Journal of Information Hiding and Multimedia Signal Processing ©2012 ISSN 2073-4212
Ubiquitous International Volume **3**, Number **3**, July **2012**

Restricted Nearest Feature Line with Ellipse for Face Recognition

Qingxiang Feng[1], Jeng-Shyang Pan[2,*], and Lijun Yan[3]

[1]Department of Computer Science and Technology
Harbin Institute of Technology Shenzhen Graduate School
Shenzhen, China
fengqx1988@163.com

[2]Department of Computer Science and Technology
Harbin Institute of Technology Shenzhen Graduate School
Shenzhen, China
jspan@cc.kuas.edu.tw; *Corresponding Author

[3]Department of Computer Science and Technology
Harbin Institute of Technology Shenzhen Graduate School
Shenzhen, China
yanlijun@126.com

Received January 2012; revised June 2012

Abstract. *In this paper, a novel classifier based on nearest feature line is proposed, which is called as restricted nearest feature line with ellipse (RNFLE). NFL successfully improves the classification ability. However there are still some drawbacks in NFL that limit their further application in practice. To improve the miss-classification of nearest feature line when the prototypes in NFL are far away from the query sample, RNFLE uses the ellipse to restrict the feature lines. A large number of experiments executed on ORL and AR face database confirm the usefulness of the proposed algorithm.*
Keywords: Nearest Feature Line; Nearest Neighbor; Face Recognition.

1. **Introduction.** Recently, there are a lot of methods for face recognition. For instance PCA [1], LDA [2], ICA [3] and other methods [4, 5, 6, 7, 8, 9]. One of the most popular methods among them is the nearest neighbor (NN) classifier [10]. However, the performance of NN is limited by the available prototypes in each class. To overcome this drawback, nearest feature line (NFL) [11] 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 passing through each pair of the samples belonging to the same class. NFL shows good performance in many applications, including face recognition [12, 13], audio retrieval [14], speaker identification [15], image classification [16], object recognition [17] and pattern classification [18]. 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 fail when the prototypes in NFL are far away from the query sample, which is called as extrapolation inaccuracy of NFL. The detailed information of extrapolation inaccuracy is shown in Figure 2.

To solve the above problem, extended nearest feature line [19] (ENFL) and shortest feature line segment [20] (SFLS) are proposed. They gains better performance in some situation. However, they are not so good in other situation.

In this paper, a new algorithm is given for improving the extrapolation inaccuracy of NFL which is called as the restricted nearest feature line with ellipse. A large number of experiments are executed on ORL and AR face database. And detailed comparison result is given.

The rest of this article is organized as follows. In Section II, we introduced the background. In section III, we describe the RNFLE. In section IV, the analysis of RNFLE is introduced. In the fifth quarter we compare the RNFLE, NFL, NN, SFLS and ENFL by the experiment on ORL face database and AR face database. Finally, a brief summary is given.

2. **Background.**

In this section, we will introduce nearest feature line, extended nearest feature line and shortest feature line segment. 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 ith 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.**

In this part, the main content contains feature line metric, the steps of NFL and extrapolation inaccuracy of NFL.

2.1.1. *Feature line metric.*

The core of NFL is the feature line metric. As is shown in Figure 1, the NFL classifier doesnt compute the distance of query sample y and y_i^c; doesnt calculate the distance of y and y_i^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:

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

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.

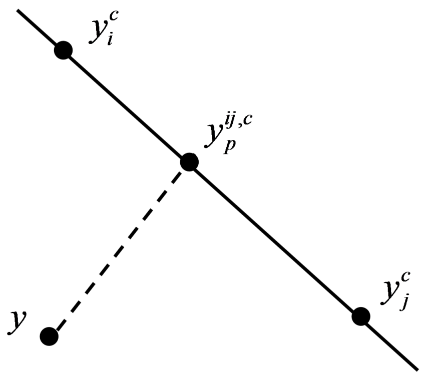

FIGURE 1. the metric of NFL

The projection point $y_p^{ij,c}$ is calculated by $y_p^{ij,c} = y_i^c + t\left(y_j^c - y_i^c\right)$ where $t \in R$, which is the positional parameters. After simple deformation, we can see that the location parameter $t = \frac{\left(y - y_i^c\right)^T\left(y_j^c - y_i^c\right)}{\left(y_j^c - y_i^c\right)^T\left(y_j^c - y_i^c\right)}$. The location parameter t describes the positional relationship of $y_p^{ij,c}$, y_i^c and y_j^c. When $t = 0, y_p^{ij,c} = y_i^c$. When $0 < t < 1, y_p^{ij,c}$ is an interpolation point between y_i^c and y_j^c. When $t > 1, y_p^{ij,c}$ is a "forward" extrapolation point on the y_j^c side. When $t < 0, y_p^{ij,c}$ is a "backward" extrapolation point on the y_i^c side.

2.1.2. *The classification steps of NFL classifier.*

Given the query sample feature points y, the classification process with nearest feature line algorithm is as follows:

The first step: according to equation (1), calculate the distance between query sample point y and all the feature lines which are belonged to c-class, where $1 \le c \le M$.

The second step: the distances are sorted in ascending order, each being associated with a class identifier, the corresponding two feature samples, and the corresponding location parameter t.

The Third step: the NFL distance is the first rank distance:

$$d_{\min}^{i_0 j_0, c_0} = \min_{1 \le c \le M} \min_{1 \le i,j \le N_c, i \ne j} d(y, \overline{y_i^c y_j^c}) \tag{2}$$

The first rank gives the NFL classification composed of the best matched class c_0 and the two best matched prototypes i_0 and j_0 of the c_0-class.

2.1.3. *The extrapolation inaccuracy of nearest feature line.* As shown in Figure 2, the query sample point y is surrounded by the samples belonging to c-class, however, the distance between y and feature line $\overline{y_i^c y_j^c}$ is shorter than the distance between y and feature line $\overline{y_i^s y_j^s}$. Eventually y is classified into c-class. The fail is called extrapolation inaccuracy of nearest feature line.

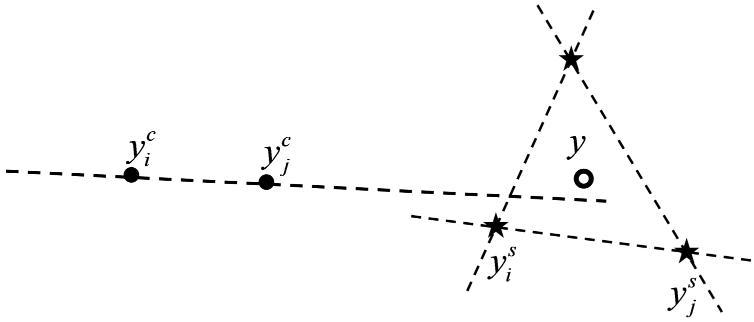

FIGURE 2. the extrapolation inaccuracy of NFL

2.2. **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 Figure 3. The new distance metric of ENFL is described as

$$d_{ENFL}(y, \overline{y_i^c y_j^c}) = \frac{||y - y_i^c|| \times ||y - y_j^c||}{||y_i^c - y_j^c||} \tag{3}$$

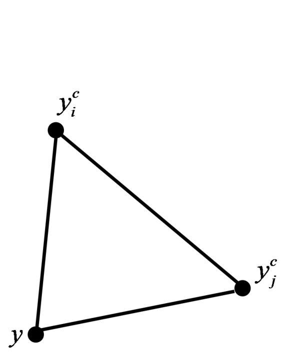

FIGURE 3. the metric of ENFL

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

2.3. **Shortest feature line segment.** Instead of calculating the distance between the query sample and the feature line, SFLS tries to find the shortest feature line segment which satisfies the given geometric relation constraints together with the query sample. As shown in Figure 4. The pair of samples in the sample class constitutes a feature line segment. If the query sample is inside or on the hyper sphere centered at the midpoint of the feature line segment, the corresponding feature line segment will be tagged and the distance metric of SFLS can be calculated as

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

In the worst case, there is no tagged feature line for a query sample y, and then SFLS uses the rule of NN to make the classification decision for the query y.

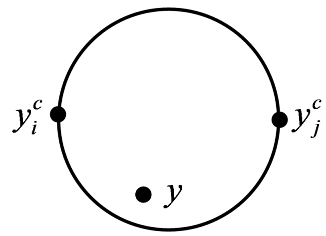

FIGURE 4. the metric of SFLS

3. **The proposed methods.** NFL enhances the representational capacity of a sample set of limited size by using the lines passing through each pair of the samples belonging to the same class. However, the length of line can be extended infinitely, which will be dangerous for classification. Considering the above situation, we propose the RNFLE method. The detailed information of RNFLE is as follows.

3.1. **The idea of restricted nearest feature line with ellipse.** The main reason of extrapolation inaccuracy of NFL is that the feature lines length is extended infinitely. So RNFLE use ellipse to restrict the feature line, which is the main idea of RNFLE.

As is shown in Figure 5, RNFLE does not directly calculate the feature line distance between query sample y and feature line $\overline{y_i^c y_j^c}$, while RNFLE judges whether query y is inside or on the ellipse, the focus of which are two prototype samples y_i^c and y_j^c. If the query sample y is inside the ellipse, shown in Figure 5 (a), the distance between the query sample y and the corresponding feature line $\overline{y_i^c y_j^c}$ is described as $d(y, \overline{y_i^c y_j^c}) = ||y - y_p^{ij,c}||$, where $y_p^{ij,c}$ is the projection point of y on the feature line $\overline{y_i^c y_j^c}$. If not, shown in Figure 5 (b), the distance between the query sample y and the corresponding feature line $\overline{y_i^c y_j^c}$ is described as $d(y, \overline{y_i^c y_j^c}) = \min(||y - y_i^c||, ||y - y_j^c||)$.

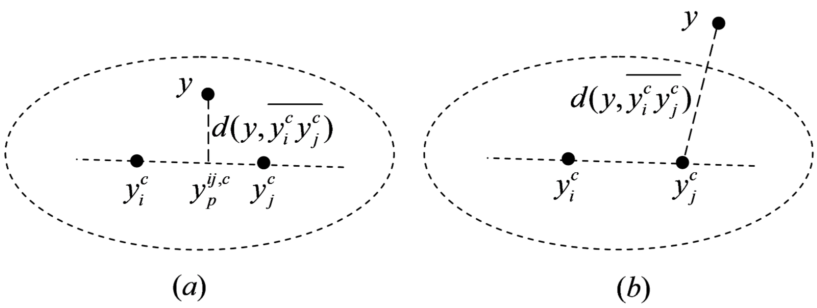

FIGURE 5. the idea of RNFLE. (a)the query sample is inside the ellipse. (b)the query sample is outside the ellipse.

The procedure of judging whether query y is inside or on the ellipse is shown in Figure 6. Here, set a_0 threshold , which is the ratio between the length of ellipses long axis and the focus length of ellipse. According to the second definition of ellipse, we can know that the detailed procedure of judging is as follows. If $||y - y_i^c|| + ||y - y_j^c|| \leq a_0||y_i^c - y_j^c||$, shown in Figure 6 (a), the query sample y is inside or on the ellipse. If $||y - y_i^c|| + ||y - y_j^c|| > a_0||y_i^c - y_j^c||$, shown in Figure 6 (b), the query sample y is outside the ellipse.

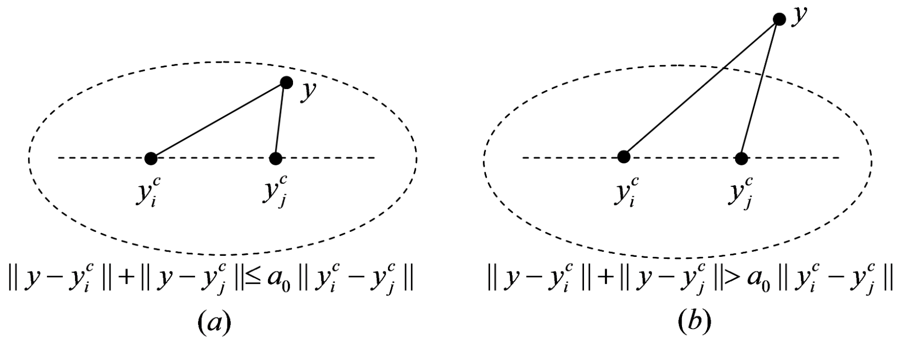

FIGURE 6. the procedure of judging whether query y is inside the ellipse. (a)the query sample is inside the ellipse. (b)the query sample is outside the ellipse

4. **Analysis of the new methods.** In this section, we mainly introduce three aspects of RNFLE classifier. They are described as follows.

4.1. **Improve the extrapolation inaccuracy.** In Figure 7, the query sample y is inside the ellipse produced by prototype samples y_i^s and y_j^s, at the same time, it is outside the ellipse produced by prototype samples y_i^c and y_i^c. And the distance between query sample y and feature line $\overline{y_i^s y_j^s}$ is $||\text{y} - y_p^{ij,c}||$, which is shorter than $\min(||\text{y} - y_i^c||, ||\text{y} - y_j^c||)$, so sample y is classified into s-class.

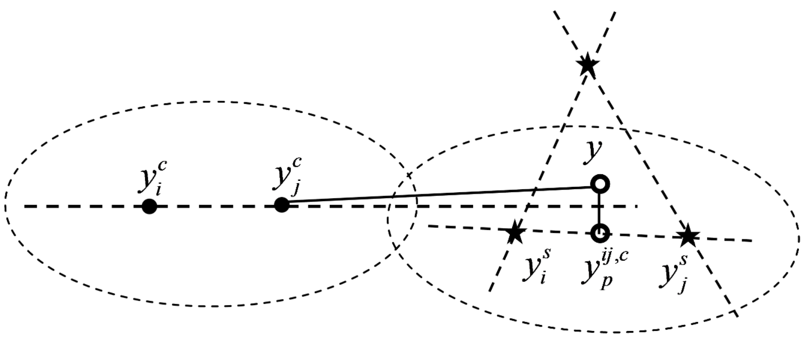

FIGURE 7. improve the extrapolation inaccuracy

4.2. **Vehicle tracking.** Suppose that N_c is the number of samples belonging to class c in the prototype set, feature vector of each sample has Z dimension. There are $N_c(N_c - 1)/2$ feature lines in the class c. The computation in RNFLE for each class includes $3Z \times N_c(N_c - 1)/2$ multiplication operations which is less than that of original NFL: $(3Z + 1) \times N_c(N_c - 1)/2$.

4.3. **The relationship among RNFLE, NFL and NN.** As is shown in section III, it is easy for us to know that the relationship among RNFLE, NFL and NN is as follows. The metric of NN is the distance between query sample and a prototype sample. The metric of NFL is the distance between query sample and a feature line. And the metric of RNFLE is composed by the metric of NN and the metric of NFL with the specific limited situation. RNFLE is almost equal to NFL when the threshold a_0 trends to infinity. And RNFLE is almost equal to NN when the threshold a_0 trends to 1.

5. **Experimental results.** The classification performance of RNFLE is compared with NFL, NN and ENFL classification approach. The experiments are executed on face database ORL and AR. The Cambridge (ORL) [21] database contains 40 distinct persons, each person having ten different images, taken at different times, varying lighting slightly, facial expressions (open/closed eyes, smiling/no-smiling), and facial details (glasses/no glasses). All the images are taken against a dark homogeneous background and the persons are in upright, frontal position (with tolerance for some side movement). One subjects face images of ORL database are shown in Figure 8.

FIGURE 8. one subjects face images of ORL face database

The AR [22] database contains over 4000 face images of 126 subjects (70 men and 56 women). To reduce the computational complexity, the subset of AR database includes 1680 face images of 120 individuals with fourteen face images of different expressions and lighting conditions except wearing sun glasses and wearing scarf per subject, and all images in AR database were manually cropped into 50×40 pixels. One subjects face images of AR database are shown in Figure 9.

FIGURE 9. one subjects face images of the subset of AR face database

Two test schemes are taken for comparison. Firstly "leave-one-out" scheme: All images within database ORL or AR are taken as the test samples. When an image is used as the test sample, it is not used as a prototype, it is removed from the prototype set, during the classification; Secondly "randomly-chose-N" scheme: five images per person are randomly chosen from the ORL or AR as prototype set. The rest images of ORL or AR are used for testing. The whole system runs 20 times. To test the robustness of new algorithms, the average recognition rate and the average running time are used to weigh the performance of new algorithms

5.1. **Comparison of recognition rate using "leave-one-out" scheme on ORL and AR database.** In the first experiment, we adopt the "leave-one-out" scheme on ORL face database. The result is shown in Figure 10. In the figure, the horizontal axis is the threshold a_0; the longitudinal axis is the recognition rate of RNFLE and NFL with different threshold a_0. From the Figure 10, we can know that the recognition rate of RNFLE is not less than the recognition rate of NFL when threshold a_0 belongs to $[1.8, \infty)$.

In the second experiment, we adopt the "leave-one-out" scheme on AR face database. The result is shown in Figure 10. In the figure, the horizontal axis is the threshold a_0; the longitudinal axis is the recognition rate of RNFLE and NFL with different threshold a_0.From the Figure 10,

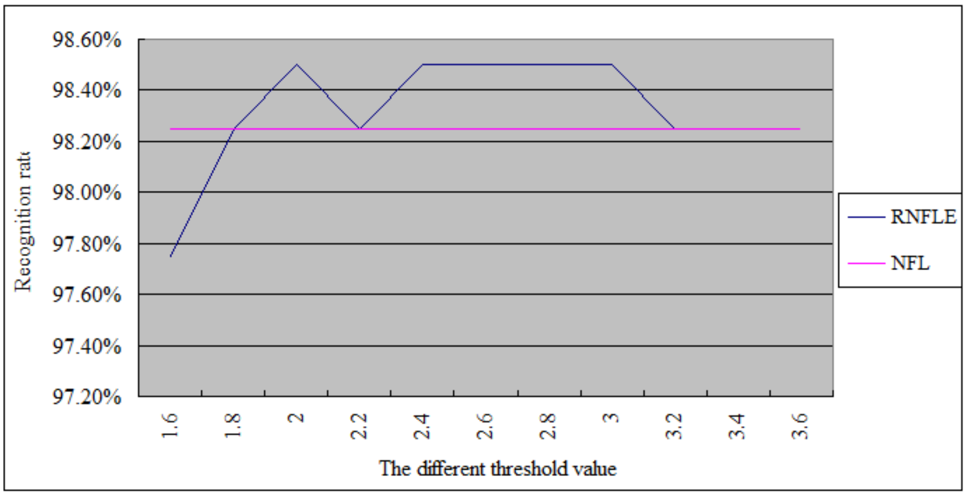

FIGURE 10. the recognition rate of RNFLE and NFL with different threshold a0 on ORL face database

we can know that the recognition rate of RNFLE is not less than the recognition rate of NFL when threshold a_0 belongs to $[1.8, \infty)$.

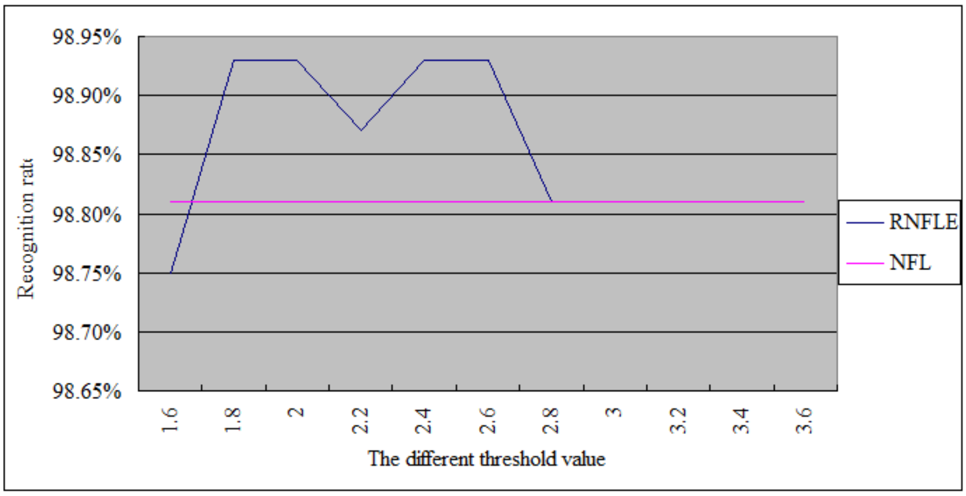

FIGURE 11. the recognition rate of RNFLE and NFL with different threshold a0 on AR face database

5.2. **Analysis of threshold a_0.** The purpose of RNFLE is to improve the extrapolation inaccuracy of NFL. From the experiment result shown in Figure 10 and Figure 11, we can know that RNFLE gains better performance than NFL when the threshold a_0 is appropriate. When the threshold a_0 trends to ∞, RNFLE will be equal to NFL and the experiment results on database ORL and AR show that. How to take the value of a_0, which has not the theory basis. However, the experience value can be getted. According to the experiment result, we suggest that the threshold a_0 takes 2.4

5.3. **Comparison of recognition rate using "randomly-choose-N" scheme on ORL and AR.** In this part, let the threshold a_0 be 2.4. In the third experiment, we adopt the "randomly choose N" scheme on ORL face database. The result is shown in Figure 12.

In the fourth experiment, we adopt the "randomly-choose-N" scheme on AR face database. The recognition rates of RNFLE, NFL and ENFL are shown in Figure 13.

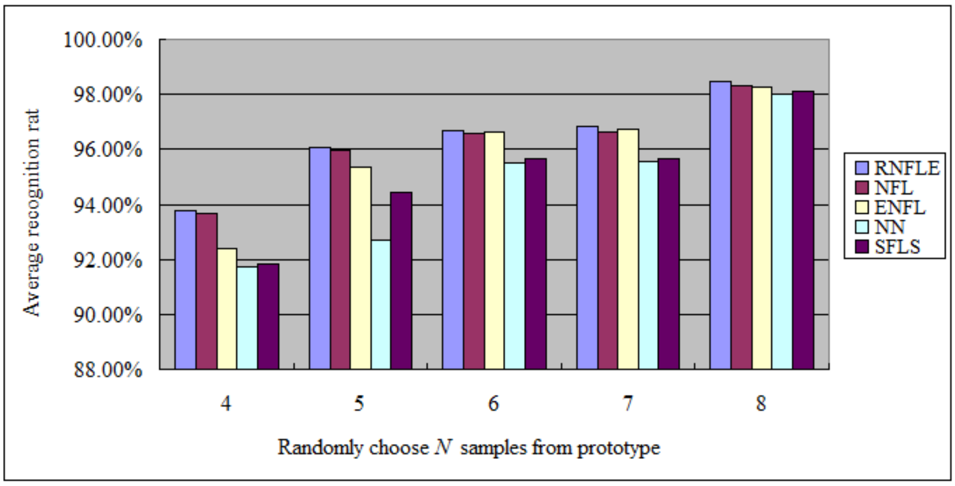

FIGURE 12. the recognition rate of RNFLE, NFL, ENFL, NN and SFLS using "randomly-choose-N" scheme on ORL face database

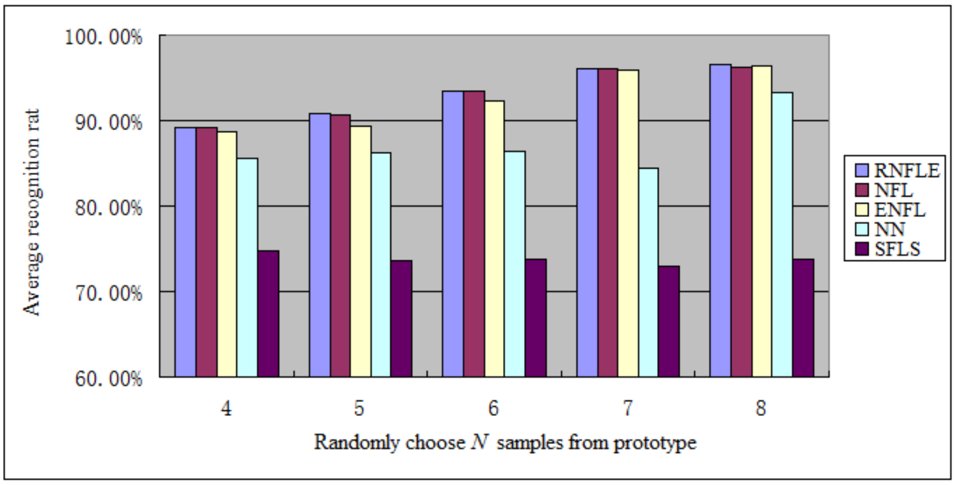

FIGURE 13. the recognition rate of RNFLE, NFL, ENFL, NN and SFLS using "randomly-choose-N" scheme on AR face database

From the Figure 12 and Figure 13, we can know that the recognition rate of RNFLE is better than the recognition rate of NFL, ENFL, NN and SFLS on ORL face database and AR face database.

6. **Conclusion.** Nearest feature line algorithm obtains good experimental result on face recognition. However, NFL will fail when the prototypes in NFL are far away from the query point. To solve the above problems, this paper proposes the RNFLE algorithm. Since RNFLE algorithm calculates the feature line distance between query sample and feature line after judging whether the query sample is inside the specific ellipse, so RNFLE improves extrapolation inaccuracy of NFL when the threshold a_0 is appropriate. A large number of experiments are executed on ORL and AR face database, which shows that the recognition rate of RNFLE is more than that of NFL when the threshold a_0 is appropriate.

REFERENCES

[1] M. Turk and A. Pentland, Eigenfaces for recognition, *Journal of Cognitive Neuroscience*, vol. 3, no. 1, pp.71-86, 1991.
[2] P. Belhumeur, J. Hespanha and D. Kriegman, Eigenfaces vs. fisherfaces: recognition using class specific linear projection, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 711-720, 1997.

[3] M. S. Bartlett, J. R. Movellan, and T. J. Sejnowski, Face recognition by independent component analysis, *IEEE Trans. Neural Networks*, vol. 13, no. 6, pp. 1450-1464, 2002.

[4] X. He, S. Yan, Y. Hu, P. Niyogi and H. J. Zhang, Face recognition using laplacianfaces, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 27, no. 3, pp. 1-13, 2005.

[5] H. B. Kekre and K. Shah, Performance comparison of Kekre's transform with PCA and other conventional orthogonal transforms for face recognition, *Journal of Information Hiding and Multimedia Signal Processing*, Vol. 3, No. 3, pp. 240-247, 2012.

[6] X. Zhou, Z. Nie, Y. Li, Statistical analysis of human facial expressions, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 1, no. 3, pp. 241-260, 2010.

[7] D. Y. Huang, C. J. Lin and W. C. Hu, Learning-based face detection by adaptive switching of skin color models and AdaBoost under varying illumination, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 2, no. 3, pp. 204-216, 2011.

[8] W. C. Hu, C. Y. Yang, D. Y. Huang and C. H. Huang, Feature-based face detection against skin-color like backgrounds with varying illumination, *Journal of Information Hiding and Multimedia Signal Processing*, Vol. 2, No. 2, pp. 123-132, 2011.

[9] C. Y. Chang, C. W. Chang, and C. Y. Hsieh, Applications of block linear discriminant analysis for face recognition, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 2, no. 3, pp. 259-269, 2011.

[10] T. M. Cover, and P. E. Hart, Nearest neighbor pattern classification, *IEEE Trans. Information Theory*, vol. 13, no. 1, pp. 21-27, 1967.

[11] S. Z. Li and J. Lu, Face recognition using the nearest feature line method, *IEEE Trans. Neural Networks*, vol. 10, no. 2, pp. 439-443, 1999.

[12] J. T. Chien and C. C. Wu, Discriminant waveletfaces and nearest feature classifiers for face recognition, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 24, no. 12, pp. 1644-1649, 2002.

[13] J. Lu and Y. P. Tan, Uncorrelated discriminant nearest feature line analysis for face recognition, *IEEE Signal Processing Letters*, vol. 17, no. 2, pp. 185-188, 2000.

[14] S. Z. Li, Content-based audio classification and retrieval using the nearest feature line method, *IEEE Trans. Speech Audio Process*, Vol. 8, no. 5, pp. 619V625, 2000.

[15] K. Chen, T. Y. Wu, and H. J. Zhang, On the use of nearest feature line for speaker identification, *Journal of Pattern Recognition Letters*, vol. 23, no. 14, pp. 1735-1746, 2002.

[16] S. Z. Li, K. L. Chan, and C. L.Wang, Performance evaluation of the nearest feature line method in image classification and retrieval, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 22, no. 11, pp. 1335-1339, 2000.

[17] J. H. Chen and C. S. Chen, Object recognition based on image sequences by using inter-feature-line consistencies, *Journal of Pattern Recognition Letters*, vol. 37, no. 9, pp. 1913-1923, 2004.

[18] W. Zheng, L. Zhao, and C. Zou, Locally nearest neighbor classifiers for pattern classification, *Journal of Pattern Recognition Letters*, vol. 37, no. 6, pp. 1307-1309, 2004.

[19] Y. L. Zhou, C. S. Zhang, and J. C. Wang, Extended nearest feature line classifier, *Proc. of 8th Pacific Rim International Conference on Artificial Intelligence*, vol. 3175, pp. 183-190, 2004.

[20] D. Q. Han, C. Z. Han, and Y. Yang, A novel classifier based on shortest feature line segment, *Journal of Pattern Recognition Letters*, vol. 32, no. 3, pp. 485-493, 2011.

[21] AT&T Laboratories Cambridge, The Database of Faces, 1994, `http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html`

[22] A. M. Martinez and R. Benavente, *The AR Face Database*, CVC Technical Report, vol. 24, 1998.