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Weighted Marginal Fisher Analysis with Spatially Smooth for aircraft recognition

Wei Zhenzhong *, **Liu Chang**, **Li Nan**

Precision Opto-mechatrionics Technology, Key Laboratory of Education Ministry, Beihang University, Beijing 100191, China

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Abstract Due to limitations to extract invariant features for recognition when the aircraft presents various poses and lacks enough samples for training, a novel algorithm called Weighted Marginal Fisher Analysis with Spatially Smooth (WMFA-SS) for extracting invariant features in aircraft recognition is proposed. According to the Graph Embedding (GE) framework, Heat Kernel function is firstly introduced to characterize the interclass separability when choosing the weights of penalty graph. Furthermore, Laplacian penalty is applied to constraining the coefficients to be spatially smooth in this algorithm. Laplacian penalty is able to incorporate the prior information that neighboring pixels are correlated. Besides, using a Laplacian penalty can also avoid the singularity of Laplacian matrix of intrinsic graph. Once compact representations of the images are obtained, it can be considered as invariant features and then be performed in classification to recognize different patterns of aircraft. Real aircraft recognition experiments show the superiority of our proposed WMFA-SS in comparison to other GE algorithms and the current aircraft recognition algorithm; the accuracy rate of our proposed method is 90.00% for dataset BH-AIR1.0 and 99.25% for dataset BH-AIR2.0.

1. Introduction

Researches on recognizing 3D objects from 2D images are becoming increasingly popular.[1] Analyzing features of aircraft as typical 3D dynamic objects and identifying their patterns are always attracted by many scholars. Concerning the issues for diversities of aircraft's poses such as variation of 3D scale, transformation and rotation, it makes recognition of aircraft images quite difficult.

The current methodologies of recognition for aircraft objects are to extract invariant features based on shape information and then to discriminate aircraft patterns combined with various classifiers. Invariant features, such as affine moment, wavelet moment, sift feature, etc. have been extensively adopted as effective feature extraction means, which have appeared pros and cons in certain specific applications. Among invariant features mentioned above, different features appear different tolerance for invariance on condition of images taken by various poses of aircraft. Flusser[2] proposed the affine moment, which is able to keep invariant to image distortion or twisting caused by small aircraft's roll angle and pitch angle variation; wavelet

* Corresponding author. Tel.: +86 10 82338768.
E-mail addresses: zhenzhongwei@buaa.edu.cn (Z. Wei), vincentliubuaa@gmail.com (C. Liu).

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moment[3] is capable of keeping invariant to aircraft's scaling variation; SIFT feature[4] can keep invariant to affine variation and resists noise quite well. However, one kind of invariant features can only satisfy recognition requirement limited in a specific circumstance and might not acquire a satisfying results shifting into another circumstance. Therefore, it is not feasible to apply single kind of features combining classifiers to construct an aircraft image recognition system that acquires high recognition rate on condition of aircraft's pose diversity.

According to the principle of integration, it is feasible to construct a more general aircraft image recognition system that can effectively acquire higher recognition rate on condition of different circumstances if invariant features are combined based on different rules. Zhu[5] proposed a method of aircraft recognition based on Multiple Classifier Fusion with Multiple Invariants (MCF-MI), which fused four different aircraft image features: affine moment, Zernike moment, wavelet moment and gradient module of SIFT feature descriptor and combined support vector machine to construct four kinds of classifiers. Moreover, an adaptive weighted voting method is adopted to carry out multiple classifier fusion for improving aircraft recognition rate, which is higher than the recognition rates using the classifiers constructed with single invariant features. However, it cannot satisfy the real-time requirement in the process of aircraft recognition because the choice of invariant features and the fusion of invariant features and classifiers are determined by different aircraft image conditions. Specifically, under the conditions of wide angle rotation of aircrafts, invariant features suffer trivial-solutions, leading to a dramatic a reduction in recognition accuracy.

Recently, there are considerable interests into visual analysis and dimension reduction. One hopes that estimating geometrical and topological properties of the manifold from random points lies on this unknown sub-manifold. Along this direction, many researchers[6–8] proposed lots of subspace learning algorithms to explore the local geometric structure embedded in high dimensional data. Some popular ones include Locality Preserving Projection (LPP),[9] Neighborhood Preserving Embedding (NPE)[10] and Marginal Fisher Analysis (MFA).[11] When using these methods, we usually represent an image of size $m_1 \times m_2$ pixels by a vector in an $m_1 \times m_2$ dimensional space. Although various poses of aircraft lead to huge difference in the same pattern of aircraft images and the dimensionality of data is extremely high when aircraft images are represented as vectors, there might be an intrinsic properties of the high manifold embedded in a low sub-manifold, which leads us to consider methodologies of subspace learning to extract invariant features from high-dimensional aircraft manifolds.

In this paper, we introduce a method called Weighted Marginal Fisher Analysis with Spatially Smooth for extracting invariant features in aircraft recognition. Based on the Graph Embedding framework,[12] we firstly introduce Heat Kernel function[13] to characterize the relationship between different pattern of aircraft images. Furthermore, we use Laplacian penalty[14] to constrain the coefficients to be spatially smooth in this algorithm. Instead of considering the basis function as a $m_1 \times m_2$ dimensional vector, we consider it as a matrix, or a discrete function defined on a $m_1 \times m_2$ lattice. So the discretized Laplacian operator can be applied to measuring the smoothness of basis function along the horizontal and vertical directions. Because the discretized Laplacian operator is a finite difference approximation to the second derivative operator, we sum over all directions. The choice of Laplacian penalty allows us to incorporate the prior information that neighboring pixels are correlated. Besides, using a Laplacian penalty can also avoid the singularity of Laplacian matrix of intrinsic graph. After we acquire representations of images in the subspace, we can consider them as invariant features and then perform classification to recognize different patterns of aircraft.

The method presents two essential characteristics:

(1) Before acquiring the optimized projections that maximize the interclass separability represented by penalty graph and minimize the intraclass compactness represented by intrinsic graph, the choice of Heat Kernel function as weights of penalty graph can characterize the interclass separability better than simple-minded function used by MFA in neighborhood relationships.
(2) Although PCA as a pre-projection to avoid the singularity of Laplacian matrix of intrinsic graph works very well in various object recognitions like face recognition,[15] it failed in aircraft recognition for huge difference caused by pose variation between the same pattern of aircrafts. Therefore, we introduce Laplacian penalty as the regularization to avoid the singularity of Laplacian matrix of intrinsic graph and to avoid over-fitting[16] because the number-of-dimensions to the sample-size ratio is too high.

The rest of the paper is structured as follows. In Section 2, we define the feature extraction as a subspace learning representation in aircraft recognition and provide a brief review of the Graph Embedding framework and Laplacian smoothing. Section 3 introduces our proposed algorithm called Weighted Marginal Fisher Analysis with Spatially Smooth. The extensive experimental results are presented in Section 4. Finally, we provide some conclusive remarks and suggestions for future work in Section 5.

2. Problem definition and theoretical background

2.1. Problem definition

For a general classification problem, each image of the aircraft sample set is rearranged from size of $m_1 \times m_2$ to a vector $\boldsymbol{x}_i \in \mathbf{R}^m$, where $m = m_1 \times m_2$. The aircraft sample set for model training can be represented as a matrix $\boldsymbol{X} = [\boldsymbol{x}_1\ \boldsymbol{x}_2\ \ldots\ \boldsymbol{x}_N]$, where N is the sample number and m the data dimension. For supervised learning problems, the class label of sample $\boldsymbol{x}_i$ is assumed to be $c_i = \{1, 2, \ldots, N_c\}$, where N_c is the number of classes. We also let π_c and n_c denote the index set and number of samples belonging to the class, respectively. The linear feature extraction is to find a mapping matrix $\boldsymbol{A} = [\boldsymbol{a}_1\ \boldsymbol{a}_2\ \ldots\ \boldsymbol{a}_l] \in \mathbf{R}^{m \times l}$, which transforms sample $\boldsymbol{x}_i$ to a specific representation $\boldsymbol{y}_i$, where, typically, l m and $\boldsymbol{y}_i = \boldsymbol{A}^{\mathrm{T}} \boldsymbol{x}_i$.

2.2. A brief review of Graph Embedding framework

Let $G = \{\boldsymbol{X}, \boldsymbol{W}\}$ be an undirected weighted graph with vertex set $\boldsymbol{X}$ and similarity matrix $\boldsymbol{W} \in \mathbf{R}^{N \times N}$. Each element of the real symmetric matrix $\boldsymbol{W}$ measures, for a pair of vertices, its similarity, which might be negative. In this work, the Graph