Adaptively Weighted Sub-pattern PCA for Face Recognition

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Abstract: Adaptively weighted Sub-pattern PCA (Aw-SpPCA) for face recognition is presented in this paper. Unlike PCA based on a whole image pattern, Aw-SpPCA operates directly on its sub-patterns partitioned from an original whole pattern and separately extracts features from them. Moreover, unlike both SpPCA and mPCA that neglect different contributions made by different parts of the human face in face recognition, Aw-SpPCA can adaptively compute the contributions of each part and then endows them to a classification task in order to enhance the robustness to both expression and illumination variations. Experiments on three standard face databases show that the proposed method is competitive.

Keywords: Principal component analysis (PCA), Modular PCA (mPCA), Adaptively weighted sub-pattern PCA (Aw-SpPCA), face recognition.

1. Introduction

As a classical self-organized learning method, Principle Component Analysis (PCA) is widely used in data compression and feature extraction [1]. There are two basic approaches to the computation of principal components: batch and adaptive methods. The batch methods include the method of eigen-decomposition and the method of singular value decomposition (SVD), while the adaptive methods are exemplified by Hebbian-based neural networks, such as generalized Hebbian algorithm (GHA) and adaptive principal components extraction (APEX) etc [2] [3]. Despite these different implementations of PCA, their essences are the same, namely, to explain the variance-covariance structure of the data through a few linear combinations of the original variables. So in this paper we adopted the batch methods for PCA implementation.

Currently, PCA has also become one of the most popular appearance-based algorithms applied to

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face recognition [4] [5]. However, due to only utilizing the global information of face images, this method is not very effective under different facial expression, illumination condition and pose etc. The recently-proposed mPCA method [6] is one of the methods which try to overcome such ineffectiveness by exploring the face's local structure. In this method, a face image is first partitioned into several smaller sub-images, and then a single conventional PCA is applied to each of them. Consequently, variations in expression or illumination in the image will only affect some sub-images in mPCA rather than the whole image in PCA, and thus the local information of a face image may be better represented. However, such a local representation in mPCA ignores the mutual spatial relationship among sub-images partitioned from the original face image, so some spatial information in the original face image is more likely lost and the different contributions made by different parts of face are de-emphasized. In our previous work [7], we have demonstrated the usefulness of Sub-pattern PCA (SpPCA). In the first step of this method, an original whole pattern denoted by a vector is partitioned into a set of equally-sized sub-patterns in a non-overlapping way and then all those sub-patterns sharing the same original feature components are respectively collected from the training set to compose a corresponding sub-pattern's training set. In the second step, PCA is performed on each of such sub-pattern's training set to extract its features. At last, a single global feature for the original whole pattern is obtained by concatenating each sub-pattern's PCA projected features together. Although such a concatenation can formally generate a global feature for the original whole pattern and avoids the problems with mPCA, the SpPCA algorithm only utilizes the separately extracted local information from each sub-pattern set, but it does not concern different contributions made by different sub-patterns, in other words, it endows equal importance to different parts of a pattern in classification. As a result, the global vector more likely contains redundant or even useless local information, which will degrade final classification performance as shown in the face recognition experiments in section 3.

Aw-SpPCA proposed here aims to compensate for the shortcomings of the above mentioned algorithms and focuses on the application of face recognition. Not only is the spatially-related information in a face image considered and preserved in each sub-pattern, but also the different contributions made by different parts of the face are emphasized. Moreover, these different contributions make classification accuracy improved. In Section 2 the algorithm is detailed. Experiments are carried out in Section 3 to evaluate Aw-SpPCA, SpPCA, PCA and mPCA methods using three standard face databases. Finally, Section 4 concludes this paper.

2. Proposed Algorithm

There are three main steps in Aw-SpPCA algorithm: 1) partition face images into sub-patterns, 2) compute contributions of each sub-pattern, 3) classify an unknown image.

2.1 Image Partition

In the Aw-SpPCA algorithm, a face image can be partitioned to a set of equally- or unequally-sized sub-images, depending on user options, while all sub-images partitioned in the mPCA are strictly confined to equal size due to the mPCA's inherent limitation. In this paper without loss of generality, we still adopt equally-sized partition for a face image. Suppose that there are N $W_1 \times W_2$ images belonging to M persons in the training set, these persons possess $N_1, N_2, N_3 \dots N_M$ face images respectively. Each image is first divided into L equally-sized sub-images in a non-overlapping way which are further concatenated into corresponding column vectors with dimensionality of $W_1 \times W_2/L$, then we collect these vectors at the same position of all face images to form a specific sub-pattern's training set, in this way, L separate sub-pattern sets are formed. This process is illustrated in Fig. 1.

(Fig.1 Here)

2.2 Computing Contributions

We first generate a gallery set and a probe set for each sub-pattern and thus possess corresponding L sub-patterns' gallery and probe sets respectively. The gallery set is identical to the sub-pattern's training set, but the probe set is generated by both the "sub-pattern median face" and the "sub-pattern mean face" of each person in this sub-pattern's training set rather than by one validation set independent from the gallery set as usual. The reason why we select the sub-pattern median and mean faces from the training set is to use these sub-pattern representatives to determine contributions made by different parts to face classification. A process of computing the contributions consists of the two following steps. In the first step, we compute sub-pattern median and mean faces and define a similarity between two samples; the second step is to compute so-needed contributions.

Step 1: For the jth sub-pattern, so-called sub-pattern median face of the ith person is first computed by

$$I_{ij\_median} = Median(I_{ij1}, I_{ij2} \dots I_{ijNi}) \tag{1}$$

and similarly the sub-pattern mean face by

$$I_{ij\_mean} = \frac{1}{N_i} \sum_{k=1}^{N_i} I_{ijk} \tag{2}$$

where I_{ijk} denotes the column vector corresponding to the vectorized ith person's jth sub-image in the kth image of this person. And then the conventional PCA is applied to the jth sub-pattern's gallery set, and the respective projection matrix U_j is constructed by selecting first M' eigenvectors associated with the first largest M' eigenvalues. The similarity between sub-pattern samples x and y is defined as

$$Similarity(x, y) = -(x-y)^T U_j U_j^T (x-y) \tag{3}$$

Step 2: Compute the contribution of a sub-pattern to classification as follows:

For a sub-pattern sample from the probe set, the similarities between it and every sample in this sub-pattern's gallery set are first computed, then the gallery samples are ranked in the descending order of the obtained similarities, and the identity of the top 1 sample in the rank list is considered as the recognition result. The result is true if the resulted identity and the probe's identity are matched, else false. After the computation is completed for all probe set samples of the jth sub-pattern, we denote by C_j the number of how many probe set samples of the jth sub-pattern are correctly classified. Finally, the contributions made by the jth sub-pattern to classification is defined as

$$W_j = C_j/2M \tag{4}$$

2.3 Classification

In this process, in order to classify an unknown face image $\boldsymbol{p}$, the image is also first partitioned into L sub-patterns in the same way previously applied to the training images. Then in this image's each sub-pattern, the unknown sub-pattern sample's identity is determined in a similar way described in subsection 2.2 step 2. Since one classification result for the unknown sample is generated independently in each sub-pattern, there will be total L results from L sub-patterns. To combine L classification results from all sub-patterns of this face image $\boldsymbol{p}$, a distance matrix is constructed and denoted by $D(\boldsymbol{p}) = (d_{ij})_{N\times L}$ with the size of $N \times L$, where d_{ij} denotes the distance between the corresponding jth sub-patterns of the $\boldsymbol{p}$ and the ith person, and d_{ij} is set to W_j if the computed identity of the unknown sample and the ith person's identity are identical, 0 otherwise. Consequently, a total confidence value that the $\boldsymbol{p}$ finally belongs to the ith person is defined as

$$TC_i(p) = \sum_{j=1}^{L} d_{ij} \tag{5}$$

And the final identity of this $\boldsymbol{p}$ is determined by

$$Identity(\boldsymbol{p}) = \arg\max_i (TC_i(\boldsymbol{p})) \qquad 1 \le i \le N \tag{6}$$

3. Experiments

3.1 Face Image Databases

We carry out the experiments on 3 face databases: AR face database [8], Yale face database [9] and the ORL face database [10].

100 people (50 males and 50 females) are selected from total 126 people in AR face database in our experiment. 14 images per person are used. In Yale face database, there are 165 images of 15 adults, 11 images per person while ORL database contains 400 images of 40 adults, 10 images per person. Images in AR and Yale databases feature frontal view faces with different facial expression and illumination condition. Besides these variations, images in ORL database also vary in facial details (with or without glasses) and head pose.

In the preprocessing step, faces images in AR database and Yale database are rotated to make eyes horizontal and cropped to size 66×48 and 50×50 respectively. Some preprocessed images from Yale database are illustrated in Fig 1. In the ORL database, face images are resized to 56×46 without any other preprocessing.

3.2 Experimental Results

As noted above, 100 people, 14 images of each person in AR database are used. These images come from two sessions. We use 7 images per person from the first session for training, the rest 7 images per person from the second session for testing. The sub-image's size in Aw-SpPCA and SpPCA is set to be 6×6, while in mPCA 22×8. Our preliminary experiments show that the sub-image's size in these three algorithms affects their classification performance. The sub-image's size listed in this section is the result we have optimized as much as possible to achieve their individually best performances.

(Fig. 2 Here)

Fig. 2 shows three sample images from AR database and the contribution matrix computed in the experiment. The contribution matrix lies at the right end of this figure. The darker the color of a block is, the greater contributions it makes. From the visualized contribution matrix, we can see that the areas near mouth and nose are brighter, while the areas near eyes and the outline of face are comparatively darker.

Experiments on ORL database are conducted by each time randomly selecting 5 images per person for training, the rest 5 per person for testing. This experiment is independently repeated 40 times, and the averages of these experiments' results are presented in Table 1. The sub-image's sizes in Aw-SpPCA and SpPCA are both set to 7×2, while in mPCA to 16×2.

Experiments on the Yale database are carried out by leaving out one image per person each time for testing, the rest 10 images per person for training. This experiment is repeated 11 times by leaving out a different image per person each time. Results listed in Table 1 are the average of 11 times results. For the Yale face database, the sub-image's sizes in Aw-SpPCA and SpPCA are both set to be 5×10, while in mPCA to 5×5.

(Table 1 Here)

In Table 1, σ is defined as

$$\sigma = (\text{number of selected eigenvectors / number of all the eigenvectors}) \times 100\ \% \qquad (6)$$

Here all the eigenvectors are sorted in the descending order of their corresponding eigenvalues, and selected eigenvectors are associated with the largest eigenvalues.

It can be seen from Table 1 that on AR face database, Aw-SpPCA achieves up to 7% performance improvement over mPCA, up to 15% improvement over SpPCA and PCA. Moreover, the experiments on ORL and Yale face database also show that the performance of proposed Aw-SpPCA is competitive. Although mPCA's performances are impressive on AR and Yale databases, it does even worse than PCA on ORL database. So we can say that not only does Aw-SpPCA get the first place in the performance contest, but also this method exhibits stability and high robustness on all three datasets of different properties.

4. Conclusions

We propose Aw-SpPCA in this paper and compare it with PCA, mPCA and SpPCA in face recognition. The experiment results indicate that our proposed approach not only is effective but also outperforms them under different facial expression and illumination condition. It is worth to note that although we only adopted the batch methods for PCA computation in our experiments; however, in practice, we can use the Hebbian-based neural networks to more effectively implement PCA in order to overcome the batch methods' restrictions on both storage and computation and thus make Aw-SpPCA applicable to build practical face recognition system.

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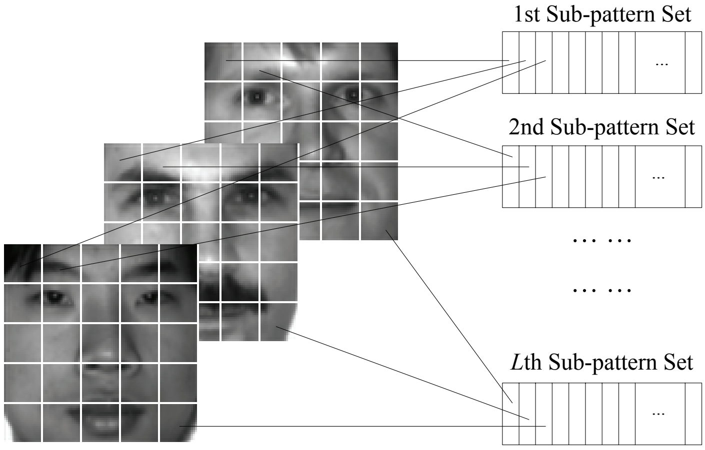

Fig. 1 Face Images Sub-pattern Sets Construction (Images are from Yale Face Database [9])

Fig. 2 Images from AR Database [8] and the Contribution Matrix generated in experiment

Table 1 Classification accuracy comparison of Aw-SpPCA, mPCA , SpPCA and PCA

	σ (%)	Aw-SpPCA	mPCA	SpPCA	PCA
AR	100	**0.9357**	0.8586	0.7814	0.7814
	75	**0.9300**	0.8586	0.7814	0.7757
	50	**0.9200**	0.8614	0.7786	0.7729
	25	**0.9043**	0.8614	0.7757	0.7557
ORL	100	**0.9650**	0.9115	0.9423	0.9423
	86	**0.9645**	0.9133	0.9423	0.9395
	71	**0.9648**	0.9167	0.9413	0.9380
	57	**0.9675**	0.9180	0.9433	0.9373
Yale	100	**0.8788**	0.8667	0.8121	0.8121
	80	**0.8788**	0.8667	0.8121	0.8121
	70	**0.8848**	0.8667	0.8121	0.8121
	60	**0.8909**	0.8727	0.8121	0.8061