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A TARGET RECOGNITION METHOD USING ORTHOGONAL MAXIMUM MARGIN CRITERION PROJECTION

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Based on Maximum Margin Criterion (MMC), an Orthogonal Maximum Margin Criterion Projection (OMMCP) is proposed in this paper. The purpose of the proposed method is to find an optimal projecting matrix to maximize the inter-class scatter while simultaneously minimizing the intra-class scatter after the projection, and does not suffer from the small sample size problem. Compared with MMC method, in OMMCP, intra-class and inter-class scatter matrices are computed by the class-relationship matrix and the scatter matrices are regulated by a parameter, and the class number and the sample number of each class do not need to compute. Experimental results on an aircraft image database show that the method can recognize the aircraft images efficiently.

Keywords: Maximum Margin Criterion (MMC); Feature Extraction; Aircraft Target Recognition; Orthogonal Maximum Margin Criterion Projection

1. Introduction

Aircraft recognition is an important area of target recognition. As the resolution of remote sensing image improves continually, it has a significant meaning in military area to recognize the aircraft type correctly in complicated satellite images. Scholars at home and abroad have had a continuous exploration and research on this problem. Dudani et al. [1] extract the aircraft's invariant moment as a feature, using the Bayes principle and K-neighboring principle to recognize respectively, both of which reach over a 90 percent rate of recognition. Nicoli L P et al. [2] use elliptic Fourier descriptor to identify targets with different shapes and the experimental data has shown the descriptor's effectiveness in target recognition. Chen Yongmei et al. [3] combine D-S evidence reasoning with invariant moment theory, proposing an information-fusion image recognition algorithm and applying it to recognizing three-dimensional aircraft target. Hou Jun et al. [4] propose a sequential image target recognition method based on BP neural network and DSm T(Dezert Smarandache Theory). Robustness of the two methods mentioned above needs further discussion in the case of incomplete

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information or image features with severe distortion. Chen Li etal.[5] fuse the features obtained from Support Vector Machine (SVM) method and K-neighboring classifier method, experimental result of which indicates that its recognition rate is higher than using SVM or K-neighboring classifier method individually. Wang Weipeng et al.[6], using kernel clustering algorithm to cluster angular points in the background area of the image and the aircraft area in accordance with special structure of the aircraft itself, has gained fairly good testing result. Based on combination of rough set and SVM, Ma Qi[7] introduces a pattern classification method integrated with military aircraft target recognition in remote sensing images to conduct a theory analysis and experimental research.

It's hard to conduct the research on aircraft target recognition because of the difficulty to obtain a complete target feature library, which needs plenty of basic researches and experiments, and the cost is very high. In aircraft target recognition, the essential condition is the acquisition of a complete target feature library, which ,in most cases, can't always be met and there for requires multiple types of cooperating targets working with the computer video for the purpose of recording data[8,9]. Dimension reduction and feature extraction are key links to aircraft target recognition. There are few classic dimension reduction and feature extraction algorithms being able to process the aircraft video image data effectively. Low dimensional feature subspace calculated on the basis of MMC (maximum margin criterion) is not orthogonal [10]. Ye et al.[11] has proved that by using orthogonal projective subspace, classification capability of the algorithm will be improved. Based on the MMC, this paper proposes an Orthogonal Maximum Margin Criterion Projection algorithm, which is then applied to aircraft target recognition. By orthogonal zing low dimensional subspace, influence of the noise in observation date will be removed so that classification capability of the algorithm can be enhanced. We have obtained higher recognition rate by applying our algorithm to aircraft target recognition.

2. Related work

2.1Maximum margin criterion (MMC)

MMC uses divergence matrix difference between inter- and intra-class as an objective function. This can avoid divergence matrix inversion within the class and thereby lead to an effective solution of SSS (Small Samples Size) problem, which makes itself a very efficient and stable algorithm.

By introduction of the class edge separation degree information, MFA (Marginal Fisher Analysis） [12] not only can reach the goal of LPP(Locality

Preserving Projection)[13] but also will make targets of different classes more away from each other after being projected, however, the SSS problem still exists.

Therefore, on the basis of MMC, this paper has introduced a new local divergence matrix for both intra- and inter- class to describe information among the data, which will make intra-class local divergence minimal while the inter-class local divergence maximal. This will lead to classes of the same or different kind being closer or further from each other after feature extraction.

MMC algorithm, based on the maximization of the inter-class average edge, searches for the optimal linear subspace. Let S_w and S_b represent intraclass divergence and interclass divergence of the samples respectively:

$$S_w = \sum_{i=1}^{c} \sum_{j=1}^{n_i} (x_j^i - m_i)(x_j^i - m_i)^T, \tag{1}$$

$$S_b = \sum_{i=1}^{c} n_i (m_i - m)(m_i - m)^T, \tag{2}$$

Here, c is class numbers of the samples. M is the total sample average vector $m = \frac{1}{n}\sum_{i=1}^{n} x_i$, m_i is the sample average vector of class I $m_i = \frac{1}{n_i}\sum_{j=1}^{n_i} x_i^j$. n_i denotes sample number of class i. x_j^i denotes the j*th* sample of class i. The objective function of MMC algorithm under the projection matrix W represented as:

$$J(W) = tr\{W^T (S_b - S_w) W\}. \tag{3}$$

Within the constraint condition of W's column vector being a unit vector, the optimal W corresponding to MMC algorithm can be obtained by solving the characteristic equation below: $(S_b - S_w)w = \lambda w.$ (4)

Compared with the LDA(Linear Discriminant Analysis) algorithm[14-15], the MMC algorithm does not require inversion of the intra-class divergence matrix. Thus with the calculation efficiency improvement of the algorithm, it also avoids the SSS problem effectively simultaneously.

2.2 Orthogonal Maximum Margin Criterion Projection (OMMCP) method

Assume that $\{x_1, x_2, ..., x_n\} \in R^{D \times n}$ is the n sampling points in high dimensional space. $x_i \in R^D$ corresponds to the class value c_i . Main steps of the OMMCP are described as follows:

2) Establish class matrix.

For the convenience of obtaining sample intra-class and inter-class divergence matrix, the author establishes a class matrix, which elements denote as:

$$R_{ij} = \begin{cases} 1, if\ \ c_i = c_j, i \neq j \\ 0, else \end{cases} \tag{5}$$

The class matrix R_{ij}, defined in equation (5), has similar function as the class matrix R in LPP algorithm but with difference of taking full advantage of class information of samples.

To be consistent with statement of "the neighborhood locality" in LPP, hence in our paper, matrix defined in equation (1) and (3) are intra- and inter- class local divergence matrix so that our objective function maintains intra- and inter- local information simultaneously.

It is necessary to point out that, in feature space, by utilizing optimal matrix calculated from equation (5) to conduct feature extraction, we will have classes of the same kind closer to each other and classes of different kinds further from each other in terms of distance. That's the effect that we have expected to have.

2) Intra-class and inter-class divergence matrix definition.

Sample intra-class and inter-class divergence matrix represented by R_{ij} as follows:

$$S_w^{'} = \sum_{i=1}^{n}\sum_{j=1}^{n}(R_{ij}x_j - m_i^{'})(R_{ij}x_j - m_i^{'})^T \tag{6}$$

$$S_b^{'} = \sum_{i=1}^{n}(m_i^{'} - m)(m_i^{'} - m)^T \tag{7}$$

where $m_i^{'} = \frac{1}{n_i^{'}}\sum_{j=1}^{n} R_{ij}x_j, n_i^{'} = \sum_{j=1}^{n} R_{ij}$.

3) Establish objective function and solve the problem.

Similar to the MMC algorithm, the objective function established by the author as follows:

$$J(V) = tr\{V^T(S_b - \alpha S_w)V\} \quad \text{s.t. } V^T XX^T V = I. \tag{8}$$

where, α is an adjustment parameter.

Using Lagrangian multiplier method, we will have

$$\frac{\partial}{\partial V} tr\left\{V^T(S_b-\alpha S_w)V-\lambda\left(V^T XX^T V-I\right)\right\}=0. \tag{9}$$

Equation (9) can be translated into solution of the generalized eigenvalue problem as follows:

$$(S_b-\alpha S_w)v=\lambda XX^T v \tag{10}$$

where λ and v are eigenvalue and eigenvector of the generalized characteristic equation (10).

We assume that $v_1,v_2,...,v_d$ is the eigenvector corresponding to the first d minimum eigenvalues of the generalized characteristic pair $\left((S_b-\alpha S_w)\,,XX^T\right)$. The linear transformation matrix V that minimizes objective function (8) can be denoted as:

$$V=[v_1,v_2,...,v_d]. \tag{11}$$

Because of the SSS problem that we would always encounter in practical application, it may cause XX^T singular. To avoid this problem, the data needs PCA preprocessing, which projects the data onto PCA subspace and selects appropriate projection dimension, making XX^T nonsingular.

4) Orthogonalization feature vector.

Generalized eigenvector calculated by equation (10) is non-orthogonal. A new method is applied to the orthogonalization of low-dimension feature subspace to remove the noise effect, thereby acquiring a better classification and recognition capability of the algorithm.

Let $L{=}S_b-\alpha S_w$. Purpose of the OMMCP algorithm is to find a set of orthogonal basis vectors $v_1,v_2,...,v_d$ through solution of the optimization problem below:

$$\begin{aligned} &\min tr\{V^T LV\} \\ &\text{s.t. } v_1^T v_2=v_1^T v_3=...=v_{d-1}^T v_d=0 \\ &\quad v_1^T XX^T v_1=v_2^T XX^T v_2=...=v_d^T XX^T v_d=1. \end{aligned} \tag{12}$$

It can be verified that v_1 is the corresponding eigenvector to the minimum eigenvalue of the generalized eigenvalue equation $Lv=\lambda XX^T v$.

In order to obtain the k*th* orthogonal basis vector v_k , minimization of the objective function below is required:

$$\begin{aligned} &\min\{v_k^T L v_k\} \\ &\text{s.t. } v_1^T v_k = v_2^T v_k = \ldots = v_{k-1}^T v_k = 0 \\ &\quad v_k^T X X^T v_k = 1. \end{aligned} \tag{13}$$

We use Lagrangian multiplier method to solve the optimization problem written above:

$$J_k = v_k^T L v_k - \lambda(v_k^T X X^T v_k - 1) - \mu_1 v_1^T v_k - \ldots - \mu_{k-1} v_{k-1}^T v_k.$$

Let $\frac{\partial J_k}{\partial v_k} = 0$, so that

$$2Lv_k - 2\lambda X X^T v_k - \mu_1 v_1 - \ldots - \mu_{k-1} v_{k-1} = 0. \tag{14}$$

Multiply the left side of equation (14) with v_k^T, and we will have:

$$2v_k^T L v_k - 2\lambda v_k^T X X^T v_k = 0. \tag{15}$$

Then multiply the left side of equation (14) with each element of $v_1^T (XX^T)^{-1}, \ldots, v_{k-1}^T (XX^T)^{-1}$ respectively, we will have (k-1) equations as follows:

$$\begin{aligned} &\mu_1 v_1^T (XX^T)^{-1} v_1 + \ldots + \mu_{k-1} v_1^T (XX^T)^{-1} v_{k-1} = 2v_1^T (XX^T)^{-1} L v_k \\ &\mu_1 v_2^T (XX^T)^{-1} v_1 + \ldots + \mu_{k-1} v_2^T (XX^T)^{-1} v_{k-1} = 2v_2^T (XX^T)^{-1} L v_k \\ &\qquad \ldots\ldots \\ &\mu_1 v_{k-1}^T (XX^T)^{-1} v_1 + \ldots + \mu_{k-1} v_{k-1}^T (XX^T)^{-1} v_{k-1} = 2v_{k-1}^T (XX^T)^{-1} L v_k. \end{aligned} \tag{16}$$

Define μ_{k-1}, V_{k-1} and Q_{k-1} by $\boldsymbol{\mu}_{k-1} = [\mu_1, \ldots, \mu_{k-1}]^T$, $\boldsymbol{V}_{k-1} = [v_1, \ldots, v_{k-1}]$ and $\boldsymbol{Q}_{k-1} = \boldsymbol{V}_{k-1}^T (XX^T)^{-1} \boldsymbol{V}_{k-1}$, thus equation (16) can be denoted in matrix form:

$$\boldsymbol{Q}_{k-1}\boldsymbol{\mu}_{k-1} = 2\boldsymbol{V}_{k-1}^T (XX^T)^{-1} L v_k.$$

hence

$$\boldsymbol{\mu}_{k-1} = 2\boldsymbol{Q}_{k-1}^{-1}\boldsymbol{V}_{k-1}^T (XX^T)^{-1} L v_k. \tag{17}$$

Now multiply the left side of equation (14) with $(XX^T)^{-1}$, and we will have:

$$2(XX^T)^{-1} L v_k - 2\lambda v_k - \mu_1 (XX^T)^{-1} v_1 - \ldots - \mu_{k-1} (XX^T)^{-1} v_{k-1} = 0. \tag{18}$$

The equation written above can be denoted in a matrix form:

$$2(XX^T)^{-1} L v_k - 2\lambda v_k - (XX^T)^{-1} \boldsymbol{V}_{k-1}\boldsymbol{\mu}_{k-1} = 0. \tag{19}$$

Combined with equation (17), the equation written above denotes as:

$$\{\boldsymbol{I} - (XX^T)^{-1}\boldsymbol{V}_{k-1}\boldsymbol{Q}_{k-1}^{-1}\boldsymbol{V}_{k-1}^T\}(XX^T)^{-1} L v_k = \lambda v_k. \tag{20}$$

From equation (15) we know that $\lambda = \frac{v_k^T L v_k}{v_k^T XX^T v_k}$ is just the objective function value that needs optimizing. The minimization of equation (13) is equivalent to getting the minimum value of eigenvalue λ in equation (20).

Let

$$\boldsymbol{R}_k = \{\boldsymbol{I} - (XX^T)^{-1}\boldsymbol{V}_{k-1}\boldsymbol{Q}_{k-1}^{-1}\boldsymbol{V}_{k-1}^T\}(XX^T)^{-1}L, \tag{21}$$

so that the *k*th orthogonal basis vector v_k that we intend to solve is the corresponding eigenvector of R_k 's minimum eigenvalue.

5) Mapping.

We can obtain the orthogonal basic vector $V = [v_1, v_2, ..., v_d]$ with d elements of the feature subspace from equation (20) and therefore the projection $Y = V^T X$ on the d dimensional feature subspace of sample set X will be obtained.

2.3 Procedures of OMMCP algorithm.

According to the analysis listed above, the specific implementation steps of OMMCP algorithm and flowchart (Fig. 1) in this paper can be concluded as follows:

Step1: For each of the sample points x_i in the given training sample set, *k* of its neighboring points $X_i = [x_{i1}, x_{i2}, \cdots, x_{ik}]$ will be determined by KNN(K-Nearest Neighbor) [16]criterion; the class matrix *M* will be obtained through classification in accordance with the eigenvalue in the training process;

Step2: Calculate the sample intra- and inter- divergence matrixes represented by R_{ij} , and the local tangent space coordinate O_i of neighborhood X_i according to equation (6) and (7);

Step3: Construction of the objective function J(V) according to equation (8);

Step4: Use Lagrangian multiplier method to get the related generalized eigenvalue. The minimized linear transformation matrix V will be obtained by equation (10). In order to avoid the singularity of XX^T , a PCA(Principal Component Analysis)[17] processing need to be conducted on data. Project the data set *X* onto the PCA subspace and select suitable projection dimension that makes XX^T nonsingular.

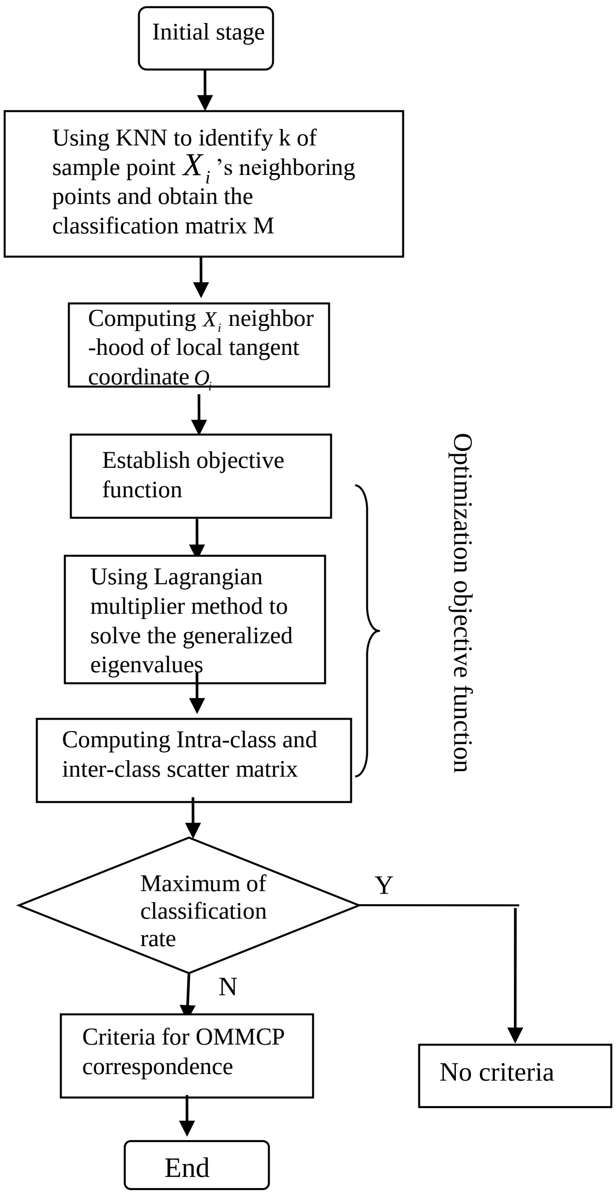

Fig. 1 The flowchart of arithmetic

Step5: Calculate the matrix $X_{PCA}MX_{PCA}$;

Step6: Calculate the intra-class divergence matrix S_b, the inter-class divergence matrix S_w and their difference $S_b - \alpha S_w$ of the sample set X_{PCA};

Step7: Optimize the objective function according to equation (15) and minimize equation (13). The kth orthogonal basis vector v_k is the corresponding eigenvector of R_k's minimum eigenvalue.

Step8: Calculate the orthogonal basis vector with d elements of the feature subspace according to equation (21) and obtain the projection $Y = V^T X$ of sample set X in the d-dimension feature subspace.

3. Result and analysis of the experiment

In order to evaluate the capability of the proposed algorithm, we will apply it to the recognition of aircraft target. Due to the lack of public image database of moving aircraft target at the moment, the author utilizes the image database, established by our lab and Xidian University, to conduct the experiment. For a better analysis of the experimental result, We will perform a simulation of the algorithm proposed out of our aircraft image database: the traditional subspace dimension reduction algorithms including PCA (Principal Component Analysis), LDA (Linear Discriminant Analysis), MMC (Maximum Margin Criterion) and aircraft target recognition algorithm including aircraft image target MFF(Multi-feature Fusion) method, Rough/SVM as well as a comparison between them. All of the aircraft images are converted and resized into32×32 grey-scale images followed by normalization. Then each of the processed images will be denoted as a vector, dimensionally reduced by using MMC, LDA and OMMCP. Finally the aircraft target will be recognized by using nearest neighbor classifier and the aircraft classification will be carried out by using function KNN Classify in the Matlab toolbox. For MFF and Rough/SVM, the aircraft target recognition will be conducted by calculating the class eigenvector directly. The simulation is conducted in the environment of Matlab 7.0. In order to perform the experiment, we select images from seven categories in the database, each of which has thirty images of aircrafts in different attitudes. Fig. 2 includes part of the images in seven categories. Fig. 3 includes thirty-six images of the first category aircraft in different conditions.

Fig. 2 Seven kinds of airplanes model

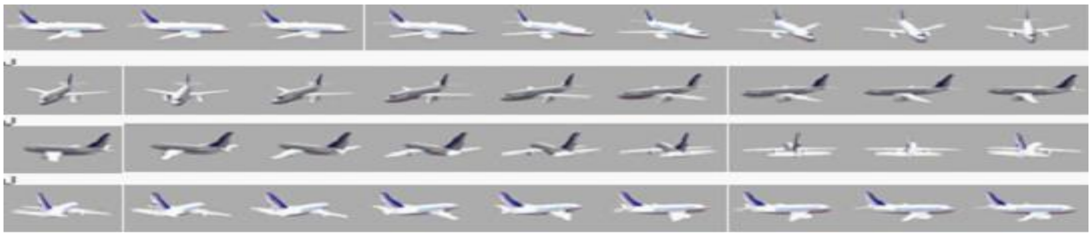

Fig. 3 36 images in different states of the first aircraft

For aircraft in each category, we randomly select 20 images as the training samples and the rest of these pictures as the testing sample. The parameter α can be determined by the maximum value of the classification rate in the classification experiment. We make α =0.3. Repeat the experiment fifty times independently and calculate the average recognition rate. Table 1 is the maximum average recognition rate and standard deviation. From Table 1 we can see that, among the six methods, the proposed OMMCP method, based on orthogonal locality preserving projections, has gained the highest correct classification rate. Classification of the MMC and LDA methods are fairly the same.

Table 1

The maximal average recognition rates and the corresponding standard deviations (%) for LDA 、MMC、MFF、Rough/SVM and OMMCP on the aircraft image database.

Method	PCA	LDA	MMC	MFF	Rough/SVM	OMMCP
recognition rate	88.12±1.86	94.92±1.77	95.01±1.86	94.79±1.90	94.21±1.92	95.42±2.00
standard deviations	88.53±2.45	92.52±1.91	93.23±1.25	91.05±0.79	90.52±3.07	94.07±2.45

What's different from PCA and LDA is the adjustment parameter α introduced by OMMCP which avoids the inversion of large matrix like in PCA and LDA. Compared with MMC and LDA, OMMCP has used the classification matrix of samples to avoid calculating the classification number of the sample and the sample number of each class, enhancing the practicality of the algorithm. And the orthogonality of OMMCP helps improve the algorithm's classification capability.

Algorithms used in the experimental comparison includes PCA, MMC, MFF and Rough SVM, adopting the nearest neighboring classifier based on the Euclidean distance to conduct the classification. Comparison of the highest recognition rate among these six algorithms is listed in Figure 3, from which we can see that the correct recognition rate can reach over 97% percentage when we apply the OMMCP method proposed in the paper to the recognition of target in the training database.

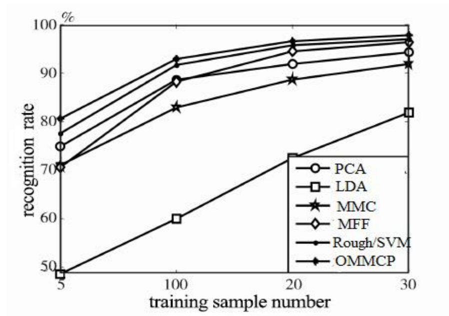

Fig. 4 The highest recognition rate of the 6 algorithms comparing

Result analysis: The OMMCP algorithm has the best performance of classification capability in the experiment. It is mainly for the reason that the linear feature extraction method based on Manifold Learning can detect nonlinear manifold structure effectively. It can be observed from the identification result from table 1 and figure 4 that 1) compared with other method, MMC mapping method has a higher recognition rate which maintains above ninety-seven percent basically; 2)as the size of the recognition target becomes smaller, the mapping method based on MMC has a stable recognition with high robustness of the target; MMC mapping method has an obvious advantage over other algorithms when it is applied to shrunken target and the recognition rate improves greatly.

4. Conclusion and future work

Aiming at characteristics such as inaccuracy, indeterminacy, inadequacy of aircraft target images which result in low recognition rate of the classic methods, this paper has proposed an aircraft target recognition algorithm based on the OMMCP, the correct recognition rate of which can reach over 97%. Furthermore, some features of the eigenvector could be affected severely by the image quality. It could potentially be helpful to the enhancement of target recognition rate if the image quality is guaranteed before the feature extraction by the image fusion technique [14-17]. Nonetheless, there are still some difficulty and improvement which need further research existing in this paper, 1) the choice of parameter α to the effect of correct recognition rate, complex procedure of orthogonalization; 2) the general problem in the research of manifold learning algorithm of how to acquire orthogonal mapping matrix; 3) In order to overcome the singular value problem in the algorithm, the algorithm is extended to tensor form. We will focus on those three problems in our further research.

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