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Target Recognition Based on Fuzzy Dempster Data Fusion Method

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ABSTRACT

Data fusion technology is widely used in automatic target recognition system. Problems in data fusion system are complex by nature and can often be characterised by not only randomness but also by fuzziness. To accommodate complex natural problems with both types of uncertainties, it is profitable to construct a data fusion structure based on fuzzy set theory and Dempster Shafer evidence theory. In this paper, after representing both, the individual attribute of target in the model database and the sensor observation or report as fuzzy membership function, a likelihood function was constructed to deal with fuzzy data collected by each sensor. The method to determine basic probability assignments of each sensor report is proposed. Sensor reports are fused through classical Dempster combination rule. A numerical example is illustrated to show the target recognition application of the fuzzy-Dempster approach.

Keywords: Evidence theory, fuzzy set theory, multisensor fusion, target recognition, data fusion technology, automatic target recognition system, Bayesian theorem, Dempster shafter evidence theory

1. INTRODUCTION

Today, multiple sensors are being increasingly used in the design of automatic target recogniser to enhance performance and reliability of automatic target recognition (ATR) system[1-3]. One of the important components in ATR system is its classifier. How to improve the ability of classifier by multisensor data fusion technology is an open issue. Bayesian theorem is an effective tool for reasoning under condition of uncertainty and yields promising results in many realistic application systems[4,5]. It is well known that problems in data fusion system are complex by nature and can often be characterised by not only randomness but also fuzziness[6-8]. However, in general, current Bayesian methods can only account for randomness. To accommodate complex natural problems with both types of uncertainties, it is profitable to improve existing approach by incorporating fuzzy theory into classical techniques. What's more, due to it's efficiency to handle more uncertain information than probability theory, Dempster Shafer evidence theory is often employed in target recognition systems. It is shown that evidence theory can deal with both fuzziness and randomness information in a more flexible way, which is one of the most important aspects in data fusion systems.

In this paper, after representing both the individual attribute of target in the model database and the sensor observation or report as fuzzy membership function, a likelihood function has been constructed to deal with fuzzy data collected by each sensor. The basic probability assignment (BPA) can be obtained through the transformation of likelihood function. Then, sensor data from different sources can be fused based on the Dempster combination rule.

The general process of modelling fuzzy observation is explained and an ambiguous likelihood function that models their understanding of how these observations are generated has been defined. The method to construct the likelihood function is also presented. From the individual attribute likelihood, a global likelihood has been generated for the ensemble of reports based on similarity measure. A numerical example is illustrated to show how fuzzy-Dempster approach can be used in multisensor system.

2. LIKELIHOOD FUNCTION FOR FUZZY DATA

The basic theory of Bayesian approach in target classification has been described followed by methodology to construct an ambiguous likelihood function when the sensor report is of fuzzy nature. Bayesian theorem provides a mechanism for combining prior information with sample data to make inferences on model parameters.

For a vector parameter α, Let $f(\alpha)$ be the prior distribution of α. Then for the observed data for the specified model has the likelihood $L(DATA\,|\,\alpha)$. Using Bayesian theorem, the conditional distribution of α given the data (also known as the posterior distribution of α) is

$$f(\alpha\,|\,DATA) = \frac{L(DATA\,|\,\alpha) f(\alpha)}{\int L(DATA\,|\,\alpha) f(\alpha) d\alpha} \quad (1)$$

In target recognition systems, the prior distribution can be the probabilities of all kind of the known targets.

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When the DATA collected by some sensors (for example, radar and satellite, etc), then the prior distribution is updated to posterior distribution which is influenced by the information in DATA to lead to the new probability of interesting targets. As mentioned above, the data collected by different types of sensors may be fuzzy. Thus, an obvious problem is how to get the posterior distribution that is updated from the prior distribution by fuzzy data. According to Eqn (1), the problem is what should be the likelihood function in fuzzy data case?

In ATR system, there exists a target database that includes the attributes of all the targets, called a model database. All attributes of the known target in the model database are characterised by fuzzy membership function. In the process of target recognition, the target's attributes observed by many kinds of sensors are compared with the attributes in the model database. A target is recognised when there is highest degree matching between the observation and the known model.

Let *T*(all known targets) be the class for which attribute models are known and let *t* (target) be an individual member from *T*. In general, one target has several attributes. Thus each entry in the database is characterised by a set of attributes. For simplicity, it is assumed that each target has only one attribute (for example, the transmitter frequency). The description of the attributes for the known target is called as 'model signature'. Let the fuzzy model signature be defined by a fuzzy membership function $h_t : U \to [0,1]$,where U denotes attributes parameter space. Let A be a uniformaly distributed random number on the unit interval [0,1]. Let the 'model ambiguous (fuzzy) signature' be defined as

$$\Sigma_t \triangleq \Sigma_A(h_t) = \{x \in U \mid A \le h_t(x)\} \tag{2}$$

Now, assume that a piece of fuzzy observation is collected in the form of a fuzzy membership function $g : U \to [0,1]$ on (attributes) observation space. Let the fuzzy obsearvation θ be defined as

$$\theta \triangleq \Sigma_A(g) \tag{3}$$

Then it can be surmised that a fuzzy observation θ probably corresponds to a target *t* if it matches a 'model ambiguous (fuzzy) signature' Σ_t that reflects the understanding of what a typical observation will look like if it is generated by a target . Here, if θ matches Σ_t, it means that θ does not contradict Σ_t, i.e., $\theta \cap \Sigma_t \ne \varnothing$ This implies that 'matching' is a probabilistic phenomenon. As both θ and Σ_t vary randomly they are sometimes disjoint (they contradict each other) and sometimes non-disjoint (they do not contradict each other). Intuitively, if they both match often, then it is likely that the observation θ actually originated with a target *t*; whereas if they do not match very often, it is unlikely that the observation originated with the target. Consequently, a measure of the likelihood that the observation θ originated with a target is the probability of match as follows

$$\rho(\theta \mid t) = \Pr(\theta \cap \Sigma_t \ne \varnothing) \tag{4}$$

It may be noted that

$$\theta \cap \Sigma_t = \Sigma_A(g \wedge h_t) = \{x \in U \mid A \le (g \wedge h_t)(x)\} \tag{5}$$

where $\theta \cap \Sigma_t \ne \varnothing$ if and only if $A \le (g \wedge h_t)(x)$.

Accordingly,

$$\begin{aligned}\rho(\theta \mid t) &= p(\theta \cap \Sigma_t \ne \varnothing) = p(A \le (g \wedge h_t)(x)) \\ &= \sup_x \min\{g(x), h_t(x)\}\end{aligned} \tag{6}$$

A simple example is used to understand the fuzzy data likelihood function mentioned above. Let *t* be a target in the model database whose attribute is the transmitter frequency. This attribute, together with associated ambiguities, is modelled by a Guassian fuzzy membership function derived using the mean and standard distribution of that attribute as

$$h_t = \mu_t(f) = e^{\frac{-(f-f_t)^2}{2\sigma_t^2}} \in [0,1]$$

where $\mu_t(f)$ is the model signature of target *t* which reflects the knowledge of the target's attribute, that is the transmitter frequency. A fuzzy sensor report may be represented as

$$g(f) = \mu_{rpt}(f) = e^{\frac{-(f-f_{rpt})^2}{2\sigma_{rpt}^2}} \in [0,1]$$

Here σ_{rpt} reflects the accuracy of the report's estimated mean, f_{rpt}.

Suppose the values are taken as follows:

$f = 24\,\text{MHz}$, $\sigma = 3$

$f_{rpt} = 20\,\text{MHz}$, $\sigma_{rpt} = 3$

Then, $\mu_t(f)$ and $\mu_{rpt}(f)$ are as shown in Fig. 1. According to Eqn (6), the value of $\rho(report \mid target)$, abbreviated as $\rho(r \mid t)$, is determined by the results of $\sup_x \min\{g(f), h_t(f)\}$. Obviously, the value of $\min\{g(f), h_t(f)\}$ reaches the maximum at the intersection point (22,0.8007) of $g(f)$ and $h_t(f)$.

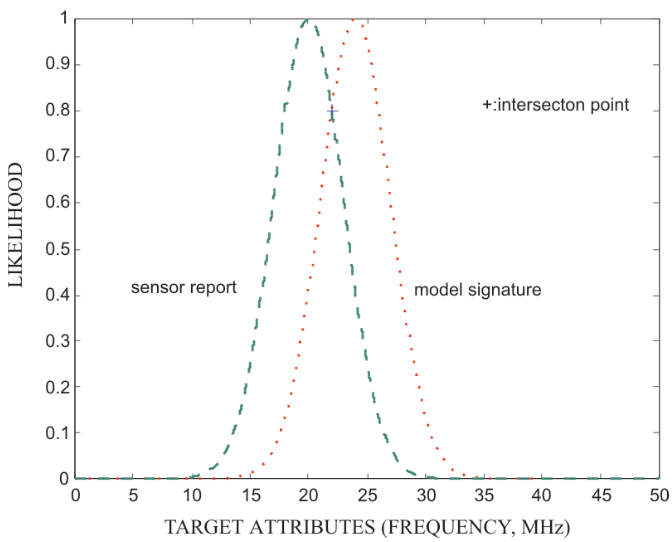

Figure 1. Fuzzy report and fuzzy model signature.

Thus, the value of the likelihood $\rho(r\,|\,t)$ is 0.8007. This means that, when the model signature of target *t* is $\mu_t(f)$, the possibility that the sensor report may be $\mu_{rpt}(f)$ is 0.8007. From another point of view, the likelihood $\rho(r\,|\,t)$ is a measurement of the intersection of the fuzzy sets $\mu_t(f)$ and $\mu_{rpt}(f)$. Higher the intersection, more is the consistency between the sensor observation and the model signature. Another way to calculate the likelihood is to use the value of the monotonous function $h_t(f_{rpt})$ instead of $\rho(r\,|\,t)$ without udergoing the searching procedure of the functions $g(f)$ and $h_t(f)$, which simplifies the calculation process.

3. DETERMINATION OF BASIC PROBABILITY ASSIGNMENTS BASED ON LIKELIHOOD FUNCTION

In real application, the identification of a target is determined based solely on the attributes measured by sensors. Typical measured attributes obtained from different sensor types include features such as shape, speed, transmitter frequency, number and type of weapons. In general, the database of ATR system includes all known objects of interest using attribute set. So, the classifier is developed to recognise target using available sensor attributes. Each sensor generates a likelihood function $\rho(\theta\,|\,t)$ to describe the probability of target *t* given the collected fuzzy data θ. After all the likelihood of individual sensor is obtained, the next key problem is how to fuse them effectively. To solve this problem, evidence theory is used. The likelihood of each sensor is transformed into basic probability assignment.

Let *T*(all known targets) be the class for which attribute models are known, and let *t* (target) be an individual member from *T*. Each entry in the database is characterised by a set of attributes. Let A_t be the set of attributes for target *t* in *T*. Each individual attribute *n* is represented as a fuzzy membership $\mu_{t,n}(x)\in[0,1]$, which represents the fuzzy set of attribute *n* for target *t*. For each attribute *n*, the ambiguous likelihood function of $\rho_n(r\,|\,t)$, where *t* means target and *r* means the report of the sensor. Suppose that the number of the attribute of target *t* is *M*, then *M* likelihood functions are obtained when a fuzzy report is collected by i^{th} sensor. Let these likelihood functions be denoted as: $\rho_1,\rho_2,\ldots,\rho_M$. If the total target is listed as: *a, b, c, d*,…, then the likelihood functions are denoted as $\rho_i(a\,|\,t)=x_a$, $\rho_i(b\,|\,t)=x_b$, $\rho_i(c\,|\,t)=x_c$…… for the i^{th} sensor.

The basic probability assignment can be determined as follows.

Step 1: Select the maximum value in ρ_i, then

$$x=\max\left(\rho_i(a\,|\,t)=x_a,\rho_i(b\,|\,t)=x_b,\rho_i(c\,|\,t)=x_c,\ldots\right) \tag{7}$$

Step 2: The likelihood to Unknown is defined as 1-x, then

$$\rho_i(U\,|\,t)=1-x \tag{8}$$

Step 3: Normalise

$\rho_i(a\,|\,t)=x_a$, $\rho_i(b\,|\,t)=x_b$, $\rho_i(c\,|\,t)=x_c$,…,

$\rho_i(U\,|\,t)=1-x$ to obtain the basic probablity assignment as follows.

$$m(\{s\})=\frac{\rho_i(s\,|\,t)}{\rho_i(a\,|\,t)+\rho_i(b\,|\,t)+\rho_i(c\,|\,t)+\cdots+\rho_i(U\,|\,t)} \tag{9}$$

For example, suppose the likelihood is obtained as follows:

$\rho_i(a\,|\,t)=0.7$ $\rho_i(b\,|\,t)=0.5$ $\rho_i(c\,|\,t)=0.1$

Then,

$$x=\max\left(\rho_i(a\,|\,t)=x_a,\rho_i(b\,|\,t)=x_b,\rho_i(c\,|\,t)=x_c\right)=0.7$$

The likelihood to unknown is

$$\rho_i(U\,|\,t)=1-x=1-0.7=0.3$$

The basic probablity assignment can be obtained through the normalisation process of Eqn. (9) as follows:

$$m(\{a\})=\frac{\rho_i(a\,|\,t)}{\rho_i(a\,|\,t)+\rho_i(b\,|\,t)+\rho_i(c\,|\,t)+\rho_i(U\,|\,t)}=\frac{7}{16}$$

$$m(\{b\})=\frac{\rho_i(b\,|\,t)}{\rho_i(a\,|\,t)+\rho_i(b\,|\,t)+\rho_i(c\,|\,t)+\rho_i(U\,|\,t)}=\frac{5}{16}$$

$$m(\{c\})=\frac{\rho_i(c\,|\,t)}{\rho_i(a\,|\,t)+\rho_i(b\,|\,t)+\rho_i(c\,|\,t)+\rho_i(U\,|\,t)}=\frac{1}{16}$$

$$m(\{U\})=\frac{\rho_i(U\,|\,t)}{\rho_i(a\,|\,t)+\rho_i(b\,|\,t)+\rho_i(c\,|\,t)+\rho_i(U\,|\,t)}=\frac{3}{16}$$

When several basic probability assignments are collected from different sensors, the data can be fused based on Dempster combination rule, as briefly introduced as follows:

Dempster's rule of combination (also called orthogonal sum), noted by $m=m_1\oplus m_2$, is the first one within the framework of evidence theory which can combine two BPA functions m_1 and m_2 to yield a new BPA function[9]:

$$m(A)=\frac{\sum_{B\cap C=A}m_1(B)m_2(C)}{1-k} \tag{10}$$

with

$$k=\sum_{B\cap C=\varnothing}m_1(B)m_2(C) \tag{11}$$

More information about Dempster combination rule, can be obtained from Shafer[9].

3. NUMERICAL EXAMPLE

In general, the database of ATR system includes all known objects of interest using attribute set. So, the classifier of ATR is developed to recognise target using available sensored attributes. The classification in ATR is represented by a probability distribution over the entire set of targets:

$$P=\{p_t\}_{t\in T},\quad \sum_{t\in T}p_t=1 \tag{12}$$

When a new fuzzy report comes in, the prior distribution

P is updated to posterior distribution P' using the ambiguous likelihood that reported attribute values could be generated from viewing each model.

$$P' = \{p_t'\}_{t\in T}\ , \quad \sum_{t\in T} p_t' = 1 \tag{13}$$

A numerical example is given as follows:

Suppose there are only two targets in the model database, say target a and target b. The prior distribution is $p_a = p_b = 0.5$. They have three attributes: low frequency, middle frequency and high frequency whose parameters are shown in Table 1.

Table 1. Three attributes of target *a* and target *b*

Attributes	target *a*	target *b*
Low frequency	$f_{al} = 12\,\text{MHz}, \sigma_{al} = 3$	$f_{bl} = 24\,\text{MHz}, \sigma_{bl} = 3$
Middle frequency	$f_{am} = 40\,\text{MHz}, \sigma_{am} = 3$	$f_{bm} = 50\,\text{MHz}, \sigma_{bm} = 3$
High frequency	$f_{ah} = 80\,\text{MHz}, \sigma_{ah} = 3$	$f_{bh} = 90\,\text{MHz}, \sigma_{bh} = 3$

Assume there are three different sensors, low frequency sensor, middle frequency sensor, and high frequency sensor, in the target recognition system. Each sensor measures the different attribute of targets and the sensor reports are shown in Table 2.

Table 2. Various sensor reports

Report	Frequency
R_l	$f_{rpt,l} = 20\,\text{MHz}, \quad \sigma_{rpt,l} = 3$
R_m	$f_{rpt,m} = 47\,\text{MHz}, \quad \sigma_{rpt,m} = 3$
R_h	$f_{rpt,h} = 92\,\text{MHz}, \quad \sigma_{rpt,h} = 3$

As the process of obtaining likelihood functions for all the three sensors is the same, the case of only low frequency sensor is explained here in detail. The attributes of targets a and b and the attribute reports collected by low frequency sensor were modelled by respective Gaussian fuzzy membership functions. The likelihood of a report for a known target is simply the maximum value at the intersection of the two Gaussian fuzzy membership functions of the target and sensor report, according to Eqn (6). In this case, the points of maximum values are obtained as 0.4111 and 0.8007 of intersection point (*) for target a and intersection point (+) for target b, respectively, as shown in Fig. 2. Similarly, the likelihood functions can be found for other two sensors (Figs 3 and 4) and the results are shown in Table 3.

Table 3. Likelihood for various sensor reports

Report	ρ(*r* | target *a*)	ρ(*r* | target *b*)
R_l	0.4111	0.8007
R_m	0.5063	0.8825
R_h	0.1353	0.9460

After all likelihood of all sensors are obtained, one can calculate the basic probability assignment by Eqns (7) to (9). For example, the basic probability assignment of low frequency sensor can be determined as follows:

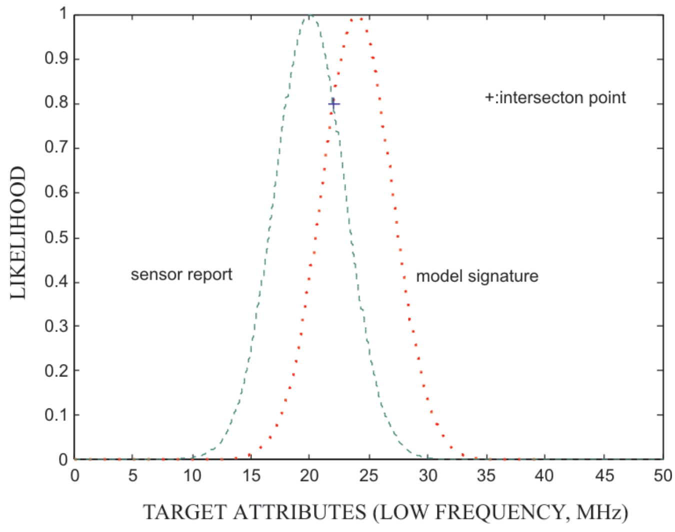

Figure 2. The report of low-frequency sensor.

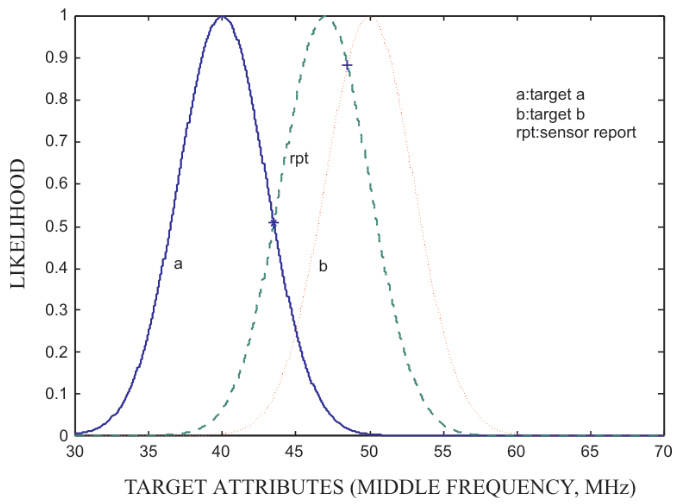

Figure 3. The report of middle-frequency sensor.

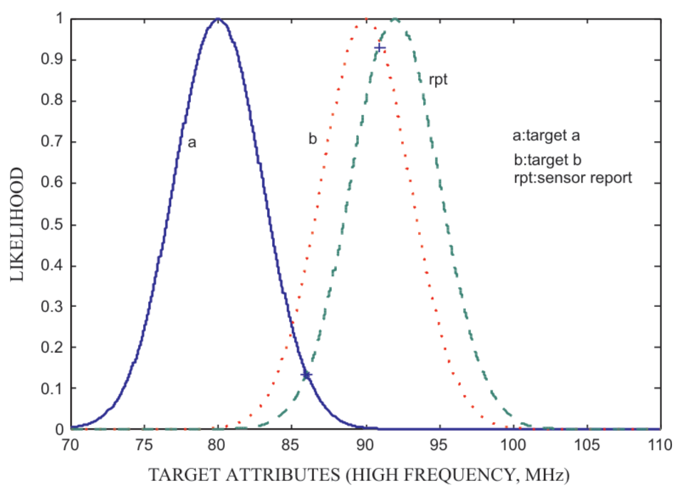

Figure 4. The report of high-frequency sensor.

$$m_l(R_a) = \left(\frac{\rho(r \mid target\ a)}{\rho(r \mid target\ a) + \rho(r \mid target\ b) + \rho_l(r \mid target\ a, target\ b)} \right)$$
$$= \frac{0.4111}{0.4111 + 0.8007 + 0.1993} = 0.29$$

$$m_l(R_b) = \frac{\rho(r \mid target\ b)}{\rho(r \mid target\ a) + \rho(r \mid target\ b) + \rho_l(r \mid target\ a, target\ b)}$$
$$= \frac{0.8007}{0.4111 + 0.8007 + 0.1993} = 0.57$$

$$m_l(R_{a,b}) = \frac{\rho(r \mid target\ a, target\ b)}{\rho(r \mid target\ a) + \rho(r \mid target\ b) + \rho_l(r \mid target\ a, target\ b)}$$
$$= \frac{0.1993}{0.4111 + 0.8007 + 0.1993} = 0.14$$

Similarly, the basic probablity assignments of middle-frequency sensor and high-frequency sensor can be determined and stated below:

$$m_m(R_a) = 0.34\ ,\ \ m_m(R_b) = 0.58\ ,\ \ m_m(R_{a,b}) = 0.08$$

$$m_h(R_a) = 0.12\ ,\ \ m_h(R_b) = 0.83\ ,\ \ m_h(R_{a,b}) = 0.05$$

Finally, the results of sensor data fusion based on Dempster combination rule can be calculated as follows:

$$m(R_a) \doteq 0.07 \quad m(R_b) = 0.93 \ \ m(R_{a,b}) \doteq 0$$

Hence, the final output of the target recognition based on mutli-sensor data fusion is target *b*.

Now, a multisensor fusion procedure has been proposed to integrating fuzzy multisource information based on the fuzzy-Dempster approach. This procedure is summarised by the following steps:

Step 1. Represents the attributes of target in model database and the sensor observation as fuzzy membership functions.

Step 2. Calculate the likelihood for fuzzy data.

Step 3. Determine the BPA functions of each piece of evidence collected from different sensors through the transformation of likelihood obtained from *Step* 2.

Step 4. Data fusion can be realised though combining all basic probability assignments based on Dempster rule.

4. CONCLUSIONS & FUTURE WORK

In ATR systems, the data collected by sensors may be fuzzy. Fuzzy Dempster approach presented in this paper can deal with uncertain data in a flexible manner and presents a promising method in target recognition. One drawback of Dempster combination rule is that it cannot efficiently deal with highly conflicting evidence[10]. Several works have been reported to handle this problem[10-14]. However, it is an open issue in ATR system due to the fact that the sensor report may be highly conflicting with each other in the combat environment. This problem is one of our future works in ATR system based on data fusion technology.

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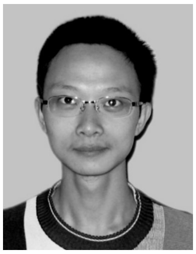

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