

Uncertain Information Fusion for Force Aggregation and Classification in Airborne Sensor Networks

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Abstract

The paper describes airborne sensor networks for target tracking and identification in military applications. The raw information about targets from airborne sensors is uncertain and often noisy. One challenge in airborne sensor networks is how to effectively fuse enormous amounts of uncertain and noisy information for better battlefield situation assessment. In this paper we present a novel approach to military force aggregation and classification using Dempster-Shafer theory and doctrinal templates. Our approach helps commanders understand operational pictures of the battlefield, e.g., enemy force levels and deployment, and make better decisions than adversaries in the battlefield. A sample application of our approach is illustrated in the simulated testbed OTBSAF and RETSINA system.

Introduction

Sensor networks are emerging as a new trend in information technology for monitoring and collecting information in both military and non-military applications. In a military context, various airborne sensors, e.g., SAR (Synthetic Aperture Radar), EO (Electro-Optical radar), and GMTI (Ground Moving Target Indicator), are deployed in the battlefield for target tracking and identification. These sensors are mounted on a number of platforms such as a C-130, F-16, or UAV. For example, a SAR sensor can recognize the location and identity of a stationary target within the bounds of the scanned area; a GMTI sensor can detect a moving target and follow the movement of the target. The raw information about targets from these airborne sensors is *uncertain* (a sensor will give a list of candidate target types with different confidence levels) and often *noisy* (a sensor may confuse a T80 tank with a T72M tank).

One challenge in airborne sensor networks is how to process and aggregate data from many sources to generate an accurate and timely picture of the battlefield (Hall & Llinas 1997; Sycara & Lewis 2002). The commanders need to develop a good understanding of the battlefield from the low-level intelligence information. The understanding of the battlefield situation, including location, movement, and deployment of enemy forces, is essential for commanders to make better decisions than adversaries in the battlefield. Current attempts to bring more information to commanders

are doomed to failure due to cognitive overload. With enormous amounts of information available for command decisions, it is impossible for commanders to fully analyze raw information for corresponding situation assessment. A mechanism is required to allow commanders to easily model and assess the dynamic situations based on the flow and fusion of collected information from various sensors.

In this paper we present a novel approach to uncertain information fusion for force aggregation and classification using Dempster-Shafer theory and doctrinal templates. We consider two frameworks for uncertain information fusion: Bayesian inference method and Dempster-Shafer theory (Russell & Norvig 2002). We choose Dempster-Shafer theory, since it relaxes the Bayesian's restriction on mutually exclusive hypotheses so that it is able to assign evidence to the union of hypotheses. Dempster-Shafer theory leads to the intuitive process of narrowing a hypothesis, where initial uncertainty is replaced with belief or disbelief as evidence is accumulated. The notion of conflict in Dempster-Shafer theory naturally captures the template matching process between a cluster of subechelons and doctrinal templates.

The idea of using Dempster-Shafer theory for uncertain information fusion is not new, e.g., multisensor target identification (Bogler 1987; Lowrance, Garvey, & Strat 1986) and force aggregation and classification (Schubert 2001). However, these approaches do not properly deal with noisy and conflicting sensor information and simply fuse sensor reports together for each target. We propose a different approach to sensor information fusion, in which we avoid fusing conflicting sensor information if we find two given sensor reports do not support the same type of target. The focus of this paper will be on information fusion for force aggregation and classification, e.g., how to analyze and aggregate the uncertain sensor information for each target and how to recognize different types of echelons. We will not consider sensor information association and correlation.¹ We assume the problem of transforming sensor information into a consistent set of entities has been solved in low-level fusion (Klein 1999; Steinberg, Bowman, & White 1999).

The rest of this paper is organized as follows. Section 2 describes the approach for force aggregation and classification. Section 3 illustrates a sample application using the simulated testbed OTBSAF and RETSINA system. Section 4 summarizes the relevant literature. Section 5 concludes this paper and presents some directions for future research.

¹For example, if tank *A* found by a SAR sensor is the same as tank *B* found by a GMTI sensor.

Force Aggregation and Classification

Commonly used algorithms for information fusion are Bayesian inference method and Dempster-Shafer theory of evidence. Suppose H is the hypothesis, E_1 and E_2 are two pieces of evidence from sensors S_1 and S_2 , respectively. The Bayes Rule for information fusion is (Hinman 2002),

$$P(H|E_1, E_2) = \frac{P(E_1, E_2|H)P(H)}{P(E_2, E_1)} \quad (1)$$

Assuming that E_1 and E_2 are independent, then we have

$$P(E_1, E_2) = P(E_1)P(E_2) \quad (2)$$

$$P(E_2|H, E_1) = P(E_2|H) \quad (3)$$

$$P(E_1, E_2|H) = P(E_1|H)P(E_2|H, E_1) \quad (4)$$

The formula $P(H|E_1, E_2)$ can be rewritten as

$$P(H|E_1, E_2) = \frac{P(E_1|H)P(E_2|H)P(H)}{P(E_1)P(E_2)} \quad (5)$$

where $P(H|E_1, E_2)$ is the posterior probability after considering two pieces of evidence E_1 and E_2 , $P(H)$, $P(E_1)$, and $P(E_2)$ are prior probabilities, $P(E_1|H)$ and $P(E_2|H)$ are conditional probabilities of the belief in E_1 and E_2 when H is considered, and $P(E_2)P(E_1)$ is a normalization factor.

Bayesian inference needs some strong assumptions and some of them are not easy to be satisfied in information fusion for the dynamic battlefield (Klein 1999). Since the battlefield is typically not repeatable in nature, the prior probability information $P(H)$ is usually not available, e.g., the probability of any vehicle as a T80 tank. Also, when multiple sensors are tasked to some specific areas, the conditional probabilities $P(E_1|H)$ and $P(E_2|H)$ are not available, either. These conditional probabilities are affected by the resolutions of sensors as well as other factors of the areas being scanned, e.g., weather, smoke, fog, and vegetation.

Dempster-Shafer theory

Both Bayesian inference and Dempster-Shafer theory can update a priori probability estimation with new observations, but we choose Dempster-Shafer theory, since it relaxes the Bayesian's restriction on mutually exclusive hypotheses so that it is able to assign evidence to propositions (i.e. union of hypotheses) (Lowrance, Garvey, & Strat 1986; Shafer 1976).²

We now introduce the key concepts of the Dempster-Shafer theory. Let $V = \{V_1, V_2, \dots, V_n\}$ be the set of possible vehicle types, and V_i mean that the type of the given vehicle is V_i . A *frame of discernment* $\Theta = \{V_i, \neg V_i\}$ is the set of propositions or hypotheses under consideration.

Definition 1 Let Θ be a frame of discernment. A *basic probability assignment (bpa)* is a function $m : 2^\Theta \mapsto [0, 1]$ where (1) $m(\phi) = 0$, and (2) $\sum_{\hat{A} \subset \Theta} m(\hat{A}) = 1$.

²In other words, Dempster-Shafer theory and Bayesian method produce identical results only when all the hypotheses are singletons and mutually exclusive.

For example, given a T80 tank, we have $m(\{T80\}) + m(\{\neg T80\}) + m(\{T80, \neg T80\}) = 1$, where $\{T80, \neg T80\}$ is the ignorance set. A bpa is similar to a probability assignment except that its domain is the subsets and not the members of Θ . The sum of the bpa's of the singleton subsets of Θ may be less than 1. For example, given $m(\{T80\}) = 0.8$, $m(\{\neg T80\}) = 0$, $m(\{T80, \neg T80\}) = 0.2$, we have $m(\{T80\}) + m(\{\neg T80\}) = 0.8$, which is less than 1.

For a subset \hat{A} of Θ , the *belief function* $\text{Bel}(\hat{A})$ is defined as the sum of the beliefs committed to the possibilities in \hat{A} . For example,

$$\text{Bel}(\{T80, \neg T80\}) = m(\{T80\}) + m(\{\neg T80\}) + m(\{T80, \neg T80\}) = 1$$

For individual members of Θ (in this case, T80 and $\neg T80$), Bel and m are equal. Thus

$$\begin{aligned} \text{Bel}(\{T80\}) &= m(\{T80\}) = 0.8 \\ \text{Bel}(\{\neg T80\}) &= m(\{\neg T80\}) = 0 \end{aligned}$$

A subset \hat{A} of a frame Θ is called a *focal element* of a belief function Bel over Θ if $m(\hat{A}) > 0$. Given two belief functions over the same frame of discernment but based on distinct bodies of evidence, *Dempster's rule of combination* enables us to compute a new belief function based on the combined evidence. For every subset \hat{A} of Θ , Dempster's rule defines $m_1 \oplus m_2(\hat{A})$ to be the sum of all products of the form $m_1(X)m_2(Y)$, where X and Y run over all subsets whose intersection is \hat{A} .

Definition 2 Let Bel_1 and Bel_2 be belief functions over Θ , with basic probability assignments m_1 and m_2 , and focal elements $\hat{A}_1, \dots, \hat{A}_k$, and $\hat{B}_1, \dots, \hat{B}_l$, respectively. Suppose

$$\sum_{i,j, \hat{A}_i \cap \hat{B}_j = \phi} m_1(\hat{A}_i)m_2(\hat{B}_j) < 1$$

Then the function $m : 2^\Theta \mapsto [0, 1]$ that is defined by $m(\phi) = 0$, and

$$m(\hat{A}) = \frac{\sum_{i,j, \hat{A}_i \cap \hat{B}_j = \hat{A}} m_1(\hat{A}_i)m_2(\hat{B}_j)}{1 - \sum_{i,j, \hat{A}_i \cap \hat{B}_j = \phi} m_1(\hat{A}_i)m_2(\hat{B}_j)} \quad (6)$$

for all non-empty $\hat{A} \subset \Theta$ is a basic probability assignment (Shafer 1976).

Bel , the belief function given by m , is called the *orthogonal sum* of Bel_1 and Bel_2 . It is written $\text{Bel} = \text{Bel}_1 \oplus \text{Bel}_2$. Note that Dempster's rule of combination is associative and commutative. This means that the processes of combining evidence from multiple sensors are independent of the order in which the sensor outputs are combined.

Confusion Sets

In the battlefield, a UAV scans an area of terrain and attempts to recognize any stationary or moving targets within the bounds of that scanned area. The output from the sensor on the UAV is a list of candidate target types (e.g., M1 tank, T80 Tank, etc.) with different confidence levels. One challenge is how to interpret and reason about the uncertain information. In this section we first introduce the notion of confusion sets, and then we describe how to convert the uncertain information, e.g., confidence levels from the sensor outputs, to belief functions in Dempster-Shafer's theory.

USSR T80	0.4
USSR T72M	0.3
US M1	0.05
US M1A1	0.05
US M1A2	0.05
USSR 2S6	0.02
USSR ZSU23 4M	0.03
US M977	0.001
US M35	0.001
US AVENGER	0.001
US HMMWV	0.001
USSR SA9	0.001
CLUTTER	0.095

(a)

USSR T80	0.7
USSR T72M	0.1
US M1	0.02
US M1A1	0.02
US M1A2	0.02
USSR 2S6	0.01
USSR ZSU23 4M	0.02
US M977	0.001
US M35	0.001
US AVENGER	0.001
US HMMWV	0.001
USSR SA9	0.001
CLUTTER	0.105

(b)

Figure 1: A list of candidate target types with different confidence levels from a low resolution sensor S_1 (a) and a high resolution sensor S_2 (b).

Let's consider the following scenario: an F-16 first locates targets in the battlefield using low resolution sensors, and then a UAV revisits some areas with groups of targets using high resolution sensors. A confusion set is a set of vehicles, where the sensor S_i may confuse one with another when we use the same sensor to scan the area. For example, a low resolution sensor S_i may confuse a $T80$ tank with a $T72M$ tank, but usually it will not confuse a $T80$ tank with a $M35$ truck; a high resolution sensor may distinguish a $T80$ tank from a $T72M$ tank.

Figure 1 describes the outputs from two sensors for a $T80$ tank on the ground. Suppose, $V = \{V_1, V_2, \dots, V_n\}$ is the set of possible vehicle types; for any vehicle type V_i , $c(V_i)$ is its confidence level. A confusion set from the output of a sensor can be formally defined as follows.

Definition 3 Let $C = \{V_1, V_2, \dots, V_m\}$ ($m < n$) be a subset of V and C is sorted by the confidence levels, e.g., $c(V_1) \geq c(V_2) \dots \geq c(V_m)$, C is a confusion set if and only if (1) for any vehicle type $V_i \in C$, $V_j \in V$ and $V_j \notin C$, $c(V_i) \geq \sigma > c(V_j)$, where σ is the identification threshold; (2) for any vehicle type $V_i \in C$, $1 \leq i \leq m - 1$, $|c(V_i) - c(V_{i+1})| \leq \rho$, where ρ is minimum distance of confidence levels.

A confusion set is sensor specific and is dynamically chosen based on confidence levels and relative distances between confidence levels. Algorithm 1 illustrates the process of determining a confusion set from the output of a sensor S_i . Given the algorithm, the confusion sets for the outputs of sensors (a) and (b) in Figure 1 can be determined as $C_1 = \{T80, T72M\}$ and $C_2 = \{T80\}$, respectively.

Now we discuss how to convert the raw uncertain information of the sensor output to belief functions. If there is only one element in the confusion set, it is easy to define the frame of discernment and the corresponding belief functions. For example, assume the confusion set for sensor S_2 is $C_2 = \{T80\}$, we can get the frame of discernment $\Theta_{21} = \{T80, \neg T80\}$ (Θ_{21} can be simplified as Θ_2 if there is only one element in the confusion set.). For the basic probability assignment, we restrict the sum of $m_2(\{T80\})$ and $m_2(\{T80, \neg T80\})$ to equal the sum of confidence levels of the elements in the confusion set, and $m_2(\{T80\})$ is the confidence level for $T80$. In the case of $C_2 = \{T80\}$, there is only one element $T80$ in the confu-

Algorithm 1 Determining a confusion set

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1: Suppose  $V = \{V_1, V_2, \dots, V_n\}$  is the set of possible
   vehicle types; for any vehicle type  $V_i$ ,  $c(V_i)$  is its con-
   fidence level;  $V$  is sorted by the confidence levels, e.g.,
    $c(V_1) \geq c(V_2) \dots \geq c(V_n)$ ;  $\rho$  and  $\sigma$  are two thresholds,
   e.g.,  $\rho = 0.1$ ,  $\sigma = 0.15$ . Initially confusion set  $C = \{\}$ .
2: if  $(c(V_1) < \sigma)$  then
3:   return  $C$  (the vehicle cannot be identified)
4: else
5:    $C = \{V_1\}$ ;  $V = V - \{V_1\}$ 
6: end if
7: if  $|c(V_1) - c(V_2)| \geq \rho$  then
8:   return  $C$  ( $V_2$  is the only vehicle type in  $C$ )
9: else
10:   $C = C \cup \{V_2\}$ ;  $V = V - \{V_2\}$ 
11:  for any  $V_k \in V$  do
12:     $V_j$  has the minimum confidence level in  $C$ 
13:    if  $|c(V_k) - c(V_j)| \leq |c(V_1) - c(V_2)|$  then
14:       $C = C \cup \{V_k\}$ ;  $V = V - \{V_k\}$ 
15:    end if
16:  end for
17:  return  $C$  ( $C$  has multiple vehicle types)
18: end if

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sion set, where $c(T80) = 0.7$. Thus, we have the frame of discernment $\Theta_2 = \{T80, \neg T80\}$, and $m_2(\{T80\}) = 0.7$, $m_2(\{\neg T80\}) = 0.3$, $m_2(\{T80, \neg T80\}) = 0.0$.

There could be multiple frames of discernment if there are more than one element in a confusion set. For example, given $C_1 = \{T80, T72M\}$, there are two frames of discernment $\Theta_{11} = \{T80, \neg T80\}$ and $\Theta_{12} = \{T72M, \neg T72M\}$. In this case, we choose one of them as the *active* frame of discernment. For example, given the confusion set $C_1 = \{T80, T72M\}$, we choose $\Theta_{11} = \{T80, \neg T80\}$ as the *active* frame of discernment since $c(T80) \geq c(T72M)$.

Definition 4 Let $C = \{V_1, V_2, \dots, V_m\}$ ($m < n$) is a confusion set, $c(V_i)$ is the confidence level of vehicle V_i ($1 \leq i \leq m$), a frame of discernment $\Theta_k = \{V_i, \neg V_i\}$ is the *default* frame of discernment for C if and only if for any vehicle type $V_j \in C$, $c(V_i) \geq c(V_j)$.

A confusion set may have multiple frames of discernment but only one of them can be active. The default frame of discernment with the maximal confidence level is initially the active one, but any other one could become active if the default frame of discernment is different from other sensors'.

Definition 5 Let $C = \{V_1, V_2, \dots, V_m\}$ ($m < n$) is a confusion set, $c(V_i)$ is the confidence level of vehicle V_i ($1 \leq i \leq m$), for any frame of discernment $\Theta_k = \{V_i, \neg V_i\}$,

$$\begin{aligned}
m(\{V_i\}) &= c(V_i) \\
m(\{V_i, \neg V_i\}) &= \sum_{V_j \in C, j \neq i} c(V_j) \\
m(\{\neg V_i\}) &= 1 - m(\{V_i\}) - m(\{V_i, \neg V_i\})
\end{aligned}$$

For example, given the output of sensor (a) in Figure 1, $\Theta_{11} = \{T80, \neg T80\}$ is the default frame of discernment for the confusion set $C_1 = \{T80, T72M\}$ and basic probability assignments are $m_{11}(\{T80\}) = 0.4$, $m_{11}(\{\neg T80\}) = 0.3$, $m_{11}(\{T80, \neg T80\}) = 0.3$. Similarly, for another frame of discernment $\Theta_{12} = \{T72M, \neg T72M\}$, basic probability assignments are $m_{12}(\{T72M\}) = 0.3$, $m_{12}(\{\neg T72M\}) = 0.3$, $m_{12}(\{T72M, \neg T72M\}) = 0.4$.

Conflict Sensor Information

Note that, even for the same target, the default frames of discernment could be different for different sensor reports. For example, in Figure 2, the default frame of discernment for the confusion set $C_1 = \{T80, T72M\}$ is $\Theta_{11} = \{T72M, \neg T72M\}$, which is different from the frame of discernment $\Theta_2 = \{T80, \neg T80\}$ for the confusion set $C_2 = \{T80\}$. In other words, the outputs from two sensors could be conflict: one supports the hypothesis the target is a $T72M$ tank, and another supports the hypothesis the same target is a $T80$ tank. In this section we discuss how to fuse this kind of conflicting sensor information using Dempster's rule of combination (Definition 2).

USSR T80	0.3	USSR T80	0.7
USSR T72M	0.4	USSR T72M	0.1
US M1	0.05	US M1	0.02
US M1A1	0.05	US M1A1	0.02
US M1A2	0.05	US M1A2	0.02
USSR 2S6	0.02	USSR 2S6	0.01
USSR ZSU23 4M	0.03	USSR ZSU23 4M	0.02
US M977	0.001	US M977	0.001
US M35	0.001	US M35	0.001
US AVENGER	0.001	US AVENGER	0.001
US HMMWV	0.001	US HMMWV	0.001
USSR SA9	0.001	USSR SA9	0.001
CLUTTER	0.095	CLUTTER	0.105

(a)

(b)

Figure 2: A list of candidate target types with different confidence levels from a low resolution sensor (a) and a high resolution sensor (b), where the low resolution sensor confuses a $T80$ tank with a $T72M$ tank.

Dempster-Shafer theory has been used for multisensor target identification and force aggregation and classification (Bogler 1987; Lowrance, Garvey, & Strat 1986; Schubert 2001). However, these approaches do not consider the noisy sensor information and simply fuse all sensor reports together for each target. They choose one frame of discernment for the whole set of propositions being considered. We propose a different approach for noisy sensor information fusion, in which we choose the common frame of discernment between the two sensor reports if it exists. We avoid fusing conflicting sensor information if we find two sensor reports do not support the same type of target, e.g., no common frame of discernment for two given sensor reports.

Suppose C_1 and C_2 are the confusion sets for the outputs from sensors S_1 and S_2 , $\Theta_{1i} = \{V_i, \neg V_i\}$ and $\Theta_{2j} = \{V_j, \neg V_j\}$ are active frames of discernment for C_1 and C_2 , respectively. Next we consider different situations when fusing the outputs from sensors S_1 and S_2 .

1. C_1 and C_2 have the same active frame of discernment, e.g., $\Theta_{1i} = \Theta_{2j}$. We can combine the belief functions directly using Dempster's rule of combination.
2. C_1 and C_2 have different active frames of discernment and $C_1 \cap C_2 \neq \phi$. We choose the maximum between $m_{1i}(\{V_i\})$ and $m_{2j}(\{V_j\})$, e.g., $m_{2j}(\{V_j\}) > m_{1i}(\{V_i\})$, then (a) if $V_j \in C_1$, then select $\Theta_{1k} = \{V_j, \neg V_j\}$ as the active frame of discernment for C_1 . We combine the belief function for the reselected frame of discernment $\Theta_{1k} = \{V_j, \neg V_j\}$ with the belief function

for Θ_{2j} ; (b) Otherwise, we say the outputs cannot be fused and use the belief function for Θ_{2j} as the fused result for sensors S_1 and S_2 .

3. C_1 and C_2 have different active frames of discernment and $C_1 \cap C_2 = \phi$. In this case, we avoid combining the conflicting information and use the belief function for Θ_{2j} as the fused result for sensors S_1 and S_2 .

In the example of Figure 2, $C_1 = \{T80, T72M\}$ and $C_2 = \{T80\}$. The active frame of discernment for C_1 and C_2 are $\Theta_{11} = \{T72M, \neg T72M\}$ and $\Theta_2 = \{T80, \neg T80\}$. We find $\Theta_{11} \neq \Theta_2$, and then we select another frame of discernment $\Theta_{12} = \{T80, \neg T80\}$ as the *active* frame of discernment for C_1 .

Doctrinal Template Matching

In this section we discuss how to recognize an echelon from the uncertain sensor information about vehicles using doctrinal templates. A doctrinal template depicts the composition and deployment of various types of echelons. For example, a template for a $T80$ tank platoon consists four $T80$ tanks. A template may also have different kinds of vehicles. For example, an anti-tank platoon consists of three tanks and six missile launchers. In general, a template T_i for an echelon can be represented as

$$T_i = \{\{V_1, N_1\}, \{V_2, N_2\}, \dots, \{V_p, N_p\}\}$$

where $V_i \in V$ ($1 \leq i \leq p$) is the possible type of vehicles, N_i is the number of the type V_i vehicles in the template. For each vehicle V_i in a template, we assume the frame of discernment is $\{V_i, \neg V_i\}$ and the corresponding basic probability assignments are $m(\{V_i\}) = 1.0$, $m(\{\neg V_i\}) = 0.0$, $m(\{V_i, \neg V_i\}) = 0.0$.

The first step in doctrinal template matching or recognizing an echelon is to identify candidate sets of vehicles to be considered as platoons or companies using an agglomerative clustering algorithm. The clustering of vehicles is based on the relative distance between any two vehicles and the number of vehicles in the template. For example, we know from the doctrine that a platoon usually has 4 to 9 vehicles and these vehicles are deployed in a $100m \times 100m$ area.

The next question is, given a cluster of vehicles and a list of doctrinal templates, how to recognize the type of echelon. In other words, suppose we have a cluster of $T80$ tanks and each of them is associated with basic probability assignments, how do we know this is a $T80$ tank platoon, and not a $T72M$ tank platoon. In order to solve this problem, we introduce the notion of conflict between two beliefs in Dempster-Shafer theory.

Definition 6 Let Bel_1 and Bel_2 be belief functions over Θ , with basic probability assignments m_1 and m_2 , and focal elements $\hat{A}_1, \dots, \hat{A}_k$, and $\hat{B}_1, \dots, \hat{B}_l$, respectively. The conflict between Bel_1 and Bel_2 is defined as

$$\sum_{i,j, \hat{A}_i \cap \hat{B}_j = \phi} m_1(\hat{A}_i) m_2(\hat{B}_j) \quad (7)$$

Obviously, the conflict is small if we match the same type of vehicles. Otherwise, the conflict will be one. Algorithm 2 describes the process of matching a cluster of vehicles with a platoon template. The algorithm can also be used to match high-level forces, e.g., a company or a battalion, where each slot in the template or the cluster is a subechelon.

Algorithm 2 Doctrinal Template Matching

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1: Given a template  $T_i = \{\{V_1, N_1\}, \dots, \{T_p, N_p\}\}$  and
   a cluster of vehicles  $CL = \{\{V'_1, m_1\}, \dots, \{V'_q, m_q\}\}$ ,
   for any vehicle type  $V_i$ ,  $N_i$  is the number of the type  $N_i$ 
   in the template;  $m_i$  is the belief function for  $V'_i$  in the
   cluster  $CL$ . Initially  $conflict = 0$ .
2: for  $V'_i \in CL$  do
3:   Select a matched type of vehicle  $V_j$  in the template
4:   if ( $V_j$  is found in template  $T_i$ ) and ( $N_j > 0$ ) then
5:      $CL = CL - \{V'_i, m_i\}$ ;  $N_j = N_j - 1$ 
6:      $conflict = conflict + m_i(\{V'_i\})$ 
7:   else
8:      $CL = CL - \{V'_i, m_i\}$ 
9:      $conflict = conflict + 1$ 
10:  end if
11: end for
12: if  $|CL| = 0$  then
13:   return conflict
14: else
15:    $conflict = conflict + |CL|$ 
16:   return conflict
17: end if
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The strategy of template matching is to minimize the conflict between a template and a cluster of vehicles. The template with the minimum conflict with the cluster of vehicles is the matched one. The confidence level of the matched template or unit type depends on the belief functions of each vehicle in the cluster. Here we use a belief function to represent the confidence level of the unit type and we give one way to compute the belief function of the matched unit type.

Definition 7 Given a cluster of vehicles $\{\{V'_1, m_1\}, \dots, \{V'_q, m_q\}\}$, assume T_i is the matched template with minimum conflicts with the cluster. We first convert the basic probability assignment for each frame of discernment $\{V_i, \neg V_i\}$ to the corresponding basic probability assignment for the evidence $\{e_i, \neg e_i\}$ supporting template T_i ,

$$\begin{aligned} m'_i(\{e_i\}) &= m_i(\{V_i\}) \\ m'_i(\{\neg e_i\}) &= m_i(\{\neg V_i\}) \end{aligned}$$

and then we compute the belief function for $\{T_i, \neg T_i\}$ as

$$m_{T_i} = m'_1 \oplus m'_2, \dots, m'_q$$

For example, suppose the sensors find four T80 tanks $\{T80_1, T80_2, T80_3, T80_4\}$ and their basic probability assignments are shown as follows,

$$\begin{aligned} m_1(\{T80_1\}) &= 0.7, m_1(\{\neg T80_1\}) = 0.3 \\ m_2(\{T80_2\}) &= 0.8, m_2(\{\neg T80_2\}) = 0.2 \\ m_3(\{T80_3\}) &= 0.7, m_3(\{\neg T80_3\}) = 0.3 \\ m_4(\{T80_4\}) &= 0.7, m_4(\{\neg T80_4\}) = 0.3 \end{aligned}$$

Then, the belief functions for a matched T80 platoon are

$$\begin{aligned} m_{T80_platoon}(\{T80_platoon\}) &= 0.97 \\ m_{T80_platoon}(\{\neg T80_platoon\}) &= 0.03 \end{aligned}$$

The above example tells us if we find four T80 tanks stay together, we can infer that it is likely a T80 tank platoon. However, sometimes we may not find all four tanks; Instead, we only find three out of four. At this time we need to adjust the combined belief functions for the tank platoon.

Definition 8 Given a cluster of vehicles $\{\{V'_1, m_1\}, \dots, \{V'_q, m_q\}\}$ with q vehicles, assume T_i is the matched template with minimum conflicts with the cluster and T_i has Q vehicles. m_{T_i} is the belief functions for $\{T_i, \neg T_i\}$. The adjusted belief functions m'_{T_i} are

$$\begin{aligned} m'_{T_i}(\{T_i\}) &= q/Q * m_{T_i}(\{T_i\}) \\ m'_{T_i}(\{\neg T_i\}) &= q/Q * m_{T_i}(\{\neg T_i\}) \\ m'_{T_i}(\{T_i, \neg T_i\}) &= 1 - m'_{T_i}(\{T_i\}) - m'_{T_i}(\{\neg T_i\}) \end{aligned}$$

Suppose the sensors only find three tanks $T80_1, T80_2$, and $T80_3$ and their basic probability assignments are the same as above. Then, the belief functions for the three tanks as a T80 platoon are

$$\begin{aligned} m_{T80_platoon}(\{T80_platoon\}) &= 0.95 \\ m_{T80_platoon}(\{\neg T80_platoon\}) &= 0.05 \end{aligned}$$

The adjusted belief functions for the three tanks are

$$\begin{aligned} m'_{T80_platoon}(\{T80_platoon\}) &= 0.7125 \\ m'_{T80_platoon}(\{\neg T80_platoon\}) &= 0.0375 \end{aligned}$$

Experiments

In this section, we first introduce a modeling and simulation environment, OTBSAF (OneSAF Testbed Baseline)³ and its integration with the RETSINA system (Reusable Environment for Task Structured Intelligent Network Agents) (Sycara *et al.* 2003). And then we discuss some experimental results of force aggregation and classification in the simulated testbed.

OTBSAF and RETSINA System

OTBSAF models common military vehicles, aircraft, and sensors, and simulates uncertainty for entities' individual and doctrinal behaviors in the battlefield. We extend OTBSAF and integrate it with our RETSINA multiagent system. One of our contributions to OTBSAF is to add three simulated mounted sensors, SARSim, EOSim, and GMTISim, to the simulation environment.

The SARSim simulates an automatic target recognition (ATR) system that receives its input from a synthetic aperture radar (SAR) that is operating in *spotlight-mode*. In spotlight-mode, a SAR scans an area of terrain, and the ATR will attempt to recognize any stationary object within the bounds of that scanned area. The output from the SARSim is a list of candidate target types (e.g., M1 tank, T80 Tank, etc.) with different confidence levels. While a real SAR/ATR system will report confidence levels for around three dozen entities, SARSim will report for a dozen entities. The GMTISim simulates a ground moving target indicator (GMTI) radar, which focuses a radar beam on one spot, and if it detects a moving target there with its ATR system, a motion tracker mechanism follows the movement of the target. While very similar in output and behavior to the SARSim, it is complementary, because it only recognizes entities that are moving, while the SARSim only recognizes entities that are stationary. The EOSim simulates an electro-optical sensor that detects targets at distances and in conditions in which they would be detectable in the ultraviolet, visible, and infrared light spectra.

³<http://www.onesaf.org/>

	T80 Platoon 1			T80 Platoon 2			T80 Platoon 3			1044
	1014	1017	1020	1024	1027	1030	1034	1037	1040	
USSR T80	0.4	0.4	0.05	0.4	0.3	0.4	0.4	0.05	-	0.3
USSR T72M	0.3	0.3	0.05	0.3	0.4	0.3	0.3	0.05	-	0.4
US M1	0.05	0.05	0.20	0.05	0.05	0.05	0.05	0.28	-	0.05
US M1A1	0.05	0.05	0.28	0.05	0.05	0.05	0.05	0.24	-	0.05
US M1A2	0.05	0.05	0.27	0.05	0.05	0.05	0.05	0.23	-	0.05
USSR 2S6	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	-	0.02
USSR ZSU23	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	-	0.03
US M977	-	-	-	-	-	-	-	-	-	-
US M35	-	-	-	-	-	-	-	-	-	-
US AVENGER	-	-	-	-	-	-	-	-	-	-
US HMMWV	-	-	-	-	-	-	-	-	-	-
USSR SA9	-	-	-	-	-	-	-	-	-	-
CLUTTER	-	-	-	-	-	-	-	-	-	-

Figure 3: The confidence levels for tanks in a $T80$ tank company from the outputs of the low resolution SAR sensor S_1 on an F-16. Tank 1044 is in the company but it does not belong to any platoon. “-” means the field is empty in the Sarsim output.

	T80 Platoon 1			T80 Platoon 2			T80 Platoon 3			1044
	1014	1017	1020	1024	1027	1030	1034	1037	1040	
USSR T80	0.8	0.8	-	0.8	0.8	0.8	0.8	0.8	-	0.8
USSR T72M	0.1	0.1	-	0.1	0.1	0.1	0.1	0.1	-	0.1
US M1	-	-	-	-	-	-	-	-	-	-
US M1A1	-	-	-	-	-	-	-	-	-	-
US M1A2	-	-	-	-	-	-	-	-	-	-
USSR 2S6	-	-	-	-	-	-	-	-	-	-
USSR ZSU23	-	-	-	-	-	-	-	-	-	-
US M977	-	-	-	-	-	-	-	-	-	-
US M35	-	-	-	-	-	-	-	-	-	-
US AVENGER	-	-	-	-	-	-	-	-	-	-
US HMMWV	-	-	-	-	-	-	-	-	-	-
USSR SA9	-	-	-	-	-	-	-	-	-	-
CLUTTER	-	-	-	-	-	-	-	-	-	-

Figure 4: The confidence levels for tanks in a $T80$ tank company from the outputs of the high resolution SAR sensor S_2 on a UAV. Tank 1044 is in the company but it does not belong to any platoon. “-” means the field is empty in the Sarsim output.

Experimental Results

We consider a simple application of our approach for SAR-Sims on the simulated testbed OTBSAF and RETSINA system, where there are three $T80$ tank platoons, P_1 , P_2 , and P_3 , on the ground, and each platoon consists of three $T80$ tanks. An F-16 is tasked to scan the area first using a low resolution Sarsim and then a UAV is tasked to scan the same area using a high resolution Sarsim. Figure 3 and Figure 4 show a list of possible target identities with different confidence levels for each $T80$ tank on the ground. Note that the highest confidence identification in a series of low-confidence is not necessarily the correct classification, e.g., target 1020, 1027, 1037, and 1044 in Figure 3. Also, tank 1020 is only found by sensor S_1 and tank 1040 is not found by either sensor.

Given Sarsim outputs for a tank V_i , we first convert the outputs to belief functions and then combine the belief functions using Dempster’s rule of combination. Suppose C_1^i (or C_2^i) is the confusion set for the outputs for tank V_i from sensor S_1 (or S_2). We consider the following situations when fusing the outputs from sensors S_1 and S_2 .

1. We can combine the belief functions directly, where C_1^i and C_2^i have the same active frame of discernment $\{T80, \neg T80\}$, e.g., tank 1014, 1017, 1024, 1030, 1034.
2. We need to reselect the active frame of discernment for C_1^i , where C_1^i and C_2^i have different active frames of discernment and $C_1^i \cap C_2^i \neq \phi$, e.g., tank 1027 and 1044.
3. We use belief functions for the active frame of discernment $\{T80, \neg T80\}$ of C_2^i as the fused result, where C_1^i and C_2^i have different active frames of discernment and $C_1^i \cap C_2^i = \phi$, e.g., tank 1037.
4. We choose the only available belief functions as the fused results, where either $C_1^i = \phi$ or $C_2^i = \phi$, e.g., tank 1020 is only found by sensor S_1 .

Next we discuss how to recognize the type of a given echelon solely based on the outputs of low resolution Sarsim S_1 , or based on the fused outputs of two Sarsims S_1 and S_2 through Dempster-Shafer’s theory. We assume tanks or vehicles have been clustered into platoons according to the distances between them.

Platoon Level Classification In the platoon level, we choose 7 platoon templates from OTBSAF: US M1 platoon, US M1A1 platoon, US M1A2 platoon, USSR T72M platoon, USSR T80 platoon, USSR SA8 platoon, and USSR 2S6 platoon. Table 1 describes the number of each type of vehicles in different platoon templates.

Platoon templates	Vehicles
US M1 platoon	4 M1s
US M1A1 platoon	4 M1A1s
US M1A2 platoon	4 M1A2s
USSR T72M platoon	3 T72Ms
USSR T80 platoon	3 T80s
USSR SA8 platoon	4 SA8s
USSR 2S6 platoon	2 2S6s

Table 1: The number of each type of tanks or vehicles in different platoon templates

Templates	P_1		P_2		P_3	
M1 pl.	3	3	3	3	1.25	2
M1A1 pl.	2.45	2.45	3	3	2	2
M1A2 pl.	3	3	3	3	2	2
T72M pl.	3	3	2.3	3	2	2
T80 pl.	1.6	1.36	1.6	0.56	1.3	0.38
SA8 pl.	3	3	3	3	2	2
2S6 pl.	3	3	3	3	2	2

Table 2: The conflicts of three clusters of tanks, P_1 , P_2 , P_3 , with platoon templates, where the conflicts based on fused outputs of sensors S_1 and S_2 are in bold.

Table 2 describes the conflicts of three clusters of tanks with platoon templates using Algorithm 2. Given the outputs of sensor S_1 , clusters of tanks, P_1 and P_2 , have minimal conflicts with T80 platoon template, and can be classified as T80 tank platoons. However, cluster P_3 has minimal conflict with M1 platoon template and is classified as a M1 tank platoon, instead of a T80 tank platoon. Note that our algorithm is tolerant to noisy sensor information. For example, although tank 1020 in P_1 is identified as a M1A1 tank, we can still identify the cluster P_1 of two T80 (1014, 1017) and one M1A1 (1020) as a T80 tank platoon. Cluster P_3 is confused as a M1 tank platoon, since the sensor only finds two out of three tanks in the cluster and one of them is recognized as a M1 tank. In next section we will show our algorithm can still recognize the right type of echelon in the company level even with the outputs from the low resolution sensor. Also, if we match the three cluster of tanks with templates using the fused outputs from sensors S_1 and S_2 , we find the results enhance the template matching, where the conflicts are minimized and all three clusters of tanks are classified as T80 tank platoons.

The basic probability assignments for each cluster of tanks, P_1 and P_2 , as a T80 tank platoon can be computed according to Definition 7 and results are shown as in Table 3, where frame of discernment for P_1 and P_2 is $\{T80.platoon, \neg T80.platoon\}$. Similarly, the basic probability assignments and adjusted basic probability assignments for P_3 are shown in the same table, but its frame of

discernment is $\{M1.platoon, \neg M1.platoon\}$ for the outputs of sensor S_1 , and is $\{T80.platoon, \neg T80.platoon\}$ for the fused outputs.

$m_1(\{P_1\})$		$m_1(\{\neg P_1\})$	
0.56	0.935	0.37	0.065
$m_2(P_2)$		$m_2(\{\neg P_2\})$	
0.55	0.987	0.39	0.013
$m_3(\{P_3\})$		$m_3(\{\neg P_3\})$	
0.47	0.948	0.36	0.052
$m'_3(P_3)$		$m'_3(\{\neg P_3\})$	
0.31	0.632	0.24	0.035

Table 3: Basic probability assignments for clusters of tanks, P_1 , P_2 , and P_3 , where basic probability assignments based on fused outputs of sensors S_1 and S_2 are in bold. Note that $m'(\{P_3\})$, $m'(\{\neg P_3\})$, $m'(\{P'_3\})$, $m'(\{\neg P'_3\})$ are adjusted basic probability assignments for P_3 since the sensor only finds two out of three tanks in the cluster.

Company Level Classification In this section we discuss the problem of recognizing the type of echelons in company level from platoons. We choose six templates in the company level: US M1 company, US M1A1 company, US M1A2 company, USSR T72M company, USSR T80 company, USSR 2S6 battery (see Figure 4). Some platoons are included in the template of a battalion level force directly, e.g., USSR SA8 platoon. Companies may have some extra vehicles besides the vehicles in the platoons. For example, a USSR T80 company has three T80 platoons and one extra T80 tank. In our experiments we do not consider the extra vehicles during template matching.

Company templates	Platoons
US M1 company	3 M1 platoons
US M1A1 company	3 M1A1 platoons
US M1A2 company	3 M1A2 platoons
USSR T72M company	3 T72M platoons
USSR T80 company	3 T80 platoons
USSR 2S6 battery	3 2S6 platoons

Table 4: The number of each type of platoons in different company templates

Templates	T80 company	
M1 company	2.24	3
M1A1 company	3	3
M1A2 company	3	3
T72M company	3	3
T80 company	1.76	0.113
2S6 battery	3	3

Table 5: The conflicts of the assumed T80 company with company templates, where the conflicts based on fused outputs of sensors S_1 and S_2 are in bold.

Table 5 describes the conflicts of the assumed T80 company with company templates. Obviously, the assumed T80

company has the minimal conflicts with $T80$ tank company template. The conflict with the $T80$ company template changes to 0.113 when we use the fused outputs of sensors S_1 and S_2 . The basic probability assignments for the $T80$ company are, where the frame of discernment for the $T80$ company is $\{T80_company, -T80_company\}$.

	$m(\{T80_C\})$	$m(\{-T80_C\})$
$T80_C$	0.66	0.999
	0.30	0.001

Table 6: Basic probability assignments for the cluster of tank platoons, where basic probability assignments based on fused outputs of sensors S_1 and S_2 are in bold.

Related Work

Lowrance et al. apply Dempster-Shafer theory in reasoning about the locations and activities of multiple ships from intelligence reports (Lowrance, Garvey, & Strat 1986). Bogler use Dempster-Shafer theory in the field of multisensor target identification systems (Bogler 1987). Schubert extends those approaches to force clustering and classification (Schubert 2001), where elements, e.g., intelligence reports, vehicles, and echelons, are clustered into subsets. Schubert uses the conflict of Dempster’s rule as an indication of whether the elements belong together. However, their approach is not fully evaluated due to the complexity of the algorithm. They choose one frame of discernment for the whole set of propositions being considered, while we only choose the active one for information fusion from multiple frames of discernment for possible propositions. We avoid combining conflicting sensor information if we cannot find a common frame of discernment for them.

Bayesian techniques have been utilized for force aggregation (Hinman 2002). Given the prior knowledge of each target and sensor in the battlefield, a Bayesian classifier has been developed for matching the observed echelon with different templates. For example, Bakert and Losiewicz partition the force into a mutually and exclusive set of units (Bakert & Losiewicz 1998). In their approach, the posterior probability for each node is computed using Bayesian methods and is propagated through the hierarchy network of military force as positive or negative evidence for the inclusion of each unit in the partition. In this paper we use a bottom-up approach, instead of the top-down approach as described in (Bakert & Losiewicz 1998), for force aggregation and classification. It would be interesting to study the possibility of combining these two approaches in force aggregation and classification.

Conclusion

An understanding of force level and deployment is essential for battlefield situation assessment and threat assessment. In this paper we present a novel approach to force aggregation and classification using Dempster-Shafer theory and doctrinal templates. Our goal is to develop dynamic operational pictures of battlefields for better assessing the situation in terms of potential opportunities and threats for rapidly evolving environments, e.g., determining the likely courses of action for engagement and the consequences of those courses of action.

Just as for a real SAR sensor, the SARSSim may report “false positive” targets where they do not exist in the simulation. In the future work we plan to use the context of terrain and redundant sensor data to identify false positive targets in sensor reports. We also plan to study spatial template matching for threat assessment. In this paper we do not consider deployment patterns and disposition of enemy forces such as locations and spatial constraints of enemy subechelons within an echelon. A good understanding of spatial template will help us reason about the movement and disposition of enemy forces in the context of terrain.

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References

- Bakert, T., and Losiewicz, P. B. 1998. Force aggregation via bayesian nodal analysis. In *Proceedings of Information Technology Conference*, 6–9.
- Bogler, P. L. 1987. Shafer-dempster reasoning with applications to multisensor target identification systems. *IEEE Transactions on System, Man, and Cybernetics* 17(6):968–977.
- Hall, D. L., and Llinas, J. 1997. An introduction to multi-sensor data fusion. In *Proceedings of the IEEE*, 6–23.
- Hinman, M. L. 2002. Some computational approaches for situation assessment and impact assessment. In *Proceedings of the Fifth International Conference on Information Fusion*, 687–693.
- Klein, L. A. 1999. *Sensor and Data Fusion: Concepts and Applications*. SPIE Optical Engineering Press.
- Lowrance, J. D.; Garvey, T. D.; and Strat, T. M. 1986. A framework for evidential reasoning system. In *Proceedings of the Fifth National Conference on Artificial Intelligence (AAAI)*, 896–901.
- Russell, S. J., and Norvig, P. 2002. *Artificial Intelligence: A Modern Approach*. Prentice Hall, second edition.
- Schubert, J. 2001. Reliable force aggregation using a refined evidence specification from dempster-shafer clustering. In *Proceedings of the Fourth International Conference on Information Fusion*.
- Shafer, G. 1976. *A Mathematical Theory of Evidence*. Princeton, NJ: Princeton University Press.
- Steinberg, A. N.; Bowman, C. L.; and White, F. E. 1999. Revisions to the JDL data fusion model. In *Proceedings of the SPIE Sensor Fusion: Architecture, Algorithms, and Applications*, 430–441.
- Sycara, K., and Lewis, M. 2002. From data to actionable knowledge and decision. In *Proceedings of the Fifth International Conference on Information Fusion*, 577–584.
- Sycara, K.; Paolucci, M.; van Velsan, M.; and Giampapa, J. 2003. The RETSINA MAS infrastructure. *Autonomous Agents and Multi-Agent Systems* 7(1):29–48.