Fusion of Multi-Sensor Data Collected by Military Robots

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***Abstract*—This paper addresses the fusion processing techniques of multi-sensor data perceived through IR sensors of the military robots for surveillance, in which they are positioned in a limited range with a close distance between each of the robots. To combine multi-sensor data from distributed battlefield robots, we propose a set of fusion rules to formulate the combined prediction from multi-source data expressed in degrees of reliability for the type of a target that has the mathematical properties of probabilities. We have implemented three fusion operators to compare the capabilities of their fusion processing, and have experimented them in simulated, uncertain battlefield environments. The experimental results show that the fusion of multi-sensor data from military robots can be successfully tested in randomly generated military scenarios.**

***Index Terms*—Military surveillance robots, Multi-sensor fusion, Techniques for fusion processing**

I. Introduction

Battlefield robots for surveillance equipped with IR sensors keep a close watch on moving targets. These military robots are semi-autonomously operated; that is, their actions are mostly decided by themselves, but sometimes controlled by their commanders. The multiple robots periodically scan regions and, when they spot any possible threats, inform the control center of their estimations. The control center then fuses evidences multi-sensed from different military robots. The commander at the control center [1] provides feedbacks on the estimations of the multiple robots based upon the results of fusion processing.

Information fusion from different sensors has become a crucial component in distributed military surveillance environments [2]. In this paper, we focus on the information fusion processing that refines the estimation of types for a specific target and improves the reliability of its identification, continuously seeking out its positions. We suggest a set of fusion operators [3] to formulate the combined prediction from multi-source data expressed in degrees of reliability for the type of a target that has the mathematical properties of probabilities.

In the following section, we will describe how to combine multi-sensor data from military robots for surveillance. In Section III, we validate our framework empirically and present the experimental results using our simulator. In conclusion, we summarize our results and discuss further research issues.

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II. Combining Multi-Sensor Data from Distributed Robots

We combine multi-sensor data from distributed battlefield robots. The battlefield robots estimate the types of targets using their sensors in a given environment. After getting the sensor data, the multiple robots inform the control center of their estimations. The control center then fuses evidence multi-sensed from different military robots.

A. Combined Prediction Using Fusion Rules

The combined prediction given a specific target for the commander is defined as

$$\gamma^{t_k} = \gamma_i^{t_k} \otimes \gamma_j^{t_k} \text{ for } k=1, 2, 3, \ldots \quad (1)$$

where

- $\gamma_i^{t_k}$ and $\gamma_j^{t_k}$ represent the confidence of the possible type of a specific target, t_k, from a robot *i* and a robot *j*, respectively;
- $0 \le \gamma_i^{t_k}$ and $\gamma_j^{t_k} \le 1$;
- $\sum_k \gamma_i^{t_k} = 1$ and also $\sum_k \gamma_j^{t_k} = 1$.

We propose a set of fusion rules to formulate the combined prediction from multi-source data expressed in degrees of reliability for the type of a target that has the mathematical properties of probabilities. Given confidence values of $\gamma_i^{t_k}$ and $\gamma_j^{t_k}$ for *k=1, 2*, the aggregation operators, $\otimes = \{\Psi_1, \cdots, \Psi_n\}$, in this paper, are as follows:

- Mean (Ψ_1): $\gamma^{t_k} = (\gamma_i^{t_k} + \gamma_j^{t_k})/2$;
- Product (Ψ_2): $\gamma^{t_k} = \gamma_i^{t_k} \times \gamma_j^{t_k}$;
- Dempster-Shafer theory [4-6] (Ψ_3):

$$\gamma^{t_k} = \frac{\gamma_i^{t_k} \times \gamma_j^{t_k}}{1 - ((1 - \gamma_i^{t_k})\gamma_j^{t_k} + \gamma_i^{t_k}(1 - \gamma_j^{t_k}))}.$$

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The combined prediction representing the overall degrees of belief on the type of a specific target can be obtained by applying aggregation operators to multi-source data. The goal of fusion processing is to combine the estimations from distributed military robots when each of them estimates the probability of reliability on the type of a target, and another goal is to produce a single probability distribution that summarizes their probabilities.

Among the aggregation operators, the mean operator simply extends a statistic summary and provides an average of $\gamma_i^{t_k}$'s coming from different robots. The product rule summarizes the probabilities that coincide with $\gamma_i^{t_k}$ and $\gamma_j^{t_k}$. In this case, neither of $\gamma_i^{t_k}$ and $\gamma_j^{t_k}$ should be zero, since the product operator suffers from the limitation that if one operand is zero, the entire product will be zero. To avoid the zero results of combined prediction using the product operator, in general, they assume that these zero's could be replaced with very small positive number being close to zero [7]. Dempster's rule for combining degrees of belief produces a new belief distribution that represents the consensus of the original opinions [4]. Using Dempster's rule, the resulting values of γ^{t_k} 's indicate the degrees of agreement on different robots' probabilities of reliability on the type of a target; however, they completely exclude the degrees of disagreement or conflict. The advantage of using the Dempster's rule in our fusion processing is that no priors and conditionals are needed.

The normalization of combined prediction is given as

$$\hat{\gamma}^{t_k} = \frac{\gamma^{t_k}}{\sum_{t_k} \gamma^{t_k}} \quad \text{for } k=1, 2, 3, \qquad \text{...(2)}$$

taking into account all of the estimations about types of a target. The normalized prediction, thus, represents the overall confidence on a set of uncertain estimations, and it translates the combined prediction into a specific value where $\sum_{t_k} \hat{\gamma}^{t_k} = 1$.

B. *Example of Combined Prediction*

Let $\gamma_i^{t_k}$ = {0.60, 0.10, 0.20, 0.10} and $\gamma_j^{t_k}$ = {0.70, 0.20, 0.05, 0.05} from a robot *i* and a robot *j* for *k=1, 2, 3, 4.* This is interpreted that there are two surveillance robots, *i* and *j*, monitoring a specific target, which is uncertain of its type that is one of four types. Given confidence values, aggregation rules can be applied to get combined prediction, as defined in (1). The outputs of combined prediction are summarized in Table 1.

For example, when we use Ψ_3 as an aggregation operator, the combined prediction of γ^{t_1} according to Dempster-Shafer theory is calculated as follows:

$$\gamma^{t_1} = \frac{0.6 \times 0.7}{1 - [0.6 \times 0.2 + 0.6 \times 0.05 + 0.6 \times 0.05 + 0.7 \times 0.1 + 0.7 \times 0.2 + 0.7 \times 0.1]} = 0.778 .$$

TABLE I. THE EXAMPLE OF COMBINED PREDICTION USING THREE FUSION RULES

$\gamma_i^{t_k}$ = {0.60, 0.10, 0.20, 0.10} $\gamma_j^{t_k}$ = {0.70, 0.20, 0.05, 0.05}	
Fusion rules	γ^{t_k}
Mean (Ψ1)	{0.650, 0.150, 0.125, 0.075}
Product (Ψ2)	{0.420, 0.020, 0.010, 0.005}
Dempster-Shafer (Ψ3)	{0.778, 0.027, 0.013, 0.006}
Fusion rules	$\hat{\gamma}^{t_k}$
Mean (Ψ1)	{0.650, 0.150, 0.125, 0.075}
Product (Ψ2)	{0.923, 0.044, 0.022, 0.011}
Dempster-Shafer (Ψ3)	{0.944, 0.033, 0.016, 0.007}

When mean aggregator is used, among the fusion operators, the resulting distribution of combined prediction similarly reflects the distribution of confidence values from each robot's perspective. In cases of product and Dempster-Shafer theory, however, the γ^{t_1} 's (0.420 and 0.778) of the combined prediction are much bigger than the other combined values (0.020 and 0.027, 0.010 and 0.013, 0.005 and 0.006), compared with the original distributions of their estimations. Normalizing the combined prediction $\hat{\gamma}^{t_k}$, as defined in (2), makes the confidence values on types of a target being compared with each other in the range of 0 and 1.

III. EXPERIMENTATION

We have implemented an individual fusion process using the aggregation operators of Mean, Product, and Dempster-Shafer theory in C# programming language, as depicted in Fig. 1. Military robots can be selected for up to six, i.e., from Robot1 to Robot6, and the possible types of a specific target monitored by them are assumed to be an SUV, Truck, APC, and Tank. Given input values of confidence for each type of a target, the combined prediction button calculates the fusion of confidence values according to (1) using three fusion operators. The normalization button returns a normalized output value, which is computed by (2). The plot button displays a graph whose bar is representing accumulated confidence values on each type of target, as shown in the right side of Fig. 1. The reset button initializes the fusion processing.

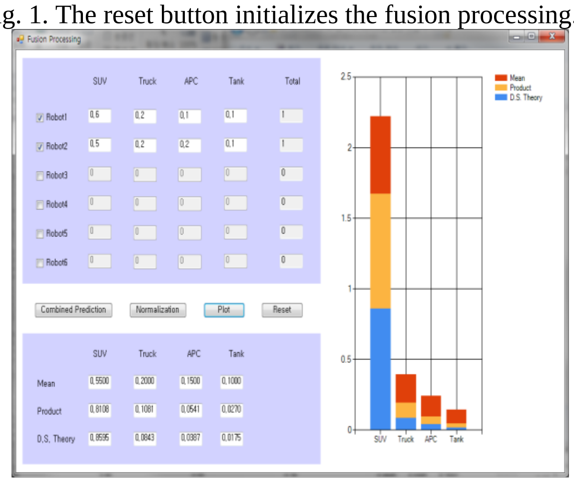

Figure 1. Fusion processing

To evaluate our fusion process in simulated, uncertain military environments, we have also implemented a simulator, as depicted in Fig. 2.

The goal of our experiment using the simulator is to investigate the distribution of confidence values, as the result of applying three fusion operators to surveillance data perceived by IR sensors of different robots. In the experiment, we assume that two military robots simultaneously monitor a specific target at a randomly generated distance. In this case, we categorize the distance between a battlefield robot and a target into three ranges: short range, middle range, and long range. Short range targets and long range targets each make up 30% of the total, and 40% of the total is comprised of middle range targets.

Fig. 2 is divided into two parts, one of which is the situation panel, as described in the left side of Fig. 2, and the other, the graph panel, as depicted in the right side of Fig. 2. The situation panel consists of a distance from robot1, a distance from robot2, robot1's confidence value on a specific target given a distance, robot2's confidence value on the same target given another distance, and lastly the results of fusion processing according to three aggregation operators. When the combined prediction button is pressed, the information above and the results of fusion processing are automatically generated over 100 situations. On the graph panel, when targets are generated at a short range or middle range from the robots, the resulting confidence values produced by the product operator and the Dempster-Shafer theory operator have overall larger values than those values produced by the mean operator.

IV. Conclusion

We propose a set of fusion operators to combine multi-sensor data from military robots and have implemented a simulator to repeatedly assess fusion processing in distributed battlefield environments. As part of ongoing work, we are developing an integrated battlefield simulator that has targets moving on pre-planned paths. Military surveillance robots search for possible threats among these targets. Other than the paths that the targets follow, the position and number of obstacles can also be programmed in advance and thus test whether the robots can track threats and communicate the results of fusion processing even when they momentarily do not have a visual on these targets. We hope to develop our simulator that can successfully create simulated, uncertain battlefield environments in which military robots can be repeatedly tested for their coordinated decision-making, target allocation, and the continuous tracking of the subsequent movements of targets.

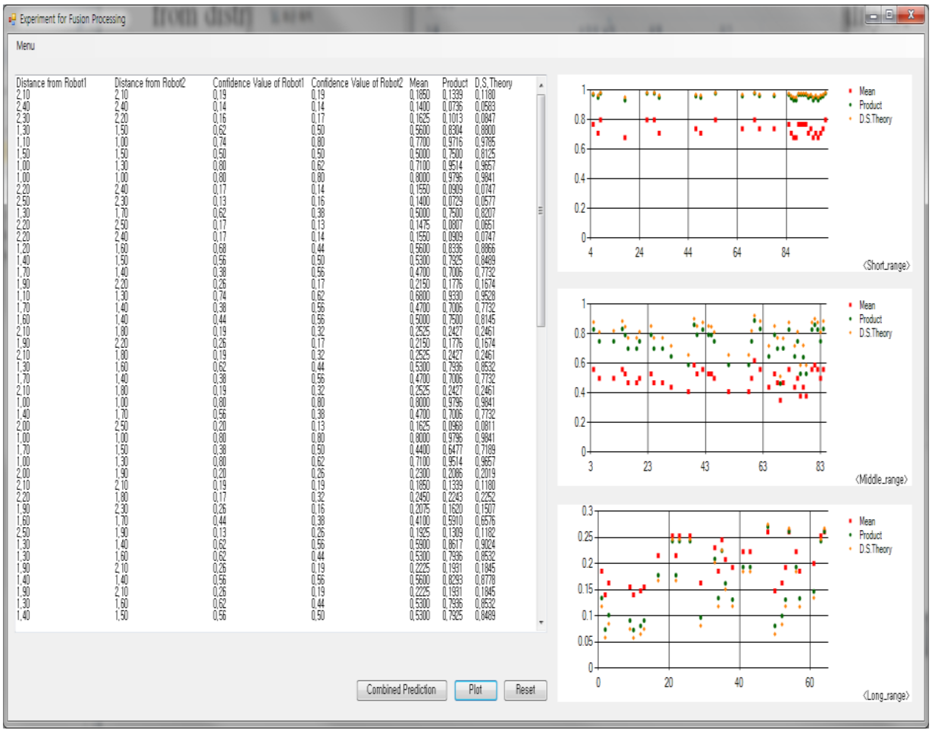

Figure 2. Experiment for fusion processing

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