

# Making FLDA Applicable to Face Recognition with One Sample per Person

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**Abstract:** In face recognition, the Fisherface approach based on Fisher linear discriminant analysis (FLDA) has obtained some success. However, FLDA fails when each person just has one training face sample available because of nonexistence of the intra-class scatter. In this paper, we propose to partition each face image into a set of sub-images with the same dimensionality, therefore obtaining multiple training samples for each class, and then apply FLDA to the set of newly-produced samples. Experimental results on the FERET face database show that the proposed approach is feasible and better in recognition performance than E(PC)<sup>2</sup>A.

**Keywords:** Face recognition, Fisher linear discriminant analysis (FLDA), One training sample per person, Pattern recognition.

## 1. Multiple-class FLDA and its inapplicability

FLDA is a popular feature extraction and discriminating approach [1] in pattern recognition. Formally it can briefly be formulated as follows: Given  $c$  pattern classes  $\mathbf{X}^{(i)} = [\mathbf{x}_1^{(i)}, \mathbf{x}_2^{(i)}, \dots, \mathbf{x}_{N_i}^{(i)}]$ ,  $i = 1, 2, \dots, c$  with  $N_i$   $p$ -dimensional patterns in the  $i$ -th class respectively. FLDA attempts to seek a set of optimal discriminating vectors

to form a transform  $\Phi_d = [\varphi_1, \varphi_2, \dots, \varphi_d]$  by maximizing the Fisher criterion denoted as  $J(\Phi_d) \stackrel{def}{=} \frac{\text{tr}(\Phi_d^T \mathbf{S}_b \Phi_d)}{\text{tr}(\Phi_d^T \mathbf{S}_w \Phi_d)}$ ,

where  $^T$  denotes matrix transpose,  $\text{tr}()$  denotes the trace of matrix,  $\mathbf{S}_b$  is the inter-class scatter matrix

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$$\mathbf{S}_b = \sum_{i=1}^c N_i (\mathbf{m}_i - \mathbf{m})(\mathbf{m}_i - \mathbf{m})^T \text{ and } \mathbf{S}_w \text{ is the intra-class scatter matrix } \mathbf{S}_w = \sum_{i=1}^c \sum_{j=1}^{N_i} (\mathbf{x}_j^{(i)} - \mathbf{m}_i)(\mathbf{x}_j^{(i)} - \mathbf{m}_i)^T, \mathbf{m}_i \text{ and}$$

$\mathbf{m}$  denote the means of the  $i$ -th class and the whole training set, respectively. Now the maximization of the criterion  $J(\Phi_d)$  gives a so-needed  $\Phi_d$  by which we can extract discriminating features for any input pattern for subsequent classification. Here the rank,  $d$ , of  $\Phi_d$ , i.e., the number of the discriminating vectors able to be extracted, is at most  $\min(c-1, p)$  [1]. Although FLDA has obtained some success in face recognition, it obviously can not be applied to cases where any class or person only has one training pattern available because of the nonexistence of  $\mathbf{S}_w$  in  $J(\Phi_d)$ . In this paper, we will propose an approach to address this issue.

## 2. Proposed approach

### 2.1 Constructing multiple training patterns from single image for each class

A key to making FLDA applicable in a single training pattern scenario may be to increase the number of training patterns of each class. Previous works used virtual patterns [2] or new assembled patterns [3] for this purpose, where an enlarged or a new re-assembled training set for each class is obtained through slightly changing and perturbing the training sample. Different to these methods, we simply partition the whole pattern into a set of non-overlapping sub-patterns with specified dimensionality, e.g. 25 or 15 respectively for  $5 \times 5$  or  $5 \times 3$  partitioned sub-image blocks, to construct a new training sub-set for each class. As a consequence, a new training set containing the same number of class as the original recognition problem does can be obtained, where each class has multiple training samples. It is obvious that FLDA is applicable to the new training set.

### 2.2 Classification

After acquiring so-needed optimal discriminating vectors with multiple-class FLDA described in Section 1, the next step is to classify an unknown face image. Unlike the recognition method based on a whole face, we now are, instead, based on a set of sub-patterns partitioned from the global (face) pattern. Hence, we first project all

partitioned sub-patterns of the unknown face onto the discriminating vectors by  $\Phi_d$  and then use them for recognition. In this paper, we propose two classification strategies (CS1 and CS2): classification based on a pattern which is obtained by assembling all projected sub-patterns using 1-nearest neighbors (1-NN), and classification based on majority-voting for all k-NN decisions on each projected sub-pattern respectively. Below is a brief description for both CS1 and CS2.

Let  $I$  be an unknown face image to be recognized with  $m \times n$  dimension and be partitioned into  $K$  non-overlapping sub-patterns  $\{I_1, I_2, \dots, I_K\}$  with  $p$  dimension each, where  $p$  is taken as 25 or 15 corresponding to  $5 \times 5$  or  $5 \times 3$  partitioned sub-image. Now, we project all  $I_k$  through  $\Phi_d$  to generate corresponding projected sub-patterns  $\{pI_k = (\Phi_d)^T I_k, k=1, 2, \dots, K\}$ . In CS1, we first assemble them into a global projected vector  $pI = [pI_1, pI_2, \dots, pI_K]^T$  and then classify it with 1-NN. While in CS2, instead of assembling, we first separately classify each projected sub-patterns,  $pI_k$ , of the unknown face image using k-NN rule to obtain a corresponding multiple class label set  $CL_k (k=1, 2, \dots, K)$  (for example,  $CL_k = \{class1, class3, class5\}$ ) and then employ the majority-voting rule to make final classification for the presented unknown face image  $I$  based on all obtained class labels  $CL_k (k=1, 2, \dots, K)$ . Here the occurrence of the multiple-class labels attributes to such a fact that several different faces or patterns may share some sub-patterns that are exactly  $k$  nearest neighbors to some sub-patterns of the face to be recognized.

### 3. Experimental results

#### 3.1 Dataset

We conduct experiments on a subset of the FERET face database [2][4]. The database comprises 400 gray-level frontal view face images from 200 persons, with the size of  $256 \times 384$ . There are 71 females and 129 males, each of whom has two images (**fa** and **fb**) with different race, different gender, different age, different expression, different illumination, different occlusion, different scale, etc. The **fa** images are used for training while the **fb**

images for testing. Some raw images are shown in Fig. 1. In our experiments, all faces are normalized to satisfy some constraints so that each face could be appropriately cropped. Those constraints include that the line between the two eyes is parallel to the horizontal axis, the inter-ocular distance (distance between the two eyes) is set to a fixed value, and the size of the image is fixed. Here the eyes are manually located and after a series of rotating and resizing, the cropped image size is 30×30 pixels and the inter-ocular distance is 28 pixels.



Fig. 1 Some raw images in the experimental database

### 3.2 Results

We compare the obtained classification results with those of E(PC)<sup>2</sup>A [2]. E(PC)<sup>2</sup>A applies principle component analysis (PCA) to extract features on an enlarged or modified training set for subsequent classification and achieves an optimal recognition rate of 85.5% on the experimental database. Table 1 and Table 2 show that the maximum of our recognition rates exceed this value, dependent on the number  $d$  of the selected projections. Concretely, the recognition rate is 86.5%, raising 1 percent point compared to the E(PC)<sup>2</sup>A method. Table 2 discloses that different  $k$  values in k-NN have different influences on recognition performance. Small or large  $k$  values (such as 1 or 13) do not produce good results while the moderate  $k$  values (3 to 9) lead to relatively stable recognition results (ranging from 84% to 86.5%). Therefore, on the whole, our approach is better but it is needed to select an appropriate  $k$  value.

### 4. Conclusion

We propose a simple but effective approach to making FLDA applicable in the situation where each class just

Table 1: recognition rates (%)

CS1		CS2	
5×3	5×5	5×3	5×5
85.0(4) <sup>a</sup>	86.0(4)	86.5(14)	86.5(24)
86.0(6)	86.0(6)		

*a*: *d* in the parentheses denotes the number of selected projections

Table 2: *k* versus recognition rates (%)

<i>k</i>	1	3	5	7	9	11	13	
CS2	5×3	82.5	84.5	85.0	85.0	85.5	86.5	83.5
	5×5	84.0	86.5	85.5	84.5	85.0	83.5	82.0

*k*: the number of nearest neighbors in consideration.

has one training pattern. Experiments show that the proposed method is not only feasible but also better in recognition performance than E(PC)<sup>2</sup>A.

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