FACE RECOGNITION USING TWO NOVEL NEAREST NEIGHBOR CLASSIFIERS

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ABSTRACT

In this paper, two novel classifiers based on locally nearest neighborhood rule, called nearest neighbor line (NNL) and nearest neighbor plane (NNP), are presented for face recognition. The underlying idea of both classifiers is the local linear combination technique that has been previously used in locally linear embedding (LLE) for nonlinear dimension reduction. Comparison to other linear combination based classifiers such as the nearest feature line (NFL) and the nearest feature plane (NFP), the proposed method takes much lower computation cost. Furthermore, the experimental results on the ORL face database have shown that the performance of both proposed methods are competitive to the NFL and NFP in face classification.

1. INTRODUCTION

Pattern classification takes a very important role in face recognition [9,10]. Up to now, a lot of classifiers have been proposed. One of the most popular classifiers is the nearest neighbor (NN) classifier [11]. However, the performance of NN is limited by the available prototypes in each class. To overcome this drawback, Li et al. presented the nearest feature line (NFL) classifier in literatures [3,4,5,6]. Following the work of NFL, Chien et al. presented the nearest feature plane (NFP) method for face classification [2]. Both methods improve the performance of the NN method by expanding the representational capacity of available prototypes of the face images. More specifically, the NFL method extends the capacity of the prototype points by using a linear model to interpolate or extrapolate each pair of the prototypes belonging to the same class [3]. Similar with NFL, the NFP method expands the capacity of the prototypes by using the linear combination of each three independent prototypes of the same class. Though both methods are very effective for pattern classification, there are still some drawbacks that limit their further applications in practice. Two main points can be summarized as follows: (1) The first point is about the computation cost: suppose that the number of the samples in the i th class is N_i, then the computation cost of NFL in this class is $\sum N_i(N_i-1)/2$ [4], and NFP is $\sum N_i(N_i-1)(N_i-2)/6$ [2]. Thus the computation cost of NFL and NFP will become very large when N_i is large; (2) Both NFL and NFP may not be appropriate for classification when the prototypes used to construct the NFL or the NFP is far away from the query point. This can be demonstrated from Figure 1, where p_1 is the projection of the query point x onto the feature line $\overline{x_1x_2}$, and p_2 is the projection onto the feature line $\overline{x_3x_4}$. It can be seen clearly from Figure 1 that x is closer to x_1 and x_2 than to x_3 and x_4. However, the distance $\|x-p_1\|$ is larger than $\|x-p_2\|$. Thus, the NFL method may fail in this case.

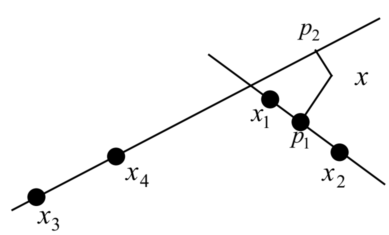

Figure 1. Examples of the case that NFL fails

To avoid the drawbacks of NFL and NFP, we present a novel linear combination based method for face recognition in this paper. Motivated by the locally linear embedding (LLE) method [1], we limit our attention to the linear combination of the nearest neighbor prototypes of the query image in each class instead of computing all the possible cases, i.e., only a feature line or a feature plane is to be computed in our proposed method.

This paper is organized as follows: In section 2, we review the NFL method and the NFP method. The NNL method and the NNP method are presented in section 3. Section 4 is devoted to the experiments. Discussion and conclusion are given in section 5.

2. NEAREST FEATURE LINE (NFL) AND NEAREST FEATURE PLANE (NFP)

NFL classifier is an extension of the NN classifier. Given a sample point set $\{x_i^j\}_{i=1,\cdots,c;j=1,\cdots,N_i}$ belonging to c classes, where x_i^j represents the j th point of the i th class, and N_i the number of the points of the i th class. Let x be the query point. For the i th class, the NFL classifier aims to expand the representational capacity of the prototypes x_i^j ($j = 1,\cdots,N_i$) by using a linear function to interpolate or extrapolate each pair of the prototypes. In other words, for any two sample points x_i^m and x_i^n, a feature line (FL) $\overline{x_i^m x_i^n}$ passing through them is generalized and the FL distance between x and $\overline{x_i^m x_i^n}$ is given as:

$$d(x,\overline{x_i^m x_i^n}) = \left\| x - p_{mn}^i \right\| \quad (1)$$

where $\|\cdot\|$ stands for the Euclidean distance, and p_{mn}^i is the projection of x onto the FL $\overline{x_i^m x_i^n}$ (Figure 2).

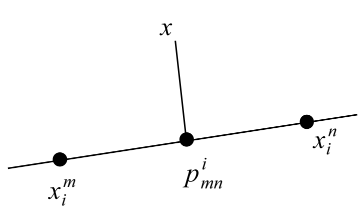

Figure 2. Feature line and feature line distance

Thus, for the i th class, there exists $N_i(N_i-1)/2$ feature lines (FLs). The total number of FLs in the c class is $\sum_{i=1}^{c} N_i(N_i-1)/2$, and the NFL is the FL corresponding to the lowest feature line distance.

The NFP method is can be seen as a simple extension for NFL to enlarge prototype capacity. According to literature [2], for any three prototypes x_i^m , x_i^n and x_i^k in the i th class, a feature plane (FP) F_{mnk}^i is defined as the linear combination of the three points, i.e.,

$$F_{mnk}^i = span(x_i^m, x_i^n, x_i^k) \quad (2)$$

Thus, there are $N_i(N_i-1)(N_i-2)/6$ feature planes (FPs) in the i th class and $\sum_{i=1}^{c} N_i(N_i-1)(N_i-2)/6$ in the total data set. The FP distance between the query x and FP F_{mnk}^i is calculated by

$$d(x, F_{mnk}^i) = \left\| x - p_{mnk}^i \right\| \quad (3)$$

where p_{mnk}^i is the projection of x onto the FP F_{mnk}^i (Figure 3). Similar with NFL, NFP is defined as the FP corresponding to the lowest feature plane distance.

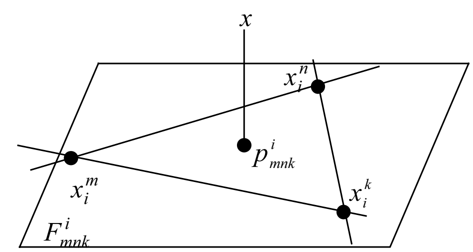

Figure 3. Feature plane and feature plane distance

3. NEAREST NEIGHBOR LINE AND NEAREST NEIGHBOR PLANE CLASSIFIERS

NFL and NFP are very effective techniques for pattern classification. However, in the use of both methods, one may face the computation complexity problem that could limit their further application. This occurs especially when the number of the samples is large.

Motivated by the LLE, we present a fast and efficient modification version of NFL and NFP, respectively, to overcome the drawbacks of NFL and NFP. Instead of using all the possible FLs or FPs of the prototypes, we only select the FL or FP whose corresponding prototypes are the neighbors of the query point. More specifically, let $x_i^{N(1)}$ and $x_i^{N(2)}$ be the two neighbors of the query point x in the i th class, then a straight line called neighbor line (NL) is defined as the line passing through $x_i^{N(1)}$ and $x_i^{N(2)}$, and is denoted as $\overline{x_i^{N(1)} x_i^{N(2)}}$. The NL distance between the query x and the NL is given as:

$$d(x,\overline{x_i^{N(1)} x_i^{N(2)}}) = \left\| x - p_{N(1)N(2)}^i \right\| \quad (4)$$

where $p_{N(1)N(2)}^i$ is the projection of the query point x onto the NL $\overline{x_i^{N(1)} x_i^{N(2)}}$. Let

$$p_{N(1)N(2)}^i = t_i^{(1)} x_i^{N(1)} + t_i^{(2)} x_i^{N(2)} \quad (5)$$

where

$$t_i^{(1)} + t_i^{(2)} = 1 \quad (6)$$

According to literatures [1,12], we obtain that

$$t_i^j = \frac{\sum_k C_{jk}^{-1}}{\sum_{lm} C_{lm}^{-1}} \quad (7)$$

where

$$C = (C_{lm})_{l=12;m=1,2} \quad (8)$$

$$C_{jk} = (x - x_i^{N(j)})^T (x - x_i^{N(k)}) \quad (9)$$

The nearest neighbor line (NNL) is the NL with the lowest neighbor line distance over all the c class. Suppose that the NNL is $\overline{x_{c^*}^{N(1)} x_{c^*}^{N(2)}}$, then we have

$$\overline{x_{c^*}^{N(1)} x_{c^*}^{N(2)}} = \arg\min_i d(x, \overline{x_i^{N(1)} x_i^{N(2)}}) \quad (10)$$

Similar with the NNL method, when three neighbors $x_i^{N(1)}$, $x_i^{N(2)}$ and $x_i^{N(3)}$ are used, we can obtain a neighbor plane (NP) $F_{N(1)N(2)N(3)}^i$ in the ith class. The nearest neighbor plane (NNP) $F_{N(1)N(2)N(3)}^{c^*}$ for all the c classes is defined as

$$F_{N(1)N(2)N(3)}^{c^*} = \arg\min_i d(x, F_{N(1)N(2)N(3)}^i) \quad (11)$$

where

$$d(x, F_{N(1)N(2)N(3)}^i) = \left\| x - p_{N(1)N(2)N(3)}^i \right\| \quad (12)$$

$$p_{N(1)N(2)N(3)}^i = t_i^{(1)} x_i^{N(1)} + t_i^{(2)} x_i^{N(2)} + t_i^{(3)} x_i^{N(3)} \quad (13)$$

the weights $t_i^{(j)}$ can be easily calculated by using equation (7), where $C = (C_{lm})_{l=12,3;m=1,2,3}$ and C_{lm} is calculated using equation (9). After obtaining the NNL or the NNP, we then use the index number c^* as the classification result of the unknown query point.

From the above computational analysis, we can see that the computation cost of NNL or NNP is much lower than that of the NFL method or the NFP method.

4. EXPERIMENTS

To test the performance of the proposed method, we use the ORL face database in Cambridge as the data set to conduct face recognition. There are 40 distinct subjects in the ORL face database. Each subject contains 10 different face images taken at different times, varying lighting slightly. The original face images were all sized 112×92 pixels with a 256-level gray scale. Figure 4 shows ten images for one subject in the face database. To reduce the computational complexity, we downsample the images to be 28×23 pixels by using the wavelet transformation method [2], and then represent each image by a raster scan vector of the intensity values. As a comparison, we perform the same experiments using the NN method, the NFL method and the NFP method, respectively. All the experiments are implemented using the MATLAB V5.3 under Pentium IV personal computer with a clock speed of 1.8 GHz.

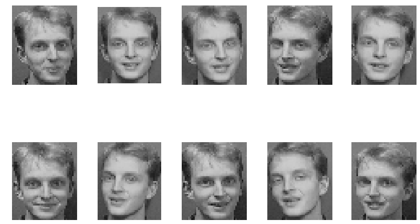

Figure 4. Ten images for one subject in ORL database

In the first experiment, we adopt the "leave-one-out" strategy: To classify a face image, we remove it from the whole face image set, and then perform the classification. Table 1 shows the experimental results of the recognition rates and the recognition times of various systems.

Table 1 Comparison of Recognition Rate Using Leave-one-out strategy On ORL database

Methods	**Recognition Rate (%)**	**Recognition Times (second)**
NN	98.25 (393/400)	0.021
NFL	98.25 (393/400)	0.552
NFP	98.25 (393/400)	1.652
NNL	98.50 (394/400)	0.034
NNP	98.50 (394/400)	0.037

To further to test the performance of the proposed methods using statistical test, we divided the face image set into the training set (known) and the test set (unknown) by the following way: ten images of each subject of the 40 persons are randomly partitioned into two sets, without overlapping between the two. We then choose one set as training set and the other set as the test set. Considering that the recognition performance is affected by the selection of the training images, we perform 20 runs with different training examples (random selection of five images from ten per subject) and select the average recognition rate over all the results. The experimental results are shown in Table 2.

Table 2 Comparison of Recognition Rate

Methods	**Recognition Rate (%)**	**Recognition Times (second)**
NN	94.65	0.018
NFL	95.63	0.125
NFP	95.80	0.153
NNL	95.18	0.027
NNP	95.75	0.029

From Table 1 and Table 2, we see that the NNL method and the NNP method achieve competitive performance with NFL and NFP in terms of the recognition rates: In Table1, the recognition rates of NNL (98.5%) and NNP (98.5%) are slightly higher than NFL (98.25%) and NFP (98.25%); In Table2, the former two methods are slightly lower than the latter two. On the other hand, we see that both NNL and NNP methods take much less recognition time than NFL and NFP in both experiments.

6. DISCUSSION AND CONCLUSION

In this paper, two fast and efficient classifiers, called NNL and NNP, are presented for face recognition. Different from the NFL classifier or the NFP classifier, which finds the class the query point belonging to by comparing all the possible FL or FP, the NNL classifier and the NNP classifier aim to overcome the drawbacks of the NFL method and the NFP method, respectively, by only computing the NL or the NP whose prototypes are the neighbors of the query point in each class. The theoretical analysis and experimental results have shown that NNL or NNP takes much less recognition times than both NFL and NFP. On the other hand, the experimental results also showed that the NNL classifier and the NNP classifier achieves competitive classification performance to NFL and NFP.

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7. REFERENCES

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