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Fusion Algorithm for Infrared, Ultraviolet, and Millimeter-Wave Composite Detection

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Abstract: Infrared, ultraviolet, and millimeter-wave composite detection is an efficient means of pre-warning about extremely low altitude radiation penetration. Based on the complexity of the recognition analysis caused by the redundant information indicators in the composite detection, a fusion algorithm is proposed. It can turn multiple information indicators into relatively few reliable pieces of information that can show the characteristics of targets although they are not effectively related. Thus, the complexity of analyzing an excessive amount of information indicators is addressed. The superiority of the composite detection is verified through simulation analysis, and the algorithm is proven effective. *Copyright © 2013 IFSA.*

Keywords: Infrared, Ultraviolet, Millimeter wave, Composite detection, Fusion algorithm.

1. Introduction

The threat of radiation from extremely low altitude field is escalating. To respond to this threat effectively, we can use infrared, ultraviolet, and millimeter-wave composite detection method [1-6]. However, in the detection process of targets, obtaining reliable detection information for target recognition often requires selecting multiple detection information indicators for analysis. These indicators may be dozens or more, and each reflects the target features from a different degree. Redundant information indicators increase the complexity of recognition analysis, and an overlap of these indicators is inevitable. Thus, we expect to integrate multiple information indicators into several ones, which can provide sufficient discrimination information [7-9]. We obtain the quantitative conclusion conducive to a decision that is made based on large quantities of data by using the mathematical statistics method. This method has been widely applied in information, economics, engineering, and other fields [10-14]. Employing the mathematical statistics method reduces the detection information indicators into several reliable ones, which can effectively reflect the feature information of targets even though they are unrelated to one another [13, 14]. A discriminant method proposed in this paper can integrate multiple information indicators into several reliable ones to solve the problems in the detection process.

2. Linear Discriminant Analysis Function

The discriminant method was originally proposed by Pearson in 1921 and mainly used in racial discrimination. It was called race-similarity coefficient method at the time. In 1936, Fisher proposed the concept of linear discriminant function

that is, discriminating the category ensemble of individuals by using the linear function method that expresses a number of feature variables. This linear discriminant method has been widely applied in later discriminant analysis [15, 16].

With the existence of large amounts of data, studying and analyzing every piece of information is impossible. Thus, certain random data are adopted for analysis by using the mathematical statistics method, and a convenient model to describe the obtained data is established. The sample data of t index are extracted from the overall data, and a discriminant function based on the principles of variance analysis is created.

$$y = c_1 x_1 + c_2 x_2 + \ \ldots \ + c_t x_t \qquad (1)$$

The determination concept of the coefficients $c_1, c_2, \ldots, c_t$ aims to maximize the discrimination between two groups of data and minimize the deviation of data within these groups.

3. Fusion Algorithm of Composite Detection Based on Linear Discriminant Function

3.1. Derivation of Discriminant Function

For a new target, we can substitute the data eigenvalues detected by each sensor into the discriminant function (1) and determine the value of y. Next, we can compare it with the discriminant threshold and discriminate the target based on the category.

We assume that the two ensembles are L_1 and L_2, which represent real target and interference target. n_1 samples are extracted from L_1 and n_2 samples from L_2.

Each sample contains t detection data features, as shown in Table 1.

Table 1. Samples of Ensemble L_1 and Ensemble L_2.

Samples of L_1	Indicators of L_1				Samples of L_2	Indicators of L_2			
	x_1	x_2	⋯	x_t		x_1	x_2	⋯	x_t
$x_1^{(1)}$	$x_{11}^{(1)}$	$x_{12}^{(1)}$	…	$x_{1t}^{(1)}$	$x_1^{(2)}$	$x_{11}^{(2)}$	$x_{12}^{(2)}$	…	$x_{1t}^{(2)}$
$x_2^{(1)}$	$x_{21}^{(1)}$	$x_{22}^{(1)}$	…	$x_{2t}^{(1)}$	$x_2^{(2)}$	$x_{21}^{(2)}$	$x_{22}^{(2)}$		$x_{2t}^{(2)}$
…	…	…	…	…	…	…	…	…	…
$x_{n1}^{(1)}$	$x_{n11}^{(1)}$	$x_{n12}^{(1)}$	…	$x_{n1t}^{(1)}$	$x_{n2}^{(2)}$	$x_{n11}^{(2)}$	$x_{n12}^{(2)}$		$x_{n1t}^{(2)}$
mean	$\bar{x}_1^{(1)}$	$\bar{x}_2^{(1)}$	…	$\bar{x}_t^{(1)}$	*mean*	$\bar{x}_1^{(2)}$	$\bar{x}_2^{(2)}$	…	$\bar{x}_n^{(2)}$

Based on the discriminant function (1), the observed values of samples in Ensemble L_1 and Ensemble L_2 are substituted into the discriminant function to obtain the following equations:

$$y_i^{(1)} = c_1 x_{i1}^{(1)} + c_2 x_{i2}^{(1)} + \ldots + c_t x_{it}^{(1)}, i = 1, \ldots, n_1 \qquad (2)$$

$$y_i^{(2)} = c_1 x_{i1}^{(2)} + c_2 x_{i2}^{(2)} + \ldots + c_t x_{it}^{(2)}, i = 1, \ldots, n_2 \qquad (3)$$

The left and right sides of Equations (2) and (3) are added. Then, the number of samples is divided. We can obtain the following equation:

$$\bar{y}^{(1)} = \sum_{k=1}^{t} c_k \bar{x}_k^{(1)}$$

$$\bar{y}^{(2)} = \sum_{k=1}^{t} c_k \bar{x}_k^{(2)}$$

To enhance the ability to discriminate the samples from different ensembles by discriminant functions, two points are expected:

The numerical difference of $\bar{y}^{(1)}$ from Ensemble L_1 and mean $\bar{y}^{(2)}$ from Ensemble L_2 is greater and better.

$y^{(1)}(i = 1, \ldots, n_1)$ from Ensemble L_1 and the sum of deviation square $\sum_{i=1}^{n_1} (y_i^{(1)} - \bar{y}^{(1)})^2$ is smaller and better. Similarly, the sum of deviation square $\sum_{i=1}^{n_2} (y_i^{(2)} - \bar{y}^{(2)})^2$ from Ensemble L_2 is smaller and better.

Basing from the above mentioned two points, we can obtain the following equation:

$$I = \frac{(\bar{y}^{(1)} - \bar{y}^{(2)})^2}{\sum_{i=1}^{n_1}(y_i^{(1)} - \bar{y}^{(1)})^2 + \sum_{i=1}^{n_2}(y_i^{(2)} - \bar{y}^{(2)})^2}$$

The value is larger and better.

We assume that

$$E = E(c_1, c_2, \ldots, c_t) = (\bar{y}^{(1)} - \bar{y}^{(2)})^2$$

as the deviation between the two groups of data.

$$G = G(c_1, c_2, \ldots, c_t) = \sum_{i=1}^{n_1}(y_i^{(1)} - \bar{y}^{(1)})^2 + \sum_{i=1}^{n_2}(y_i^{(2)} - \bar{y}^{(2)})^2$$

is the deviation within the two groups of data.

Then,

$$I = \frac{E}{G} \tag{4}$$

We solve $c_1, c_2, \ldots, c_t$ when the value of I is the maximum by using the function extremum formula.

We take the logarithms of both sides of Equation (4). If we assume that

$$\frac{\partial \ln I}{\partial c_k} = \frac{\partial \ln E}{\partial c_k} - \frac{\partial \ln G}{\partial c_k} = 0, \quad k = 1, \ldots, p$$

Then, $\frac{1}{E} \cdot \frac{\partial E}{\partial c_k} = \frac{1}{G} \cdot \frac{\partial G}{\partial c_k}$

Namely, $\frac{1}{I} \cdot \frac{\partial E}{\partial c_k} = \frac{\partial G}{\partial c_k}$

Whereas

$$E = (\bar{y}^{(1)} - \bar{y}^{(2)})^2 = (\sum_{k=1}^{t} c_k \bar{x}_k^{(1)} - \sum_{k=1}^{t} c_k \bar{x}_k^{(2)})^2$$

$$= [\sum_{k=1}^{t} c_k (\bar{x}_k^{(1)} - \bar{x}_k^{(2)})]^2$$

$$\triangleq [\sum_{k=1}^{t} c_k d_k]^2$$

In the formula, $d_k = \bar{x}_k^{(1)} - \bar{x}_k^{(2)}$,

thus, $\frac{\partial E}{\partial c_k} = 2(\sum_{l=1}^{t} c_l d_l) d_k$

Whereas,

$$G = \sum_{i=1}^{n_1}(y_i^{(1)} - \bar{y}^{(1)})^2 + \sum_{i=1}^{n_2}(y_i^{(2)} - \bar{y}^{(2)})^2$$

$$= \sum_{i=1}^{n_1}[\sum_{k=1}^{t} c_k (x_{ik}^{(1)} - \bar{x}_k^{(1)})]^2 + \sum_{i=1}^{n_2}[\sum_{k=1}^{t} c_k (x_{ik}^{(2)} - \bar{x}_k^{(2)})]^2$$

$$= \sum_{i=1}^{n_1}[\sum_{k=1}^{t} c_k (x_{ik}^{(1)} - \bar{x}_k^{(1)}) . \sum_{l=1}^{t} c_l (x_{il}^{(1)} - \bar{x}_l^{(1)})]$$

$$+ \sum_{i=1}^{n_2}[\sum_{k=1}^{t} c_k (x_{ik}^{(2)} - \bar{x}_k^{(2)}) . \sum_{l=1}^{t} c_l (x_{il}^{(2)} - \bar{x}_l^{(2)})]$$

$$= \sum_{k=1}^{t}\sum_{l=1}^{t} c_k c_l s_{kl}$$

In the formula,

$$s_{kl} = \sum_{i=1}^{n_1}(x_{ik}^{(1)} - \bar{x}_k^{(1)})(x_{il}^{(1)} - \bar{x}_l^{(1)}) + \sum_{i=1}^{n_2}(x_{ik}^{(2)} - \bar{x}_k^{(2)})(x_{il}^{(2)} - \bar{x}_l^{(2)})$$

Then, $\frac{\partial G}{\partial c_k} = 2\sum_{l=1}^{t} c_l s_{kl}$

Thus, $\frac{2}{I}(\sum_{l=1}^{t} c_l d_l) d_k = 2\sum_{l=1}^{t} c_l s_{kl}$

Namely, $\frac{1}{I}(\sum_{l=1}^{t} c_l d_l) d_k = \sum_{l=1}^{t} c_l s_{kl}, k = 1, \ldots, t$

We assume that $\beta = \frac{1}{I}\sum_{l=1}^{t} c_l d_l$

In the preceding formula, β is a constant factor and its value has nothing to do with k. The function of β is to expand β times the solutions of equations simultaneously without influencing the corresponding proportional relationship between the solutions of equations $c_1, c_2, \ldots, c_t$. When $\beta = 1$, the influence on the discriminant results does not exist. Therefore, the equation set can be expressed as follows:

$$\sum_{l=1}^{t} c_l s_{kl} = d_k, \qquad k = 1, \ldots, p$$

Namely,

$$\begin{cases} s_{11}c_1 + s_{12}c_2 + \cdots + s_{1t}c_t = d_1 \\ s_{21}c_1 + s_{22}c_2 + \cdots + s_{2t}c_t = d_2 \\ \cdots \\ s_{t1}c_1 + s_{t2}c_2 + \cdots s_{tt}c_t = d_t \end{cases}$$

Its matrix form can be expressed as

$$\begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1t} \\ s_{21} & s_{22} & \cdots & s_{2t} \\ \vdots & \vdots & & \vdots \\ s_{t1} & s_{t2} & \cdots & s_{tt} \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_t \end{bmatrix} = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_t \end{bmatrix}$$

$$\text{Thus, } \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_t \end{bmatrix} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1t} \\ s_{21} & s_{22} & \cdots & s_{2t} \\ \vdots & \vdots & & \vdots \\ s_{t1} & s_{t2} & \cdots & s_{tt} \end{bmatrix}^{-1} \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_t \end{bmatrix}$$

When the determination of the discriminant function is confirmed, we should confirm the discriminant threshold y_0, which is the weighted average of $\overline{y}^{(1)}$ and $\overline{y}^{(2)}$, namely,

$$y_0 = \frac{n_1 \overline{y}^{(1)} + n_2 \overline{y}^{(2)}}{n_1 + n_2}$$

Through the database of real targets, we can obtain $\overline{y}^{(1)}$ and $\overline{y}^{(2)}$, which satisfy $\overline{y}^{(1)} > \overline{y}^{(2)}$. Thus, the criterion is that for a new target $X = (x_1, \ldots, x_t)'$, we substitute it into the discriminant function and note the calculated value as y. If $y > y_0$, then we can confirm that $X \in L_1$. If $y < y_0$, then we can confirm that $X \in L_2$.

3.2. Calculation Steps

The calculation process consists of the following steps:

1) The discriminant function is established.

We calculate the maximum points of

$$I = \frac{E(c_1, \cdots, c_t)}{G(c_1, \cdots, c_t)}$$

Based on the principle of solving the function extremum, the following equation is constructed.

$$\begin{cases} \dfrac{\partial \ln I}{\partial c_1} = 0 \\ \dfrac{\partial \ln I}{\partial c_2} = 0 \\ \quad \vdots \\ \dfrac{\partial \ln I}{\partial c_t} = 0 \end{cases}$$

$c_1, c_2, \ldots, c_t$ are obtained and the discriminant function $y = c_1 x_1 + c_2 x_2 + \ldots + c_t x_t$ is confirmed.

2) The discriminant threshold y_0 is calculated, and the new target is discriminated by using the criterion.

3) The effects of discrimination are verified.

$$H_0: \ Ex_a^{(1)} = Ex_a^{(2)}, \ \ H_1: \ Ex_a^{(1)} \neq Ex_a^{(2)}$$

We examine the following statistics:

$$F = \frac{(n_1 + n_2 - 2) - t + 1}{(n_1 + n_2 - 2)t} T^2 \sim F(t, n_1 + n_2 - t - 1) \quad (5)$$

In the formula,

$$T^2 = (n_1 + n_2 - 2).[\sqrt{\frac{n_1 n_2}{n_1 + n_2}} (\overline{X}^{(1)} - \overline{X}^{(2)})' .S^{-1} \sqrt{\frac{n_1 n_2}{n_1 + n_2}} (\overline{X}^{(1)} - \overline{X}^{(2)})] \quad (6)$$

$$S = (s_{ij})_{t \times t} \quad (7)$$

$$s_{ij} = \sum_{\alpha=1}^{n_1} (x_{\alpha i}^{(1)} - \overline{x}_i^{(1)})(x_{\alpha j}^{(1)} - \overline{x}_j^{(1)}) + \sum_{\alpha=1}^{n_2} (x_{\alpha i}^{(2)} - \overline{x}_i^{(2)})(x_{\alpha j}^{(2)} - \overline{x}_j^{(2)}) \quad (8)$$

$$\overline{X}^{(i)} = (\overline{x}_1^{(i)}, \cdots, \overline{x}_t^{(i)})' \quad (9)$$

Based on the F distribution table, the test level α is selected to determine the critical value $F\alpha$. If $F > F\alpha$, then we deny H_0. Next, we verify if the discrimination is correct. Otherwise, the discrimination is wrong.

4. Simulation Analysis

Based on the Fisher discriminant analysis, a simulation analysis is conducted on the feature fusion method and, from the common extremely low altitude target database, five real targets and five interference targets are selected as two groups of examples. Four targets are further selected as the to-be-discriminated samples, namely, to-be-discriminated sample 1, to-be-discriminated sample 2, to-be-discriminated sample 3, and to-be-discriminated sample 4. Among them, to-be-discriminated samples 1 and 2 are the interference targets, and to-be-discriminated samples 3 and 4 are the real targets. The following test uses the feature fusion method based on the Fisher discriminant analysis to verify whether the discrimination of to-be-discriminated target is consistent with the original target category. The sample data are presented in Table 2.

Table 2. Samples of common extremely low altitude target feature data.

	Number	Target name	Infrared signature	Ultraviolet signature	Millimeter-wave signature
			Mv	**mv**	**K**
Real targets	1	Airplane 1	1.31	0.75	531
	2	Airplane 2	1.38	0.73	543
	3	Airplane 3	1.33	0.71	538
	4	Missile 1	1.39	0.79	513
	5	Missile 2	1.41	0.81	509
Interference targets	6	Interference 1	1.27	0.47	131
	7	Interference 2	1.14	0.45	156
	8	Interference 3	1.26	0.51	142
	9	Interference 4	1.32	0.49	147
	10	Interference 5	1.24	0.42	138
Unknown targets	11	To-be-discriminated target 1	1.29	0.48	126
	12	To-be-discriminated target 2	1.17	0.53	138
	13	To-be-discriminated target 3	1.31	0.83	527
	14	To-be-discriminated target 4	1.34	0.78	519

In this case, the number of detection sensors is $t = 3$, and 5 examples exist in each group of the true and false target ensembles, namely, $n_1 = n_2 = 5$. The simulation verification process is as follows:

1) The discriminant function is established.

$$\overline{X}^{(1)} = \begin{bmatrix} 1.364 \\ 0.758 \\ 526.8 \end{bmatrix} \quad \overline{X}^{(2)} = \begin{bmatrix} 1.246 \\ 0.468 \\ 142.8 \end{bmatrix}$$

$$S_1 = \sum_{\alpha=1}^{n_1} (X_\alpha{}^{(1)} - \overline{X}^{(1)})(X_\alpha{}^{(1)} - \overline{X}^{(1)})' = \begin{bmatrix} 0.00712 & 0.00484 & -1.526 \\ 0.00484 & 0.00688 & -2.392 \\ -1.526 & -2.392 & 912.8 \end{bmatrix}$$

Similarly,

$$S_2 = \sum_{\alpha=1}^{n_2} (X_\alpha{}^{(2)} - \overline{X}^{(2)})(X_\alpha{}^{(2)} - \overline{X}^{(2)})' = \begin{bmatrix} 0.01752 & 0.00446 & -1.354 \\ 0.00446 & 0.00488 & 0.028 \\ -1.354 & 0.028 & 354.8 \end{bmatrix}$$

Then,

$$S = S_1 + S_2 = \begin{bmatrix} 0.02464 & 0.0093 & -2.88 \\ 0.0093 & 0.01176 & -2.364 \\ -2.88 & -2.364 & 1267.6 \end{bmatrix}$$

The discriminant coefficients c_1, c_2, and c_3 can be determined by using the following equation:

$$\begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} = S^{-1} \begin{bmatrix} d_1 \\ d_2 \\ d_3 \end{bmatrix} = \begin{bmatrix} 28.3002 \\ 121.7403 \\ 0.5943 \end{bmatrix}$$

The discriminant function can be expressed as

$$y = 28.3002x_1 + 121.7403x_2 + 0.5943x_3$$

2) The discriminant threshold y_0 is calculated.

$$\overline{y}^{(1)} = \sum_{k=1}^{3} c_k \overline{x}_k{}^{(1)} = 443.9$$

$$\overline{y}^{(2)} = \sum_{k=1}^{3} c_k \overline{x}_k{}^{(2)} = 177.1$$

$$y_0 = \frac{n_1 \overline{y}^{(1)} + n_2 \overline{y}^{(2)}}{n_1 + n_2} = 310.5$$

3) The criterion is as follows:

When $y > y_0$, $X \in L_1$; and when $y < y_0$, $X \in L_2$.

4) The discriminant function is used to discriminate the known target categories, which are reported in Table 3.

As shown in Table 3, the discrimination has 100 % accuracy rate and the results are consistent with the target categories in the database.

5) The discriminant effects are examined.

Basing from Equations (5), (6), (7), (8), and (9), we can obtain the following:

$$F = 11.3052 > F_{0.05}(3,6) = 4.76$$

Therefore, at the test level $\alpha = 0.05$, the discriminant effects are valid.

6) The discriminant results of the unknown targets are presented in Table 4.

The discriminant results are the same as the actual storage category in the database, which indicates that the feature fusion method based on the Fisher discriminant analysis is effective.

Table 3. Verification results of known target categories.

Number	Target	Discriminant function value	Original target categories	Discriminated target categories
1	Airplane 1	443.9	Real target	Real target
2	Airplane 2	450.6	Real target	Real target
3	Airplane 3	443.8	Real target	Real target
4	Missile 1	440.4	Real target	Real target
5	Missile 2	441.0	Real target	Real target
6	Interference 1	171.0	Interference target	Interference target
7	Interference 2	179.8	Interference target	Interference target
8	Interference 3	182.1	Interference target	Interference target
9	Interference 4	184.4	Interference target	Interference target
10	Interference 5	168.2	Interference target	Interference target

Table 4. Discriminant results of the unknown targets.

Number	Unknown targets	Discriminant function value	Discriminated target categories
11	To-be-discriminated target 1	169.8	Interference target
12	To-be-discriminated target 2	179.6	Interference target
13	To-be-discriminated target 3	451.3	Real target
14	To-be-discriminated target 4	441.3	Real target

5. Conclusions

According to the simulation results, the interference target cannot simultaneously generate high-intensive radiation in three electromagnetic bands of infrared, ultraviolet, and millimeter waves. Even if one detector is fooled to produce a high output value, the discriminant output value of the detection information after the system fusion remains negligible and is lower than the discriminant threshold y0. This output value is discriminated as an inference target by the system. The compound detection method improves the accuracy, reliability, and anti-interference characteristics of the system. The fusion algorithm of the compound detection presented in this study is effective and can decrease the analytical complexity of redundant detection information indicators.

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