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Research Article

Multi-sensor Target Recognition Based on Relative Ratio Method

Lanping Li
Department of Basic Subjects, Hunan University of Finance and Economics,
Changsha 410205, P.R. China

Abstract: The aim of this study is to propose a new target recognition method for the multi-sensor with multiple characteristics indexes. Coefficient of variation is used to determine the weights of characteristic indexes. The conceptions of ideal optimal and negative ideal vectors are given first and then normalized relative ratio is used to comprehensive evaluation value. Hence the rule of target recognition is given. The method can avoid the subjectivity of the weight of characteristic indexes and improve the objectivity and accuracy of target recognition. Finally, numerical simulation illustrates the effectiveness and feasibility of the proposed method.

Keywords: Coefficient of variation, multi-sensor, relative approach degree, target recognition

INTRODUCTION

The basic task of target recognition is to identify known target by comparing the known target sample characteristics with those targets characteristics in the library. In recent years, multi-sensor data fusion has become an important means of target recognition under modern conditions. In recent years, multi-sensor target recognition problem has attracted many scholars' attention and research and many target recognition methods are put forward. For example, methods based on Dempster-Shafer evidence theory (Begler, 1987; Pang and Du, 1994; Cao *et al*., 2006; Yu *et al*., 2007) , Vague method (Yang *et al*., 2007; Wan, 2011a, b), variable fuzzy set method (Chen and Hu, 2006); extension method (Che *et al*., 2000) and extension interval deviation degree method (Wan, 2009a), etc. These methods have a better fusion result, but whether the method of evidence theory is based on the fuzzy theory, the basic probability assignment and selection of membership function with greater subjective uncertainty.

For the multi-sensor target recognition problem with multiple characteristics, variable fuzzy sets method and extension method are both artificial determined the weight of characteristics. They are too subjective and absolute objectivity. To improve target identification results, Wan (2009b) proposed entropy weight method and Wan (2011) uses objective optimization model to determine the weight of characteristic indexes. The two methods are objectively in determining weights, but the research in this field is rare, therefore this study presents a new method to determine the objective characteristics of index weight coefficient of variation method and put forward the relative ratio method of multi-sensor target recognition.

Multi-sensor target recognition model: A target recognition database contains n different target recognition category, noted as, $\pi = \{\pi_1, \pi_2, ..., \pi_n\}$ and each target has m characteristic indexes, recorded as, $o = \{o_1, o_2, ..., o_m\}$. Set θ_{ij} and σ_{ij}^2 are respectively said to the first j category π_i feature parameters (attributes) of the features (attributes) value and variance. The system has a characteristic vector matrix $X = (\theta_{ij})_{m\times n}$.

In target recognition, always through the identified target of each characteristic parameters and the observation and target database known target characteristic parameters matching to determine the identified target category. We use n different sensors to an unknown target object of study of each characteristics were observed. The first i set a sensor to detect the object first j feature index of the observed value $\theta_{0j} (j = 1,2,...,n)$ and the task of data fusion is according to the value of state $\theta_{0j} (j = 1,2,...,n)$ to determine the research object belongs.

METHODOLOGY

Variation coefficient weight method: As the variation coefficient weight method easy to use is proposed in this study, we put the original model was transformed to a minimum and maximum membership function model firstly, the feature vector matrix into the index membership degree matrix $R = (r_{ij})_{m\times n}$, where:

$$r_{ij} = \frac{\min\{\mu_{0j}, \mu_{ij}\}}{\max\{\mu_{0j}, \mu_{ij}\}} \tag{1}$$

Set $R_i = (r_{i1}, r_{i2}, \ldots, r_{in})$ be the i^{th} optional object. By (1) shows that, r_{ij} is the relative membership degree between measured value and the char acteristic values. The target recognition task is to find the closest to the target class and each sensor measurements.

If an characteristic $\mu_{ij} (i = 1,2,...,m)$ in each target category indicators are the same, then the characteristic index has no effect in target recognition, on the contrary, if the measured value of the index difference is large, then the indicators identified in the medium-term target larger role can therefore be based on the measure of the difference between the characteristic values, using the coefficient of variation to determine the weight of each characteristic index. Sinha (2003) proposed the coefficient of variation:

$$cv_j = \sigma_j / \mu_j,\ j = 1, 2, ..., n$$

As the characteristic index weights, but the disadvantage of this method is the total weight not 1. Redefine the coefficient of variation for this study weight:

$$w_{cv_j} = \frac{\sigma_j / \mu_j}{\sum_{j=1}^{n} \sigma_j / \mu_j},\ j = 1, 2, ..., n$$

As determined in this way the weights of different target category values will be different, in order to maintain the consistency of the target weight, in this study the weight of each characteristic attribute using the following formula:

$$w_j = \frac{1}{m} \sum_{j=1}^{m} w_{cv_{ij}} = \frac{1}{m} \sum_{j=1}^{m} \frac{\sigma_{ij} / \mu_{ij}}{\sum_{j=1}^{n} \sigma_{ij} / \mu_{ij}} \tag{2}$$

Obviously,

$$w_j \geq 0, \sum_{j=1}^{n} w_j = 1,\ j = 1,2,..., n$$

Relative ratio method for target recognition: In this section, we will give the calculation steps of the relative ratio method for the sensor target recognition as follows:

Step 1: Characteristic matrix into the membership matrix indicators $R = (r_{ij})_{m \times n}$

Step 2: Identify positive and negative ideal vector:

Suppose the index membership degree matrix is $R = (r_{ij})_{m \times n}$, we name:

$$\begin{aligned} R^* &= (r_1^*, r_2^*, \ldots, r_n^*) \\ &= (\max_i \{r_{i1}\}, \max_i \{r_{i2}\}, \ldots, \min_i \{r_{in}\}) \end{aligned}$$

is the positive ideal vector:

$$\begin{aligned} R^- &= (r_1^-, r_2^-, \ldots, r_n^-) \\ &= (\min_i \{r_{i1}\}, \min_i \{r_{i2}\}, \ldots, \min_i \{r_{in}\}) \end{aligned}$$

is the negative ideal vector.

Step 3: Calculating the alternative object with positive and negative ideal vector distance:

Set $w = (w_1, w_2, ..., w_n)$ as determined by the coefficient of variation characteristic of index weight, R^* and R^- are respectively positive ideal and negative ideal vector:
Set,

$$\begin{aligned} d(R_i, R^*) &= \sqrt{\sum_{j=1}^{n} w_j \mid r_{ij} - r_j^* \mid^2}, \\ d(R_i, R^-) &= \sqrt{\sum_{j=1}^{n} w_j \mid r_{ij} - r_j^- \mid^2} \end{aligned} \tag{3}$$

And are referred to as the i-th object with the alternative positive and negative desired distance vectors:

Step 4: Calculate the relative ratio of the alternative target:

Set,

$$\begin{aligned} d(R^-) &= \max_{1 \leq i \leq m} \{d(R_i, R^-), \\ d(R^+) &= \min_{1 \leq i \leq m} \{d(R_i, R^*) \end{aligned}$$

The *i*-th alternative target defines the relative ratio of:

$$\xi_i = \frac{d(R_i, R^-)}{d(R^-)} - \frac{d(R_i, R^*)}{d(R^+)},\ i = 1,2,...,m \tag{4}$$

Easy to prove that the relative ratio $\xi_i \leq 0$, which reflects the *i*-th object close to being the ideal alternative and away from negative ideal vector extent greater, indicating that the alternative *i* and the positive ideal vector objects relative distance is smaller, while the negative ideal vector larger relative distance.

Step 5: Calculate the relative approach degree.

As $\xi_i \leq 0, j = 1, 2, ..., n$, we will standardize them and gives the *i*-th alternative definition of the object relative approach degree:

$$C_i = 1 - \frac{\xi_i}{\sum_{i=1}^{m} \xi_i} \quad (5)$$

Easy to prove $0 \le C_i \le 1$ and the greater ξ_i, the C_i also greater, thus greater, indicating that the alternative object i and the relative distance is smaller the ideal vector and the vector and negative ideal larger relative distance.

Step 6: Identification rules

From the above analysis, according to the relative approach degree of candidate objects, we give target recognition rules:
If,

$$k_0 = \arg \max_{1 \le i \le m} \{C_i\}$$

Then the unknown object belonging to the target π_{k0}.

A simulation example: In order to illustrate the effectiveness of the fusion method proposed in this study, we apply the algorithm to the parts recognition example (Shao *et al*., 1996). In order to realize intelligent robots to object to be automatic recognition and classification of the method is applied to the sensor in the robot system. The system by SCARA robot, the robot control and drive, sensor system, the main computer, etc., in the multi-sensor system equipped with six d force sleep and close to sleep and contact sleep and sliding sleep and array touch, heat sensation for the sensor and the corresponding signal processor. In the experiment determined the four independent characteristics of the characteristic index to show the work piece, they were shape factor, the section center moment, surface reflection ability, surface roughness of the workpiece. A total of four kinds of different selection of the workpiece as the standard, the model of the characteristic value and variance (Table 1).

The sensor signal through the data collect and input to the computer and through the information analysis and characteristic level data fusion for some unknown characteristic of the data in Table 2.

This study presents the use of the method to identify the unknown work piece.

Step 1: Table 1 and 2 of the data and (1), (2) type get feature matrix and confidence distance matrix is as:

$$X = \begin{pmatrix} 1.30 & 1.86 & 3.07 & 2.75 \\ 2.43 & 3.71 & 2.28 & 2.34 \\ 2.18 & 1.93 & 1.37 & 1.52 \\ 1.85 & 2.52 & 2.97 & 1.93 \end{pmatrix}$$

Table 1: The model of the characteristic value and standard variance

Part	θ_1	θ_2	θ_3	θ_4
1	1.30	1.86	3.07	2.75
	(0.12)	(0.10)	(0.11)	(0.25)
2	2.43	3.71	2.28	2.34
	(0.37)	(0.17)	(0.37)	(0.07)
3	2.18	1.93	1.37	1.52
	(0.15)	(0.11)	(0.13)	(0.12)
4	1.85	2.52	2.97	1.93
	(0.19)	(0.23)	(0.25)	(0.19)

Table 2: The sensor measurement value and standard variance

Sensor	1	2	3	4
Measurement value	2.15	1.30	2.15	2.12
Standard variance	(1.30)	(0.32)	(0.17)	(0.21)

$$R = \begin{pmatrix} 0.6047 & 0.8087 & 0.9121 & 0.7709 \\ 0.8848 & 0.6199 & 0.8143 & 0.9060 \\ 0.9862 & 0.8391 & 0.4893 & 0.7170 \\ 0.8605 & 0.9127 & 0.9428 & 0.9107 \end{pmatrix}$$

Step 2: Determine the ideal point and negative ideal vectors respectively are:

$$R^* = (r_1^*, r_2^*, r_3^*, r_4^*) = (20.9862, 0.9127, 0.9428, 0.9107)$$

$$R^- = (r_1^-, r_2^-, r_3^-, r_4^-) = (0.6047, 0.6199, 0.4983, 0.7170)$$

Step 3: By above section of the given method to determine the weights of attributes vector:

$$w = (w_1, w_2, w_3, w_4) = (0.1524, 0.2535, 0.2555, 0.3935)$$

Step 4: Calculate the relative ratios ξ_i and relative approach degree C_i:

$$\xi = (\xi_1, \xi_2, \xi_3, \xi_4)^T = (-5.5338, -4.4199, -18.7163, 0)^T$$

$$C = (C_1, C_2, C_3, C_4)^T = (0.8070, 0.8458, 0.3472, 1.000)^T$$

Step 5: Due to the maximum C_4 = 1.0000, so the time to check the unknown work piece as the fourth kind of work piece. The recognition results are consistent with Shao *et al*. (1996).

RESULTS AND DISCUSSION

This study presents to compare the relative ratio method with entropy weight method (Wan, 2009b) and variable fuzzy method (Chen and Hu, 2006). That will

Table 3: Three methods support degree comparison

Work piece		1	2	3	4
This study	Support	0.8070	0.8458	0.3472	1.0000
	Deviation	0.1930	0.1542	0.6528	
Entropy weight	Support	0.7581	0.6973	0.2322	0.9192
	Deviation	0.1611	0.2219	0.6870	
Variable fuzzy	Support	0.3660	0.5810	0.5560	0.7900
	Deviation	0.4240	0.2090	0.2340	

be all kinds of methods of the evaluation of target value as the support degree. Then despite their recognition results for the fourth kind of the work piece, but four methods for all kinds of target recognition degree are different. Table 3 reflects the four methods support degree of difference. The table of the gap is the fourth kind of the work piece support and other kinds of work piece support difference.

Can be seen from Table 3, this study uses the method to get the part 4 support for 1.0000 more than other methods support and if use of the work piece and the part 4 to other part support degree difference to sum, then get three methods to support the total gap are: 1.0000, 1.0700 and 0.8670, the relative ratio method has the greater total gap than variable fuzzy method and almost the same as entropy weight method. Obviously, the greater the gap to target recognition, the higher level of recognition results, then the higher the credibility.

CONCLUSION

To fully consider the characteristics of multi-sensor indicators of the degree of importance for target recognition, we use the coefficient of variation method, based on the difference of each index to determine index weight, so that the weight data with the outside world and change, not only to better reflect the objective reality, but determine the weight to avoid the subjective arbitrariness, reducing the interference of artificial subjective factors, thus improving the results of multi-sensor target recognition objectivity, while the relative ratio of the Act defines the relative closeness of alternatives, not only taking into account the positive ideal and considering the proximity of the vector with the vector away from the negative ideal level, which is the result of better reliability and rationality of this algorithm is simple and easy to use MATLAB and other software programmable computing for solving the problem provides a new target recognition approach.

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