An Evidential Model of Multisensor Decision Fusion for Force Aggregation and Classification

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***Abstract*—**

This paper describes airborne sensor networks for target detection and identification in military applications. One challenge is how to process and aggregate data from many sensor sources to generate an accurate and timely picture of the battlefield. The majority of research in data fusion has focused primarily on level 1 fusion, e.g., using multisensor data to determine the position, velocity, attributes, and identity of individual targets. In this paper we present a novel approach to military force aggregation and classification using the mathematical theory of evidence 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 simple application of our approach is illustrated in the simulated testbed OTBSAF and RETSINA system.

I. Introduction

Sensor networks are emerging as a new trend in information technology for monitoring and collecting information in both military and non-military applications. This paper describes airborne sensor networks for target detection and identification in 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 mounted on a number of platforms. These platforms such as an F-16 or UAV (unmanned aerial vehicle) are deployed in the battlefield for target detection, tracking, and classification. For example, a SAR or EO sensor can recognize the location and identity of a stationary target; a GMTI sensor can detect a moving target and track the movement of the target.

Over the past two decades, a large number of approaches to multisensor data fusion have been developed [1]. The majority of research in data fusion has focused primarily on sensor data alignment, association, and correlation in level 1 fusion, e.g., using multisensor data to determine the position, velocity, attributes, and identity of individual targets. For example, the identity declaration from each sensor usually provides multiple identity declaration and each of them is associated with a confidence factor. Given the identity declarations of individual targets from airborne sensors, data fusion techniques seek to process identity declarations from multiple sensors to achieve a joint declaration of identity [2].

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. Current attempts to bring more information of individual targets 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 such as the behavior and intentions of enemy forces based on the flow and fusion of collected information from various sensors [3]. 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.

In this paper we present a novel approach to force aggregation and classification using the mathematical theory of evidence and doctrinal templates. A doctrinal template depicts the composition and deployment of various types of echelons. We assume the raw sensor data have been transformed into a consistent set of entities before multisensor identity fusion [2], [4], [5]. In particular, we will focus on the following three problems,

- How to interpret uncertain information from multiple sensors, so that we can fuse uncertain and inconsistent information for a target from different sensors, e.g., a $T80$ tank?
- How to recognize different types of echelons with the uncertain information for each target in a cluster of vehicles or for each subechelon in the echelon?
- What is the confidence level for a cluster of vehicles (echelons) if the cluster matches a doctrinal template, e.g., a $T80$ tank platoon?

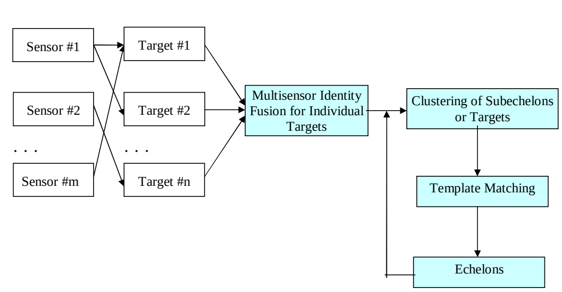

Fig. 1. The process of force aggregation and classification

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)

USSR T80	0.771
USSR T72M	0.141
US M1	0.016
US M1A1	0.016
US M1A2	0.016
USSR 2S6	0.006
USSR ZSU23 4M	0.013
US M977	0.0
US M35	0.0
US AVENGER	0.0
US HMMWV	0.0
USSR SA9	0.0
CLUTTER	0.021

Fig. 2. A low resolution sensor SAR_1 (a) and a high resolution sensor SAR_2 (b) return a list of candidate target types with different confidence levels for a ground target $T80$ tank. The right table shows the fused confidence levels for each candidate target type.

Figure 1 describes the process of force aggregation and classification, including (1) multisensor identity fusion; (2) force aggregation (clustering); (3) force classification (template matching). Typically, the process of force aggregation is hierarchical. For example, a cluster of platoons can be clustered into a company that is further included at a battalion or a higher level force.

Commonly used algorithms for multisensor information fusion are Bayesian inference method and Dempster-Shafer theory of evidence. Dempster-Shafer theory produces identical results as Bayesian inference method for multisensor identity fusion when the hypotheses about individual target's identity declarations are singletons and mutually exclusive [6], [7], [8]. We choose Dempster-Shafer theory for the following two reasons,

- Most tactical sensors are incapable of assigning all confidences to each target type. Dempster-Shafer theory allows confidences to be assigned to sets of propositions rather than to just N mutually exclusion propositions. For example, the confidence to clutter in the sensor data.
- Dempster-Shafer theory leads to the intuitive bottom-up process of force classification. The notion of conflict in Dempster-Shafer theory naturally captures the template matching process between a cluster of vehichles (or subechelons) and doctrinal templates.

The rest of this paper is organized as follows. Section 2 describes the approach for force aggregation and classification. Section 3 illustrates a simple 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.

II. Force Aggregation and Classification

In the battlefield, various platforms are deployed to scan an area of terrain and attempts to recognize any stationary or moving targets within the bounds of that scanned area. The sensor output for each target is a list of candidate target types (e.g., M1 tank, T80 Tank, etc.) with different confidence levels. Our previous work considers the problem of force aggregation and classification based upon the sensor reports from two dissimilar sensors [9]. In this paper we extend the previous approach to the case of multiple sensors. We first describe how to combine the uncertain information from multiple sensor sources in the framework of Dempster-Shafer's theory, and then we present our approach to force aggregation and classification using Dempster-Shafer theory and doctrinal templates.

A. Dempster-Shafer theory

We now introduce the key concepts of the Dempster-Shafer theory. Let $V = \{v_1, v_2, \ldots, v_n\}$ be the set of possible vehicle types, where v_i, $1 \le i \le n$, is the possible type of vehicles a SAR sensor can recognize (see Figure 2(a) and (b)). A *frame of discernment* $\Theta = \{v_1, v_2, \ldots, v_n\}$ is the set of hypotheses under consideration and $v_i \in V$, $1 \le i \le n$.

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) $m(\phi) = 0$ (ϕ is the empty set), and (2) $\sum_{\hat{A} \subseteq \Theta} m(\hat{A}) = 1$.

In this paper we consider a common frame of discernment for all SAR sensor outputs. The set of vehicle types V is $\{T80, T72M, M1, M1A1, M1A2, 2S6, ZSU23, M977, M35, AVENGER, HMMWV, SA9\}$. In our scenario, the basic probability assignment can be defined as follows: (1) for any target type $v_i \in V$, $m(\{v_i\}) = c(v_i)$, where $c(v_i)$ is the confidence level of v_i in the table; (2) for any $\hat{A} \subseteq \Theta$ and $\hat{A} \notin V$, $m(\hat{A}) = 0$; (3) $m(\Theta) = c(clutter)$.

For a subset $\hat{A}$ of Θ, the *belief function* $\mathsf{Bel}(\hat{A})$ is defined as the sum of the beliefs committed to the possibilities in $\hat{A}$. For individual members of Θ, Bel and m are equal, e.g., $\mathsf{Bel}(\{T80\}) = m(\{T80\})$

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: (*Dempster's rule of combination*) Let Bel_1 and Bel_2 be belief functions over Θ, with basic probability assignments m_1 and m_2, and focal elements $\hat{A}_1, \ldots, \hat{A}_k$, and $\hat{B}_1, \ldots, \hat{B}_l$, 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

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

for all non-empty $\hat{A} \subset \Theta$ is a basic probability assignment [10].

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.

For any $v_i \in V$, $m(\{v_i\})$ can be simplified as

$$\frac{m_1(\{v_i\})m_2(\{v_i\}) + m_1(\{v_i\})m_2(\Theta) + m_2(\{v_i\})m_1(\Theta)}{1 - \sum_{v_j \in V} m_1(\{v_j\})(1 - m_2(\{v_j\}) - m_2(\Theta))} \quad (2)$$

Similarly, we can compute $m(\Theta)$ as

$$m(\Theta) = \frac{m_1(\Theta)m_2(\Theta)}{1 - \sum_{v_j \in V} m_1(\{v_j\})(1 - m_2(\{v_j\}) - m_2(\Theta))} \quad (3)$$

Given a $T80$ tank on the ground, Figure 2 describes a list of candidate target types with different confidence levels from a low resolution sensor S_1 and a high resolution sensor SAR_2. Figure 2 also gives the fused confidence levels for each candidate target type using Dempster's rule of combination. Sometimes, the information about targets from these airborne sensors is *noisy*. For example, a sensor may confuse a $T80$ tank with an $M1A1$ tank and give a low confidence level for $T80$ and give a high confidence level for $M1A1$. Figure 3 illustrates two lists of candidate target types for a $T80$ tank using the same SAR sensor. The SAR sensor confuses the $T80$ tank with an $M1A1$ tank in list (b), where $m_2(\{T80\}) < m_2(\{M1A1\})$.

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	0.05
USSR T72M	0.05
US M1	0.20
US M1A1	0.28
US M1A2	0.27
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	0.105

(b)

Fig. 3. The two lists of candidate target types for a $T80$ tank using the same SAR sensor

For a given target v on the ground, one interesting question is if we can get a higher confidence level for target v after we fuse the two or more sensor reports from the same sensor or from sensors with similar resolutions. Figure 4 shows the fused confidence level for a $T80$ tank when we fuse multiple sensor reports from the same sensor. The figure tells us that sometimes the confidence level for a $T80$ tank could be very low from one single sensor report, e.g., $m(\{T80\}) = 0.05$. We need to fuse multiple sensor reports to improve the accuracies of target classification. Also, the fused confidence level for the $T80$ tank does not increase monotonically due to the noisy sensor data.

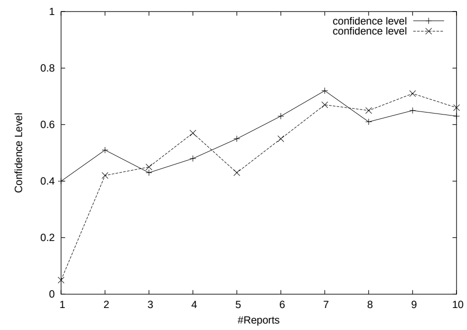

Fig. 4. The fused confidence level for a $T80$ tank using the same SAR sensor

B. Clustering Algorithm for Force Aggregation

The next step in force aggregation and classification is to identify candidate sets of vehicles to be considered as platoons or companies. We use a single-link agglomerative clustering algorithm to identify candidate sets of tanks to be considered as platoons or companies of tank. Different from other clustering algorithms like k-means algorithm, it does not require the number of clusters k as an input, but needs a termination condition. The "single-link" approach, also called "nearest-neighbor" approach, starts with each tank or vehicle forming a separate group. It successively merges the objects or clusters according to the minimum distance between any two tanks u_a and u_b, where $u_a \in S_i, u_b \in S_j$, S_i and S_j are two clusters. The clustering process is finished until all of the clusters are merged into one, or until the termination conditions meet [11].

Suppose we have observed m tanks, $\{u_1, u_2, \ldots, u_m\}$ and we have estimated locations of the tanks. For tank u_i, let x_i and y_i denote the estimated x and y locations, respectively. The distance between any two tanks can be defined as

$$d(u_i, u_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (4)$$

The distance between two sets of tanks S_i, S_j is

$$D(S_i, S_j) = min_{u_a \in S_i, u_b \in S_j} d(u_a, u_b) \quad (5)$$

Let $D(S_i, S_j)$ be the distance between cluster S_i and S_j, and $N(S_i)$ is the nearest neighbor of cluster S_i. The single-link clustering algorithm can be described as follows

1) Initialize the clusters, where each cluster is a tank or vehicle in $\{u_1, u_2, \ldots, u_m\}$
2) For each pair of cluster (S_i, S_j), compute $D(S_i, S_j)$
3) For each cluster S_i, compute $N(S_i)$
4) Repeat until we have the desired number of clusters or the termination conditions meet
   a) Determine S_i, S_j from existing clusters, such that $D(S_i, S_j)$ is minimized
   b) Cluster S_i and S_j
   c) Update each $D(S_i, S_j)$ and $N(S_i)$ as necessary
5) End of the algorithm

The clustering of vehicles is based on the relative distance between any two vehicles (or clusters) and the number of vehicles in the template. For example, we know from the doctrinal templates that a platoon usually has 4 to 9 vehicles and these vehicles are deployed in a $100m \times 100m$ area. We will get clusters of tank platoons if we define the termination conditions as (1) the maximal $D(S_i, S_j)$ as $100m$ and (2) maximal number of vehicles in a cluster as 9. Sometimes the condition cannot guarantee we can identify clusters of vehicles at the low-level force, but we still can cluster them at high-level. For example, if a company of $T80$ tank stays very close, we probably cannot recognize three $T80$ platoons but we can recognize them as a $T80$ company.

C. Doctrinal Template Matching

In this section we discuss how to recognize the type of an echelon using doctrinal templates. A doctrinal template depicts the composition and deployment of various types of subechelons or vehicles. For example, a $T80$ tank platoon template consists of four $T80$ tanks. A template may also have different kinds of vehicles. For example, an anti-tank platoon template consists of three tanks and six missile launchers. In general, a platoon template T for an echelon can be represented as $T = \{v_1, v_2, \ldots, v_p\}$, where $v_j \in V$ ($1 \leq j \leq p$) is the type of a vehicle in template T. For each vehicle v_j, we assume the frame of discernment is $\{v_j\}$ and the corresponding basic probability assignment is $m(\{v_j\}) = 1.0$.

The question is, given a cluster of vehicles $CL = \{u_1, \ldots, u_q\}$ and a list of doctrinal templates $\{T_1, T_2, \ldots, T_l\}$, how to determine the type of echelon. The basic idea here is to match the cluster of vehicles with each template. The matching process attempts to minimize the conflict between a template and cluster of vehicles. The template with the minimum conflict is the matched one for the cluster.

The matching process is simple if the template has same type of vehicles. As shown in Figure 5, each vehicle u_i in the cluster CL is associated with a list of candidate target types and basic probability assignment m_i for each target type and Θ. Given a template $T_k = \{v_1, \ldots, v_p\}$, we can randomly match any vehicle u_i with v_j and then we sum up the conflict C_k between T_k and CL. The matching algorithm can be described as follows,

1) Initially, $C_k = 0$.
2) $\forall u_i \in CL, \forall v_j \in T_k$, $C_k = C_k + 1 - m_i(\{v_j\}) - m_i(\Theta)$

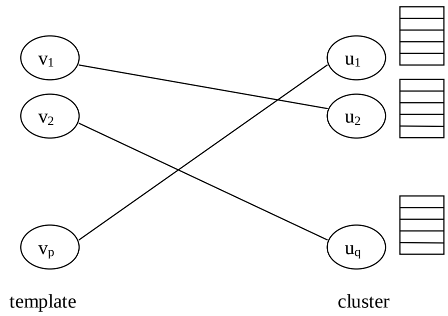

Fig. 5. The matching process between a template and a cluster of vehicles

3) $CL = CL - u_i$
4) $T_k = T_k - v_j$
5) if $CL = \phi$ or $T_k = \phi$, return $C_k = C_k + |CL|$

For templates with different types of vehicles, we have to consider the order of vehicles for matching, so that we can minimize the conflict between a template and the cluster. Obviously, the conflict is small if we match u_i with the same type of vehicle v_j in the template if u_i has the maximal bpa for vehicle type v_j. For a target u_i, we denote $v_j = \Pi(u_i, 1)$ as the target type with the highest bpa, e.g., $m_i(\{v_j\}) > m_i(\{v_k\})$ for any v_k, $v_j \in V$ and $v_k \neq v_j$. Similarly, we can define $\Pi(u_i, 2)$ as the target type with the second highest bpa.

During the first round of matching process, we choose u_i with the maximal $m_i(\{\Pi(u_i, 1)\})$ to match vehicle v_j in a template. Formally, $\forall u_k \in CL$, $\Pi(u_i, 1) = \Pi(u_k, 1)$, and $u_k \neq u_i$, $m_k(\{\Pi(u_k, 1)\}) \leq m_i(\{\Pi(u_i, 1)\})$, we call u_i as the vehicle with the maximal probability assignments in CL, denoted as $u_i = \Gamma(CL, 1)$. Given a vehicle $u_i \in CL$ and v_j is a vehicle in a template and $v_j = \Pi(u_i, 1)$, the conflict between u_i and v_j can be defined as $1 - m_i(\{v_j\}) - m_i(\Theta)$.

Note that usually the matching process has to be iterated for several rounds. For example, sometimes the target type $\Pi(u_i, 1)$ ($u_i = \Gamma(CL, 1)$) does not match any vehicle in a template, e.g., $\Pi(u_i, 1) \notin T_k$. In this case we need to choose $u_j = \Gamma(CL, 2)$ to continue the matching. The process stops when either CL or T_k becomes empty.

Algorithm 1 Doctrinal Template Matching Algorithm

```
Initially, C_k = 0, L = 1.
while (|CL| ≠ 0 and |T_k| ≠ 1) do
    u_i = Γ(CL, L)
    if (∃v_j ∈ T_k and v_j = Π(u_i, L)) then
        CL = CL − u_i
        T_k = T_k − v_j
        C_k = C_k + 1 − m_i({v_j}) − m_i(Θ)
    else
        L = L + 1;
    end if
end while
C_k = C_k + |CL|
return C_k
```

Algorithm 1 describes the process of matching a cluster of vehicles with a platoon template, where the conflict C_k is initialized as 0 and the initial round L is 1. The algorithm can also be used to match high-level forces, e.g., a company, where each slot in the template or the cluster is a platoon.

The template with the minimum conflict with the cluster is the matched one. The confidence level of the matched template or unit type depends on the belief functions of each vehicles 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 3: Given a cluster of vehicles $CL = \{u_1, u_2, \ldots, u_q\}$, assume $\{T_1, T_2, \ldots, T_l\}$ are templates for the force level, T_k is the matched template with minimum conflicts with the cluster, C_i is the conflict between CL and any template T_i. We can get the corresponding basic probability assignment m for $T_i \in \{T_1, T_2, \ldots, T_l\}$

$$m(\{T_i\}) = \frac{max(C_1, C_2, \ldots, C_l) - C_i}{\sum_{j=1}^{l} (max(C_1, C_2, \ldots, C_l) - C_j)} \quad (6)$$

The label of the CL is T_k if $m(\{(T_k\}) > m(\{T_j\})$ for any $T_j \in \{T_1, T_2, \ldots, T_l\}$ and $T_k \neq T_j$.

If we find three $T80$ tanks stay together, we can infer that it is likely a $T80$ tank platoon and its confidence level $m(\{T80Platoon\})$ is high. Sometimes we may not find all three tanks; Instead, we only find two out of three or even one. The following figure illustrates the combined belief functions for three tank platoons with one, two, or three tanks. The figure tells us the confidence level is low if the sensors only find some of the total vehicles in templates. In practice, a $T80$ tank platoon with low confidence could be misclassified as an $M1$ tank platoon at platoon level. However, the cluster of tanks can still be recognized as part of a $T80$ tank company at company level using our approach. In other words, our approach is robust against the incomplete and ambiguous information from sensors and reduces effect of the ambiguity caused by missing targets on the higher level force classification.

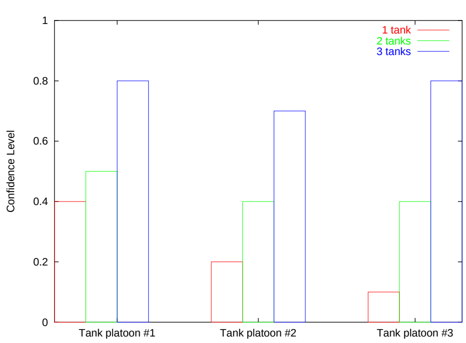

Fig. 6. The fused confidence level for a $T80$ tank platoon with different number of tanks being found

III. Experiments

In this section, we first introduce a modeling and simulation environment, OTBSAF (OneSAF Testbed Baseline) [1] and its integration with the RETSINA system (Reusable Environment for Task Structured Intelligent Network Agents) [12]. And then we discuss some experimental results of force aggregation and classification in the simulated testbed.

A. 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.

B. Experimental Results

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.

We consider a simple application of our approach for SARSims 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 7 and Figure 8 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 7. Also, tank

[1] http://www.onesaf.org/

	Cluster P_1			Cluster P_2			Cluster P_3			
	1014	1017	1020	1024	1027	1030	1034	1037	1040	1044
USSR T80	0.4	0.4	0.05	0.4	0.3	0.4	0.3	0.05	-	0.4
USSR T72M	0.3	0.3	0.05	0.3	0.4	0.3	0.4	0.05	-	0.3
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	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	-	0.001
US M35	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	-	0.001
US AVENGER	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	-	0.001
US HMMWV	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	-	0.001
USSR SA9	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	-	0.001
CLUTTER	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	-	0.095

Fig. 7. The confidence levels for tanks in a $T80$ tank company from the outputs of the low resolution SAR sensor SAR_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.

	Cluster P_1			Cluster P_2			Cluster P_3			
	1014	1017	1020	1024	1027	1030	1034	1037	1040	1044
USSR T80	0.7	0.7	-	0.7	0.7	0.7	0.7	0.7	-	0.7
USSR T72M	0.1	0.1	-	0.1	0.1	0.1	0.1	0.1	-	0.1
US M1	0.02	0.02	-	0.02	0.02	0.02	0.02	0.02	-	0.02
US M1A1	0.02	0.02	-	0.02	0.02	0.02	0.02	0.02	-	0.02
US M1A2	0.02	0.02	-	0.02	0.02	0.02	0.02	0.02	-	0.02
USSR 2S6	0.01	0.01	-	0.01	0.01	0.01	0.01	0.01	-	0.01
USSR ZSU23	0.02	0.02	-	0.02	0.02	0.02	0.02	0.02	-	0.02
US M977	0.001	0.001	-	0.001	0.001	0.001	0.001	0.001	-	0.001
US M35	0.001	0.001	-	0.001	0.001	0.001	0.001	0.001	-	0.001
US AVENGER	0.001	0.001	-	0.001	0.001	0.001	0.001	0.001	-	0.001
US HMMWV	0.001	0.001	-	0.001	0.001	0.001	0.001	0.001	-	0.001
USSR SA9	0.001	0.001	-	0.001	0.001	0.001	0.001	0.001	-	0.001
CLUTTER	0.105	0.105	-	0.105	0.105	0.105	0.105	0.105	-	0.105

Fig. 8. The confidence levels for tanks in a $T80$ tank company from the outputs of the high resolution SAR sensor SAR_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.

1020 is only found by sensor SAR_1 and tank 1040 is not found by either sensor.

Given SARSim outputs for a tank u_i, we first convert the outputs to belief functions and then combine the belief functions using Dempster's rule of combination. Next we discuss how to recognize the type of a given echelon solely based on the outputs of low resolution SARSim SAR_1, or based on the fused outputs of two SARsims SAR_1 and SAR_2 through Dempster-Shafer's theory. We assume tanks or vehicles have been clustered into platoons according to the distances between them.

1) 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 SA9 platoon, and USSR 2S6 platoon. Table I 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 SA9 platoon	4 SA9s
USSR 2S6 platoon	2 2S6s

TABLE I

THE NUMBER OF EACH TYPE OF TANKS OR VEHICLES IN DIFFERENT PLATOON TEMPLATES

Table II describes the conflicts of three clusters of tanks with platoon templates using Algorithm 1. Given the outputs of sensor SAR_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 T72M platoon template and is classified as a T72M 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 an $M1A1$ 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 T72M tank platoon, since the sensor only finds two out of three tanks in the cluster and one of them is recognized as a T72M 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 SAR_1 and SAR_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.

Templates	P_1		P_2		P_3	
M1 pl.	2.4	**2.7**	2.55	**3**	1.37	**2**
M1A1 pl	2.32	**2.6**	2.55	**3**	1.41	**2**
M1A2 pl.	2.33	**2.6**	2.55	**3**	1.42	**2**
T72M pl.	2.05	**2.57**	1.7	**2.5**	1.25	**1.7**
T80 pl.	1.85	**1.31**	1.6	**0.7**	1.35	**0.8**
SA9 pl.	2.7	**2.9**	2.7	**3**	1.7	**2**
2S6 pl.	2.8	**2.9**	2.8	**3**	1.8	**2**

TABLE II

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 SAR_1 AND SAR_2 ARE IN BOLD.

Templates	P_1		P_2		P_3	
M1 pl.	0.13	**0.07**	0.08	**0**	0.19	**0**
M1A1 pl	0.15	**0.11**	0.08	**0**	0.17	**0**
M1A2 pl.	0.15	**0.11**	0.08	**0**	0.17	**0**
T72M pl.	0.24	**0.12**	0.35	**0.18**	0.24	**0.2**
T80 pl.	0.30	**0.59**	0.38	**0.82**	0.19	**0.8**
SA9 pl.	0.03	**0**	0.03	**0**	0.04	**0**
2S6 pl.	0	**0**	0	**0**	0.0	**0**

TABLE III

BASIC PROBABILITY ASSIGNMENTS FOR CLUSTERS OF TANKS, P_1, P_2, AND P_3, WHERE BASIC PROBABILITY ASSIGNMENTS BASED ON FUSED OUTPUTS OF SENSORS SAR_1 AND SAR_2 ARE IN BOLD.

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 3 and results are shown as in Table III, where frame of discernment for P_1 and P_2 is $\{T80\_platoon, \neg T80\_platoon\}$. Similarly, the basic probability assignments for P_3 are shown in the same table.

2) 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 Table IV). Some platoons are included in the template of a battalion level force directly, e..g, USSR SA9 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.

Table V 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 0.79 when we use the fused outputs of sensors SAR_1 and SAR_2. The basic probability assignments for the $T80$ company are shown in Table VI

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 IV

THE NUMBER OF EACH TYPE OF PLATOONS IN DIFFERENT COMPANY TEMPLATES

Templates	T80 company	
M1 company	2.6	**2.93**
M1A1 company	2.6	**2.89**
M1A2 company	2.6	**2.89**
T72M company	2.22	**2.5**
T80 company	2.08	**0.79**
2S6 battery	3	**3**

TABLE V

THE CONFLICTS OF THE ASSUMED $T80$ COMPANY WITH COMPANY TEMPLATES, WHERE THE CONFLICTS BASED ON FUSED OUTPUTS OF SENSORS SAR_1 AND SAR_2 ARE IN BOLD.

Templates	T80 company	
M1 company	0.14	**0.02**
M1A1 company	0.14	**0.04**
M1A2 company	0.14	**0.04**
T72M company	0.27	**0.16**
T80 company	0.31	**0.74**
2S6 battery	0	**0**

TABLE VI

BASIC PROBABILITY ASSIGNMENTS FOR THE CLUSTER OF TANK PLATOONS, WHERE BASIC PROBABILITY ASSIGNMENTS BASED ON FUSED OUTPUTS OF SENSORS SAR_1 AND SAR_2 ARE IN BOLD.

IV. RELATED WORK

The idea of using Dempster-Shafer theory for multisensor data fusion is not new. For example, Lowrance at al. apply Dempster-Shafer theory in reasoning about the locations and activities of multiple ships from intelligence reports [13]; Bogler studies whether the targets belong to the set of friendly or the set of not friendly aircraft in multisensor target identification systems using Dempster-Shafer theory [14]. Recently, Schubert extends those approaches to force clustering and classification [15], [16], 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 and focuses on how to handle intelligence reports with multiple nonspecific and uncertain hypotheses. Our work is related to Schubert's approach, but we do not consider sensor reports clustering for each target.

Also, our approach is computationally efficient since we only consider pairwise conflicts between vehicles (or subechelon) in a cluster and elements in templates.

Bayesian inference techniques have been utilized for force aggregation [17]. 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 [18]. The units of the partition are used to create a set of unit templates in the hierarchy network of military force. In their approach, the posterior probability for each node is computing using Bayesian methods and is propagated through the hierarchy network as positive or negative evidence for the inclusion of each unit in the partition. In order to get better performance, the accumulated evidence in the network is learned through a set of randomly selected potential solutions using genetic algorithm. In this paper we use a bottom-up approach, instead of the top-down approach as described in [18], for force aggregation and classification. It would be interesting to study the possibility of combining these two approaches in force aggregation and classification.

Looney refined the fusion architecture for building a more accurate picture [19], [20]. Looney gave an alternative methods of fusing multisensor multitarget tracking data using a fuzzy clustering algorithm — C-means fuzzy clustering. Different from agglomerative clustering algorithm, fuzzy clustering assigns different degrees of membership to each entity. Thus, it allows each entity to belong to multiple clusters with various fuzzy membership values. Looney's approach makes the clustering independent of the ordering (k-means algorithm relies on the order), but the number K for a fuzzy K-cluster needs to be empirically estimated, where K is usually unknown in the battlefield with asymmetric information. More recently, Looney and Liang developed a simple clustering algorithm for force aggregation, where each target is denoted as a feature vector [21]. The clustering algorithm is similar to ours, but they only consider the case of each target having a belief value between 0 and 1 for a single target type. In this paper, we describe a framework of multisensor data fusion for force aggregation, where the decision of a sensor is a list of candidate target types with different confidence levels.

V. 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. In the future work we plan to evaluate the effectiveness of our approach at platoon and company level forces. We also plan to use the context of terrain and redundant sensor data to identify and reduce false positive targets in sensor reports [22].

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