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Modified Nearest Feature Line Method in a 3-D Face Recognition System for a Large Number of Object Classes

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Abstract: Authors have developed a novel method for achieving higher recognition capability of a 3-D face recognition system based on feature line method, which is called Modified Nearest Feature Line. Combined with our developed view-based Karhunen-Loeve transformation method as a feature extraction subsystem, the Modified Nearest Feature Line method is used as a classifier to build a 3-D face recognition system. As recognition rates are usually decreased by increasing the number of object classes, the authors evaluate and analyze the performance of this Modified Nearest Feature Line method for recognizing 3-D face images and compared with that of the conventional Nearest Feature Line method. In our experiments, each object class consists of images of persons with their viewpoint positions and expressions. Experimental results show that increasing the number of object classes influenced the recognition rates of both systems. However, the decrement slopes of the recognition system using Modified Nearest Feature Line method were lower than that of using Nearest Feature Line method. It is also shown that at every same number of persons to be recognized, our Modified Nearest Feature Line method always gave a high recognition rate than the original Nearest Feature Line method, with up to 20% in recognition rate difference.

Key words: 3-D Face Recognition System, Nearest Feature Line Method, Modified Nearest Feature Line Method, Eigenspace Representation, Karhunen-Loeve Transformation.

1 Introduction

Human has an ability to remember and identify hundreds even thousands of faces whom they meet in their social lifes. The ability in recognizing those faces still can work well although the faces have changes in certain level; such as age, expressions, and addition of accessories to its human face. Nowadays, along with the increasing demand of high technology to easier human tasks, researchers would like to transfer their ability by developing a 3-D face recognition system.

Basically, a 3-D face recognition system is a system that recognize human face by comparing an unknown image with face models that already exist in the database gallery [1]. A good 3-D face recognition system must have the ability to recognize faces with different positions, expressions, illuminations, etc. It is argued in [2,3] that 3-D recognition can also be accomplished using linear combinations of as few as four or five 2-D viewpoint images.

Recently, lots of research experiments have been conducted to develop a good classification method in recognizing human faces, such as the geometric-feature based method, image based method, neural network and its modifications. More over, in [1,4] the authors have proposed Modified Nearest Feature Line (M-NFL) method as a classification method that has high recognition capability.

In this paper, the authors examine the performance analysis of M-NFL method for recognizing 3-D face images as a function of increasing the numbers of object classes. The developed system consists of two main processes, a feature extraction subsystem and a face classification subsystem.

In the features extraction subsystem, we developed a feature space by transforming every face image as a vector in the spatial domain to be another vector in the feature eigenspace, by using the Karhunen-Loeve transformation (KLT) method [4]. In order to increase the recognition rate of the developed system, authors have introduced the Single-View KLT (SVKLT) method as transformation procedures [4,5]. In the conventional KLT method; all of images are transformed into only one eigenspace, while in our SVKLT method; every image taken from the same viewpoint will be transformed into single sub-eigenspace. Our previous researches shown that the use of SVKLT method demonstrated higher estimation rates compare with the conventional KLT method [4-6]. However, SVKLT algorithm has a drawback on its decision rule when the incoming unknown images have viewpoints in between of the already determined viewpoints in the SVKLT method. Based on those results, we propose another view-based KLT method [1], which is then called as Double-View KLT (DVKLT). In DVKLT method, all of the reference images are taken from every two nearest viewpoint positions and transformed into one sub-eigenspace. It means that every two sub-eigenspaces in SVKLT method are now being merged into only one sub-eigenspace in DVKLT method. By using *the* DVKLT method, we can classify the incoming unknown images that have viewpoints in between of the two nearest viewpoint positions. Based on our experimental results such in [1,4,5,6], the recognition rates of the system using DVKLT method were higher than that of using conventional KLT method and SVKLT method. Referring to the advantages of using DVKLT method, in this paper we use the DVKLT method as the transformation method in the feature extraction subsystem, while both of NFL method and M-NFL method are used as classifiers subsystems, as illustrated in Figure 1.

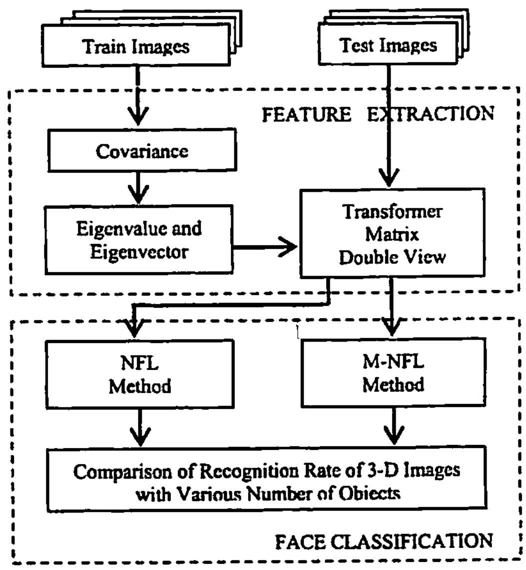

Figure 1. 3-D Face recognition system diagram

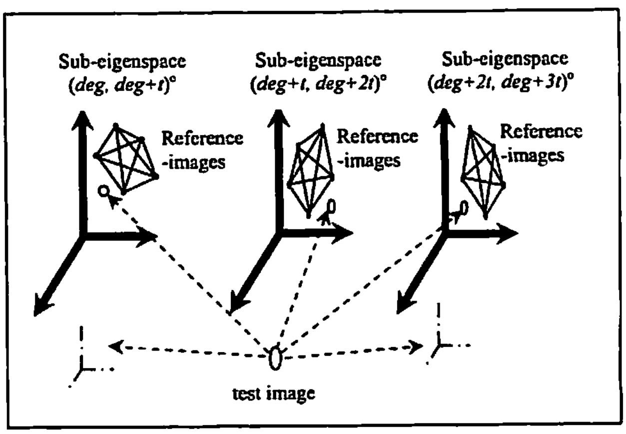

Figure 2. Construction of DVKLT sub-eigenspaces and projection of the test image into all available sub-eigenspaces

2 Double-View K-LT Method

The Karhunen-Loeve transformation is a familiar technique for projecting a large amount of data onto a small dimensional subspace in pattern recognition and image compression [7,8]. The aim of this method is to optimize pattern representation by selecting features during an initial learning stage [6]. By selecting these features, the dimension of feature space will be reduced significantly and as the consequence the computation cost of the system will also be reduced.

As already described earlier, we use DVKLT method in which reference-images from every two nearest viewpoint positions are transformed into one sub-eigenspace. As illustrated in Figure 2, where t^o is the interval of viewpoint position, reference-images (which drawn as black points in Figure 2) with deg^o viewpoint position and $(deg+t)^o$ viewpoint position are transformed into one sub-eigenspace, which determined as the $(deg, deg+t)^o$ sub-eigenspace. The other reference-images within $(deg+t)^o$ viewpoint position and $(deg+2t)^o$ viewpoint position are transformed into another $(deg+t, deg+2t)^o$ sub-eigenspace; and the process is continued for the other reference-images within another viewpoint positions, until all of reference-images are transformed into their designated sub-eigenspaces.

In its application, an unlearn face image (which drawn as circle points in Figure 2) with unknown viewpoint position is firstly represented as a feature point in every available multiple sub-eigenspaces that have been formed in the training phase.

In general, the Karhunen-Loeve transformation method is firstly done by forming a base vector of the overall d images represented in $N = n \times n$ dimensions, i.e. $x_N(k) = [x_1, x_2, \ldots, x_d]$, with $k = 1, 2, \ldots, d$, and d is number of images in the reference gallery. Then, compute the average vector μ_{x_N} and determine the covariance matrix C_{x_N} through:

$$C_{x_N} = \frac{1}{d}\sum_{k=1}^{d}(x_N(k) - \mu_{x_N})(x_N(k) - \mu_{x_N})^T \quad (1)$$

From this covariance matrix, we can derive a set of λ_{x_N} and e_{x_N} which are the eigen values and the eigen vectors. The eigenvectors are orthonormal and the corresponding eigenvalues are nonnegative. Assuming that there are no repeated eigenvalues and that they are arranged in decreasing order, $\lambda_1 > \lambda_2 > ... > \lambda_m$, a matrix transformation is then constructed based on the importance of these eigen values.

Then, construct a matrix transformation y_M to map a set of x_N image vectors in eigenspace through:

$$y_M = e_{x_N}{}^T (x_N - \mu_{x_N}) \qquad (2)$$

While the inverse reconstruction of x_N vectors can be done through:

$$x_N = e_{x_N}{}^T y_M + \mu_{x_N} \qquad (3)$$

In order to gain an optimal matrix transformation for higher estimation rate, compute the cummulative proportion of eigen values using [11]:

$$\alpha^l = \left(\sum_{i=1}^{l} \lambda_i\right) \Big/ \left(\sum_{j=1}^{m} \lambda_j\right) \qquad (4)$$

Then, recalculate the equations (2) and (3) to compute y_M' and x_N'. In this paper, we used 90%, 95%, and 99% of cummulative proportion to optimize the transformation matrix.

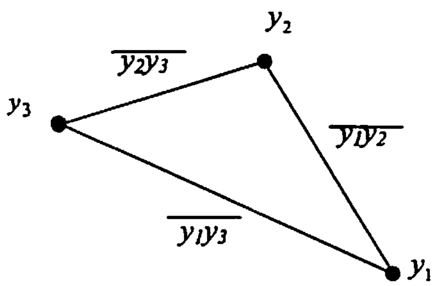

Figure 3. Construction process of feature lines using NFL method

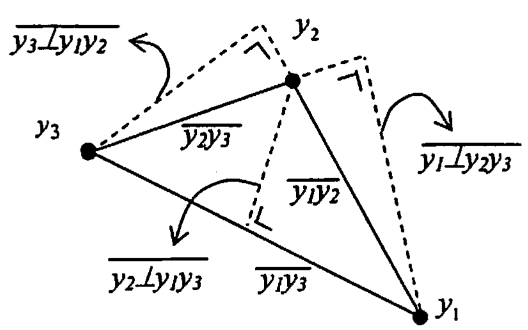

Figure 4. Construction process of feature lines using M-NFL method

3 Face Classification Using M-NFL Method

The classification process using the developed M-NFL method could be described as follows. After transforming the reference-images with DVKLT method into their sub-eigenspaces domain as feature points, do a generalization process by connecting all feature points in each sub-eigenspace. Suppose the straight line that connected two feature points in the same sub-eigenspace is called the feature line [9], it could be assumed that this feature line is composed of many feature points that are not available in the reference gallery, which is related to the feature variations of an object in their spatial domain. Hopefully, by using more information of feature variations that represented by points in the feature line, the recognition rate of the 3-D face recognition system increased significantly. Illustration of the construction process of feature lines using NFL method is shown in Figure 3 while for M-NFL method is depicted in Figure 4.

Suppose we have three feature points called y_1, y_2, and y_3. Based on conventional NFL method, the feature lines that could be formed in each sub-eigenspaces are $\overline{y_1y_2}$, $\overline{y_1y_3}$, and $\overline{y_2y_3}$. This means that for every sub-eigenspace in NFL method, we have:

$$G_c = H_c(H_c - 1)/2 \qquad (5)$$

where H_c denotes number of feature points and G_c denotes number of feature lines.

Meanwhile, in our developed M-NFL method, we construct more feature lines without any increment of feature points by projecting each feature point to all available feature lines. As illustrated in Figure 4, the additional feature lines in our M-NFL method are $\overline{y_1y_2}$, $\overline{y_1y_3}$, $\overline{y_2y_3}$, $\overline{y_1 \perp y_2y_3}$, $\overline{y_2 \perp y_1y_3}$, and $\overline{y_3 \perp y_1y_2}$. By constructing those additional feature lines, the total number of feature lines in this M-NFL method can be calculated through:

$$G_c = H_c(H_c - 1)^2 / 2 \qquad (6)$$

with H_c denotes number of feature points and G_c denotes number of feature lines.

The classification process of an unlearned face image with unknown viewpoint is depicted in Figure 5. In order to make the classification process, it is necessary to firstly transformed this image from its spatial domain into a feature point in the eigenspace domain. Suppose we have an unknown viewpoint image, then we transformed this image become point y in the eigenspace domain. Next, we projected y as a point of p in all available feature lines in the sub-eigenspaces using:

$$p = y_1 + \gamma(y_2 - y_1) \tag{7}$$

with γ as a position-parameter of the projection point p to y_1. We can calculate γ by using dot product through equation 8 below:

$$\gamma = \frac{(y - y_1)\bullet(y_2 - y_1)}{(y_2 - y_1)\bullet(y_2 - y_1)} \tag{8}$$

Then, the distances between test image (y) and its projected point p can be calculated through:

$$d(y,p) = \|y - p\| \tag{9}$$

in every available sub-eigenspace.

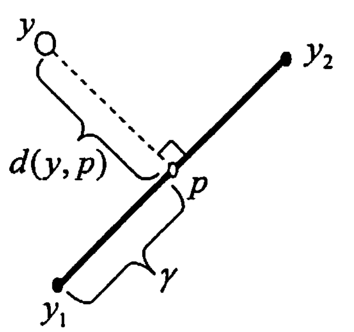

Figure 5. Distance calculation for classification of an unlearned image with unknown viewpoint

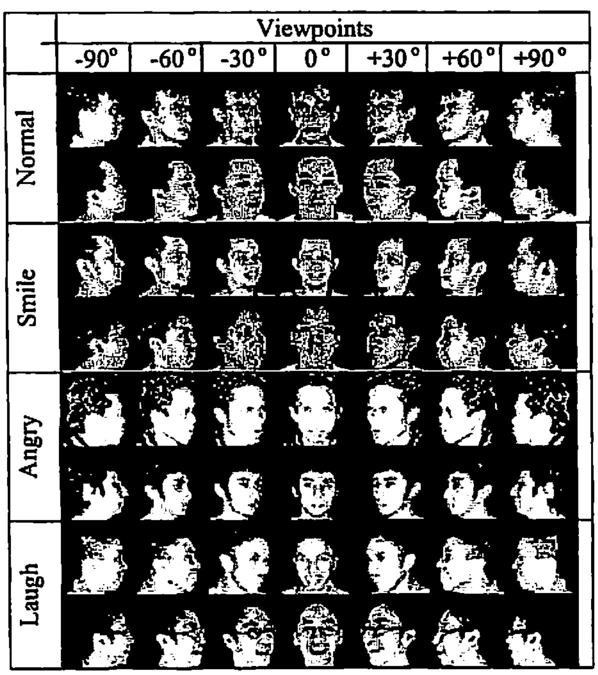

Figure 6. Example of images that are used in the experiments

The test image is then clustered into a sub-eigenspace that has the minimum distance, according to the minimum distance from the comparison of the test point y to all of the available lines in the entire sub-eigenspaces. Suppose that the minimum distance is determined in line $\overline{y_1y_2}$, which connecting two points of y_1 and y_2, then if y_1 and y_2 belong to the same object, then y will be recognized as the same object as y_1 and y_2. However, if y_1 and y_2 belong to the different object, and if $\gamma < \frac{1}{2}d(y_1,y_2)$, then y will be recognized as the same object as y_1. Otherwise, y will be recognized as the same object as y_2.

4 Results and Analysis

We implemented the system to recognize a real face images of Indonesian person with different viewpoint positions and expressions. In order to know the performance characteristic of both NFL and M-NFL methods, we also modify the number of object classes and compare its recognition rates. The experimental system used face images of four, six, and eight persons with their different expressions, such as normal, smile, angry, and laugh, which are taken from different viewpoints ranging from -90^o until $+90^o$, with an interval of 15^o. Examples of face images that are used in the experiments are shown in Figure 6.

Testing of this system is conducted to recognize an image that totally has different viewpoints with that of the trained images. The training/testing data paradigms in the experiments are shown in Table 1. The Data Set 1 has the smallest training/testing data paradigm, i.e. 30.8%: 69.2%; while Data Set 2 has 38.5%: 61.5%, and for Data Set 3 is 53.8%: 46.2%. The different training/testing data percentages are used in order to measure the stability of the recognition rate of this system in recognizing these data sets properly.

Table 1. The data sets with different percentage of training/testing paradigm

Data Set	Train Images	Test Images	Training (degree)	Testing (degree)
1	16	36	0,60,120, 180	15,30,45, 75,90,105, 135,150, 165
%	30.8%	69.2%		
2	20	32	0,45,90, 135,180	15,30,60, 75,105,120, 165
%	38.5%	61.5%		
3	28	24	0,30,60, 90,120, 150, 180	15,45,75, 105,135, 165
%	53.8%	46.2%		

Table 2. Recognition rate of 3-D face recognition system using DVKLT with NFL and M-NFL for 4 persons

Cumulative Proportions and Data Sets		Recognition rate for 4 persons	
		NFL	M-NFL
90%	Data Set 1	66.83%	70.67%
	Data Set 2	87.98%	96.15%
	Data Set 3	91.82%	100%
95%	Data Set 1	67.31%	72.11%
	Data Set 2	87.50%	96.63%
	Data Set 3	91.35%	100%
99%	Data Set 1	69.23%	73.56%
	Data Set 2	87.50%	96.25%
	Data Set 3	92.31%	100%

Table 3. Recognition rate of 3-D face recognition system using DVKLT with NFL and M-NFL for 6 persons

Cumulative Proportions and Data Sets		Recognition rate for 6 persons	
		NFL	M-NFL
90%	Data Set 1	47.12%	54.81%
	Data Set 2	74.04%	90.71%
	Data Set 3	76.60%	96.15%
95%	Data Set 1	47.76%	55.45%
	Data Set 2	70.51%	90.71%
	Data Set 3	73.08%	97.12%
99%	Data Set 1	49.36%	55.13%
	Data Set 2	70.51%	90.38%
	Data Set 3	75.64%	97.12%

Table 4. Recognition rate of 3-D face recognition system using DVKLT with NFL and M-NFL for 8 persons

Cumulative Proportions and Data Sets		Recognition rate for 8 persons	
		NFL	M-NFL
90%	Data Set 1	46.63%	55.77%
	Data Set 2	68.03%	86.30%
	Data Set 3	75.00%	94.71%
95%	Data Set 1	49.28%	56.97%
	Data Set 2	66.83%	86.30%
	Data Set 3	73.08%	94.95%
99%	Data Set 1	49.76%	57.45%
	Data Set 2	64.90%	85.33%
	Data Set 3	71.88%	95.67%

The recognition rate of the 3-D face recognition system in recognizing unlearned images with unknown viewpoints using various data sets and with different number of persons are depicted in Table 2, Table 3, and Table 4, respectively. These tables also show the comparisons of the recognition rate for both NFL and M-NFL methods for various cumulative proportions of the used eigenvectors in the eigenspace domain.

Table 2 shows the recognition rate of the developed system using DVKLT method for different classifiers methodology, i.e. NFL and M-NFL methods, for recognizing images in all three data sets of four persons. The highest recognition rate for Data Set 1 with NFL method is 69.23% with 99% cumulative proportion. Meanwhile, by using M-NFL method, the highest recognition rate could be increased up to 73.56% with 99% cumulative proportion. In Data Set 2, the highest recognition rate with NFL method is 87.98% with 90% cumulative proportion and could be increased up to 96.63% with 95% cumulative proportion for M-NFL method. While in Data Set 3, the highest recognition rate of the NFL method is 92.31% with 99% cumulative proportion and could be increased using M-NFL method up to 100% for all 90%, 95%, and 99% cumulative proportions.

Table 3 shows the recognition rate of the developed system using DVKLT method with both NFL and M-NFL methods for recognizing images in all three data sets of six persons. As can be seen in this table, the highest recognition rate using NFL method for Data Set 1 is 49.36% with 99% cumulative proportion. While, when using the M-NFL method, the highest recognition rate could reach up to 55.45% with 95% cumulative proportion. In Data Set 2, the highest recognition rate for NFL method is 74.04% with 90% cumulative proportion and is 90.71% with 90% and also for 95% cumulative proportions when using M-NFL method. While in Data Set 3, the highest recognition rate using NFL method is 76.6% with 90% cumulative proportion, and for M-NFL method could be increased up to 97.12% with 95% and also for 99% cumulative proportions.

Table 4 shows the recognition rate of the 3-D face recognition system using DVKLT method with both NFL and M-NFL methods for recognizing images in all three data sets of eight persons. The highest recognition rate for Data Set 1 with NFL method is 49.76% with 99% cumulative proportion. Meanwhile, by using M-NFL method, the highest recognition rate could be increased up to 57.45% with 99% cumulative proportion. In Data Set 2, the highest recognition rate with NFL method is 68.03% with 90% cumulative proportion, which can be upgraded up to 86.3% with 90% and also for 95% cumulative proportions using M-NFL method. While in Data Set 3, the highest recognition rate using NFL method is 75% with 90% cumulative proportion and for M-NFL method could reach up to 95.67% with 99% cumulative proportion.

Based on Table 2, Table 3, and Table 4, we can see that the increment of the training/testing paradigm could increase the recognition rate of the system. The above discussions also show that both NFL and M-NFL method could give a high recognition rate in recognizing four persons with Data Set 3, with the highest recognition rate of 92.31% for NFL method, while in M-NFL method, it could be increased up to 100%. However, when the system is used to recognize images in all three data sets of six and eight persons, the NFL method could not give a satisfactory result; the highest recognition rate is only 76.6% for recognizing images of six persons and only 75% for recognizing images of eight persons. Meanwhile, our developed M-NFL method still could give higher recognition rate, up to 97.12% for recognizing images of six persons and 95.67% for recognizing images of eight persons.

Figure 6 shows the comparison of recognition rate of our 3-D face recognition system using NFL and M-NFL methods, for recognizing images in Data Set 1 with 99% of cumulative proportion within various numbers of persons. While Figure 7 and Figure 8, illustrated the comparison of the same system as in Figure 6, for Data Set 2 and Data Set 3, respectively. As it is clearly seen in all of those figures, for both NFL and M-NFL methods, the recognition rates of the experimental systems are decreased along with the increment number of persons that being recognized.

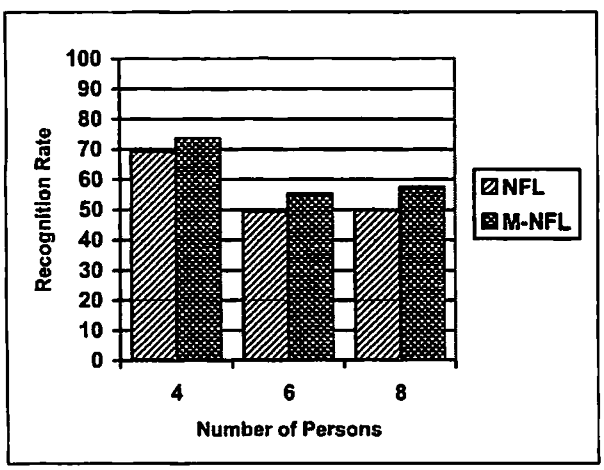

Figure 6. Comparison of recognition rate using various numbers of persons in Data Set 1

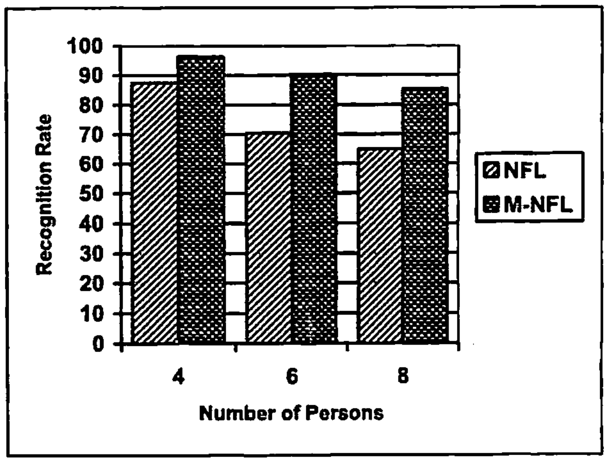

Figure 7. Comparison of recognition rate using various numbers of persons in Data Set 2

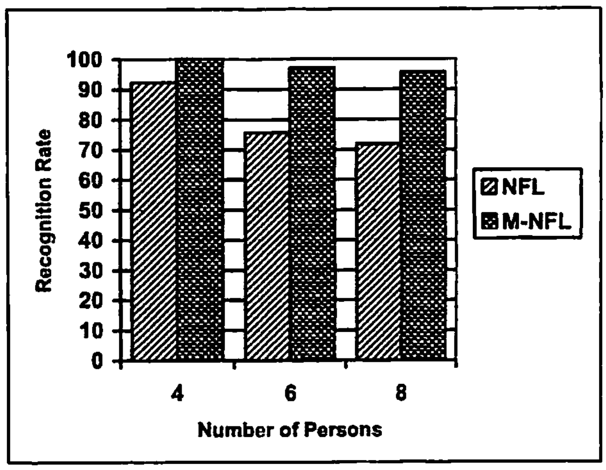

Figure 8. Comparison of recognition rate using various numbers of persons in Data Set 3

5 Conclusion

Our 3-D face recognition system is developed based on Double-View KLT technique (DVKLT) as a feature extraction subsystem and M-NFL method as a pattern classifier. This system could recognize various unlearned face images with various expressions and unknown viewpoints, which are in different viewpoints from images in the trained ones. Based on experimental results and evaluations of the 3-D face recognition system, we can conclude that for all three data sets with various numbers of persons, our proposed M-NFL method always gave higher recognition rates compared with the NFL method. The use of various numbers of persons has influenced the recognition rates of the system, and for both M-NFL and NFL methods, the recognition rates were decreased along with the increment number of persons. However, the decrement values of the recognition rates of the classifier using M-NFL method were always lower than that of using the NFL method. Experimental results show that this phenomenon was proved to be consistent for every data set within every various numbers of persons. It was confirmed by those experiments that our proposed M-NFL method always gave a higher recognition rate compare to the conventional NFL method.

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