can only judge whether it is detectable or undetectable. In this simulation, we arbitrarily classify the objects to be underwater if the radar cannot detect it in two consecutive cycles. If it is an underwater object, the classification is solely based on the prediction from the active sonar.

Then, we determine for each decision reached if the outcome is TP (True Positive), TN, FP, or FN, as shown in Table 3.

Table 3: Sensor Classification

Object	Sensor Classifies the object as	
	Friend/Neutral/Animal	Enemy
Friend/Neutral/Animal	TN	FP
Enemy	FN	TP

We repeat the above procedure a number of times for different types of objects and then we calculate the sensitivity and specificity of the sensor for each approach (Bayesian and D-S), as shown in Table 4.

Table 4: Measure of Performance for Sensor Fusion

Measure of Performance	Formula	Comments
Sensitivity The ability to detect a threat.	TP / (TP + FN)	If sensitivity = 1, then FN = 0, this means we do not miss any enemy
Specificity The ability to react to react to real threats only.	TN/(TN + FP)	If specificity = 1, then FP=0, this means we do not react to harmless objects.
Efficiency Fraction of signals (objects) correctly classified.	(TP + TN)/ (TP+FP+TN+FN)	A combined measure of performance.

The next section discusses the effect of the algorithm with respect to the number of iterations need to reach a classification of the object and the quality of the decision (sensitivity and specificity).

Note that, if the object is classified as a threat by the passive sonar, the system activates the active sonar. The fusion of passive and active sonar decisions is also done using Bayesian or D-S. The starting a-priori probabilities for the active sonar may be the same as used by the passive sonar (e.g., assumes independence of the sensors) or the a-posteriori probabilities determined by the passive sonar at the iteration when the active sonar was activated.

4.3.2 Results and discussion

Results of the simulation are listed in the table 5 and table 6 for passive sonar and active sonar respectively. These tables are summarized from 6 runs for each method with each run to classify 2000 objects.

Table 5: Statistics of Passive Sensor

	D-S	Bayesian
TN	1,409	1,402
TP	523	525
FN	46	48
FP	22	25
Sensitivity	0.9199	0.9159
Specificity	0.9846	0.9823
Efficiency	0.9663	0.9633
Mean (Iterations)	5.6961	5.6711
St.dev. (Iterations)	4.6351	4.6098

Table 6: Statistics for Active Sonar

	D-S	Bayesian
TN	1,430	1,426
TP	551	555
FN	18	19
FP	2	1
Sensitivity	0.9692	0.9676
Specificity	0.9990	0.9991
Efficiency	0.9905	0.9900
Mean (Iterations)	2.0967	2.1016
St.dev. (Iterations)	0.3962	0.4186

Based on the results, the performances of D-S and Bayesian are not significantly different. Both of them have good performance in classifying different objects. However, D-S performed slightly better.

One important observation is that the probability distribution is very important. Different probability distributions result in different performances. Thus, it is hard to pick one method over the other. However, one of the fundamental differences between the D-S and Bayesian is that Bayesian requires that the sensors should have clearly set possibilities for all the entities; however D-S allows less defined probabilities. Since Bayesian requirement of "clearly set possibilities" is not realistic, D-S would have been our choice if we had to pick one of these methods.

5 CONCLUSIONS

In this paper we evaluated the application of sensor fusion method in the navy detection system. Two different sensor fusion methods, Bayesian Inference and the Dempster-Shafer methods, have been evaluated and compared. Based on the simulation results, both Bayesian Inference and Dempster-Shafer produced good results when all of the hypotheses considered are mutually exclusive and the set of hypothesis are exhaustive.

Even though Dempster-Shafer and Bayesian Inference showed close results and performances based on the experiment, in real life situations it is unlikely to have mutually exclusive probabilities and a set of exhaustive hypotheses. So, Bayesian Inference does not appear to be suitable for multisensor fusion in Navy environment, as it does not allow us to incorporate uncertainties such as "we do not know." As a result we believe Dempster-Shafer method better suits the needs of multisensor fusion problem of the Navy ship.

For future research, further analyses of different sensor fusion methods with different possibility distributions are necessary. The sensor fusion infrastructure needs to be integrated into our Navy defense system simulation model and tested against different test scenarios.

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