Adaptively Nearest Feature Point Classifier for Face Recognition

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Abstract. In this paper, an improved classifier based on the concept of feature line space, called as adaptively nearest feature point classifier (ANFP) is proposed for face recognition. ANFP classifier uses the new metric, called as adaptively feature point metric, which is different from metrics of NFL and the other classifiers. ANFP gain better performance than NFL classifier and some others classifiers based on feature line space, which is proved by the experiment result on Yale face database.

Keywords: Nearest Feature Line; Nearest feature centre; Nearest Neighbor; Face Recognition.

1 Introduction

The procedure of face recognition contains two steps. The first step is feature extraction. For instance PCA [1], LDA [2], ICA [3] and other methods [4-6]. The second step is classification. One of the most popular classifiers is the nearest neighbor (NN) classifier [7]. However, the performance of NN is limited by the available prototypes in each class. To overcome this drawback, nearest feature line (NFL) [8] was proposed by Stan Z. Li. NFL was originally used in face recognition, and later began to be used in many other applications.

NFL attempts to enhance the representational capacity of a sample set of limited size by using the lines through each pair of the samples belonging to the same class. NFL shows good performance in many applications, including face recognition [9-12], audio retrieval [13], speaker identification [14], image classification [15], object recognition [16] and pattern classification [17]. The authors of NFL explain that the feature line can give information about the possible linear variants of the corresponding two samples very well.

Though successful in improving the classification ability, there are still some drawbacks in NFL that limit their further application in practice, which can be summarized as two main points. Firstly, NFL will have a large computation complexity problem when there are many samples in each class. Secondly, NFL may

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fail when the prototypes in NFL are far away from the query sample, which is called as extrapolation inaccuracy of NFL.

To solve the above problems, extended nearest feature line [18] (ENFL), nearest feature mid-point [19] (NFM), shortest feature line segment [20] (SFLS) and nearest feature centre [21] (NFC) are proposed. They gains better performance in some situation. However, they are not so good in other situation.

In this paper, an improved classifier based on the concept of feature line space, called as adaptively nearest feature point classifier (ANFP) is proposed for face recognition. ANFP classifier uses the new metric, called as adaptively feature point metric, which is different from metrics of NFL and the other classifiers. ANFP gain better performance than NFL classifier and some others classifiers based on feature line space. A large number of experiments are executed on Yale face database. Detailed comparison result is given.

2 Background

In this section, we will introduce nearest feature line classifier, extended nearest feature line classifier and nearest feature centre classifier. Suppose that $Y = \{y_i^c, c = 1, 2, \cdots, M, i = 1, 2, \cdots, N_c\} \subset R^D$ denote the prototype set, where y_i^c is the *i*th prototype belonging to *c*-class, *M* is the number of class, and N_c is the number of prototypes belonging to the *c*-class.

2.1 Nearest Feature Line

The core of NFL is the feature line metric. As is shown in Fig. 1, the NFL classifier doesn't compute the distance of query sample *y* and y_i^c; doesn't calculate the distance of *y* and y_j^c, while NFL classifier calculates the feature line distance between query sample *y* and the feature line $\overline{y_i^c y_j^c}$. The feature line distance between point *y* and feature line $\overline{y_i^c y_j^c}$ is defined as:

$$\mathrm{d}(y, \overline{y_i^c y_j^c}) = \| y - y_p^{ij,c} \| \tag{1}$$

where $y_p^{ij,c}$ is the projection point of y on the feature line $\overline{y_i^c y_j^c}$, $\| . \|$ means the L2-norm.

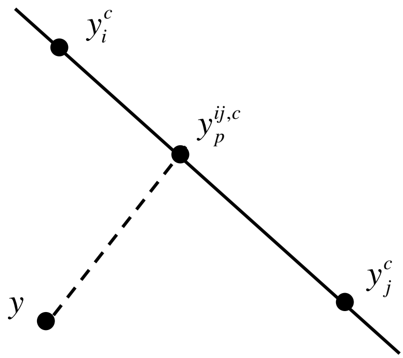

Fig. 1. The metric of NFL

The projection point $y_p^{ij,c}$ is calculated by $y_p^{ij,c} = y_i^c + t(y_j^c - y_i^c)$ where $t \in R$, which is the positional parameters. After simple deformation, we can see that the location parameter can be computed as follows.

$$t = \frac{(y - y_i^c)^T (y_j^c - y_i^c)}{(y_j^c - y_i^c)^T (y_j^c - y_i^c)} \tag{2}$$

2.2 Nearest Feature Centre

Show in the Fig. 2, NFC uses the feature center metric, which is defined as the Euclidean distance between query sample y and the feature center $y_o^{ij,c}$, which is $\mathrm{d}_{NFC}(y, \overline{y_i^c y_j^c}) = \| y - y_o^{ij,c} \|$, where $y_o^{ij,c}$ is the center of inscribed circle of the triangle $\Delta y y_i^c y_j^c$. The feature center $y_o^{ij,c}$ can be calculated as follows.

$$y_o^{ij,c} = \frac{b_{ij}^c \times y + b_{yi}^c \times y_j^c + b_{yj}^c \times y_i^c}{b_{ij}^c + b_{yi}^c + b_{yj}^c} \tag{3}$$

where $\mathrm{b}_{yi}^c = \| y - y_i^c \|$, $\mathrm{b}_{yj}^c = \| y - y_j^c \|$ and $b_{ij}^c = \| y_i^c - y_j^c \|$.

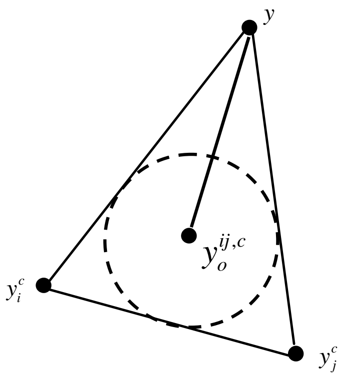

Fig. 2. The metric of NFC

2.3 Extended Nearest Feature Line

Borrowing the concept of feature line spaces from the NFL method, the extended nearest feature line (ENFL) is proposed in 2004. However, the distance metric of ENFL is different from the feature line distance of NFL.

ENFL does not calculate the distance between the query sample and the feature line. Instead, ENFL calculates the product of the distances between query sample and two prototype samples. Then the result is divided by the distance between the two prototype samples. As shown in Fig. 3. The new distance metric of ENFL is described as

$$d_{ENFL}(y, \overline{y_i^c y_j^c}) = \frac{\| y - y_i^c \| \times \| y - y_j^c \|}{\| y_i^c - y_j^c \|} \tag{4}$$

The distance between the pair of prototype samples can strengthen the effect when the distance between them is large.

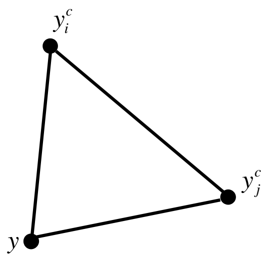

Fig. 3. The metric of ENFL

3 The Proposed Methods

Similar to NFL, ENFL and NFC, the adaptively nearest feature point (ANFP) classifier supposes that at least two prototype samples are available for each class. However, the metric is different. A better distance metric, called as adaptively feature metric, is proposed in this section. The basic idea is shown as follows. The adaptively feature point $y_o^{ij,c}$ can be computed by formula (5)-(8).

$$s_{i,j}^c = \frac{1}{b_{yi}^c \times b_{yi}^c + b_{yj}^c \times b_{yj}^c} \tag{5}$$

$$s_i^c = \frac{1}{b_{yi}^c \times b_{yi}^c} \times s_{i,j}^c \tag{6}$$

$$s_j^c = \frac{1}{b_{yj}^c \times b_{yj}^c} \times s_{i,j}^c \tag{7}$$

$$y_o^{ij,c} = \frac{s_i^c \times y_i^c + s_j^c \times y_j^c}{s_i^c + s_j^c} \tag{8}$$

where $\mathrm{b}_{yi}^c = \| y - y_i^c \|$, $\mathrm{b}_{yj}^c = \| y - y_j^c \|$ and $b_{ij}^c = \| y_i^c - y_j^c \|$.

After the point $y_o^{ij,c}$ being got, the adaptively feature metric is computed as in formula (9).

$$\mathrm{d}_{ANFP}(y, \overline{y_i^c y_j^c}) = \| y - y_o^{ij,c} \| \tag{9}$$

The detailed classification procedure of ANFP is described as follows. Firstly, the adaptively feature distance between the query sample y and each pair prototypes y_i^c and y_j^c is computed, which produces a number of distances. Secondly, the distances are sorted in ascending order, each of which is marked with a class identifier and two prototypes. Then, the ANFP distance can be determined as the first rank distance shown in the following formula (10).

$$d(y, \overline{y_{i^*}^{c^*} y_{j^*}^{c^*}}) = \min_{1 \le c \le L, 1 \le i < j \le N_c} d(y, \overline{y_i^c y_j^c}) \tag{10}$$

The first rank gives the best matched class c* and the two best matched prototypes i* and j* of the class. The query sample y will be classified into the class c*.

4 Experimental Results

The classification performance of the proposed classifiers is compared with NN, NFL, ENFL, and NFC classification approach. The experiments are executed on Yale face database.

Yale [22] face database contains 165 greyscale images in GIF format of 15 persons. There are 11 images per people, one per different facial expression or configuration: center-light, w/glasses, happy, left-light, w/no glasses, normal, right-light, sad, sleepy, surprised, and wink. All images are copped in 100×100.

"Randomly-chose-*N*" scheme is taken for comparison: *N* images per person are randomly chosen from the Yale face database as prototype set. The rest images of Yale face database are used for testing. The whole system runs 20 times. To test the robustness of new algorithms, the average recognition rate (ARR) and the average running time are used to assess the performance of new algorithms.

In the experimental, the "randomly-choose-*N*" scheme is adopt on Yale face database. The average recognition rates (ARR) of NN, NFL, ENFL, NFC and ANFP are shown in Fig. 4 and Table 1. From the Fig. 4, we can know that the recognition rate of the proposed is better than the recognition rate of NN, NFL, ENFL and NFC on Yale face database.

Table 1. The ARR of several classifiers using "randomly-choose-*7*" scheme

Classifier	RR
NN	84.33%
NFL	95.50%
ANFP	86.50%
NFC	85.00%
ENFL	84.83%

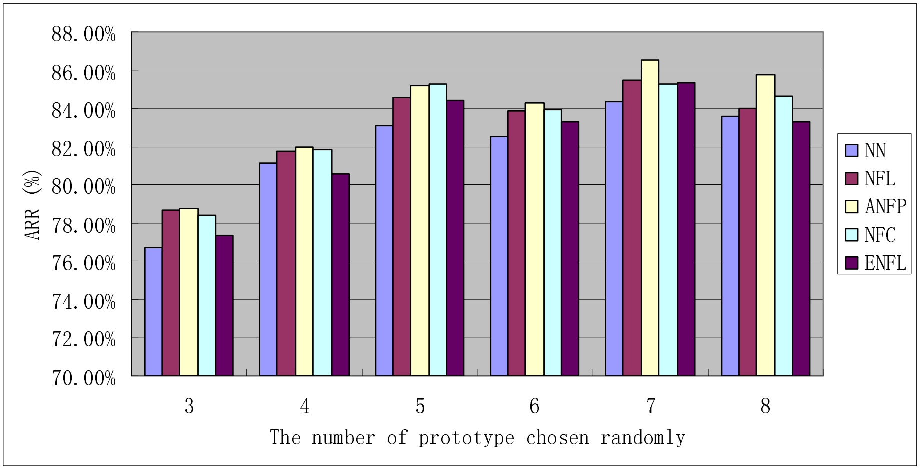

Fig. 4. The recognition rate of several classifiers using "randomly-choose-*N*" scheme on Yale face database

5 Conclusion

In this paper, a new classifier based on feature line space, called as adaptively nearest feature point classifier, is proposed. The proposed classifier uses the new metric, called as adaptively feature point metric. The average recognition rate of new classifier surpasses the other classifiers based on feature line space. Experimental result on Yale face database affirms the performance of the new classifier.

References

1. Turk, M., Pentland, A.: Eigenfaces for recognition. Journal of Cognitive Neuroscience 3(1), 71–86 (1991)
2. Belhumeur, P., Hespanha, J., Kriegman, D.: Eigenfaces vs. fisherfaces: recognition using class specific linear projection. IEEE Transactions on Pattern Analysis and Machine Intelligence 19(7), 711–720 (1997)
3. Bartlett, M.S., Movellan, J.R., Sejnowski, T.J.: Face recognition by independent component analysis. IEEE Transactions on Neural Networks 13(6), 1450–1464 (2002)
4. He, X., Yan, S., Hu, Y., Niyogi, P., Zhang, H.J.: Face recognition using laplacianfaces. IEEE Transactions on Pattern Analysis and Machine Intelligence 27(3), 1–13 (2005)
5. Kekre, H.B., Shah, K.: Performance Comparison of Kekre's Transform with PCA and Other Conventional Orthogonal Transforms for Face Recognition. Journal of Information Hiding and Multimedia Signal Processing 3(3), 240–247 (2012)
6. Zhou, X., Nie, Z., Li, Y.: Statistical analysis of human facial expressions. Journal of Information Hiding and Multimedia Signal Processing 1(3), 241–260 (2010)
7. Cover, T.M., Hart, P.E.: Nearest neighbor pattern classification. IEEE Trans. Inform. Theory 13(1), 21–27 (1967)
8. Li, S.Z., Lu, J.: Face Recognition Using the Nearest Feature Line Method. IEEE Transactionson Neural Networks 10(2), 439–443 (1999)
9. Chien, J.T., Wu, C.C.: Discriminant waveletfaces and nearest feature classifiers for face recognition. IEEE Trans. Pattern Anal. Machine Intell. 24(12), 1644–1649 (2002)
10. Lu, J., Tan, Y.-P.: Uncorrelated discriminant nearest feature line analysis for face recognition. IEEE Signal Process. Lett. 17(2), 185–188 (2010)
11. Feng, Q., Pan, J.-S., Yan, L.: Restricted Nearest Feature Line with Ellipse for Face Recognition. Journal of Information Hiding and Multimedia Signal Processing 3(3), 297–305 (2012)
12. Feng, Q., Huang, C.-T., Yan, L.: Resprentation-based Nearest Feature Plane for Pattern Recognition. Journal of Information Hiding and Multimedia Signal Processing 4(3), 178–191 (2013)
13. Li, S.Z.: Content-based audio classification and retrieval using the nearest feature line method. IEEE Trans. Speech Audio Process. 8(5), 619–625 (2000)
14. Chen, K., Wu, T.Y., Zhang, H.J.: On the use of nearest feature line for speaker identification. Pattern Recognition Lett. 23(14), 1735–1746 (2002)
15. Li, S.Z., Chan, K.L., Wang, C.L.: Performance evaluation of the nearest feature line method in image classification and retrieval. IEEE Trans. Pattern Anal. Machine Intell. 22(11), 1335–1339 (2000)
16. Chen, J.H., Chen, C.S.: Object recognition based on image sequences by using inter-feature-line consistencies. Pattern Recognition 37(9), 1913–1923 (2004)

17. Zheng, W., Zhao, L., Zou, C.: Locally nearest neighbor classifiers for pattern classification. Pattern Recognition 37(6), 1307–1309 (2004)
18. Zhou, Y., Zhang, C., Wang, J.: Extended nearest feature line classifier. In: Zhang, C., Guesgen, H.W., Yeap, W.K. (eds.) PRICAI 2004. LNCS (LNAI), vol. 3157, pp. 183–190. Springer, Heidelberg (2004)
19. Zhou, Z., Kwoh, C.K.: The pattern classification based on the nearest feature midpoints. International Conference on Pattern Recognition 3, 446–449 (2000)
20. Han, D.Q., Han, C.Z., Yang, Y.: A Novel Classifier based on Shortest Feature Line Segment. Pattern Recognition Letters 32(3), 485–493 (2011)
21. Feng, Q., Pan, J.S., Yan, L.: Nearest feature centre classifier for face recognition. Electronics Letters 48(18), 1120–1122 (2012)
22. The Yale faces database (2001), `http://cvc.yale.edu/projects/yalefaces/yalefaces.html`