Development of Modified Feature Lines for Higher Recognition of a 3-D Face Recognition System

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Abstract: In this paper, the authors propose a new 3-D face recognition system using additional feature lines in *Nearest Feature Line* method, called the *Modified Nearest Feature Line* method. The additional feature lines can be acquired by projecting each feature point to other feature lines in the same class without increasing the number of feature points. With these additional lines, the system will have the ability to capture more variations of face images, so it can increase the recognition rate of the system. The authors also propose *K-LTSubspace1* and *K-LTSubspace2* as methods in transforming the 3-D face images from its spatial domain to their eigenspace domain. The experiments use the 3-D human faces of Indonesian people in various expressions and positions. Then, the system is applied to recognize known and unknown face images with different viewpoints. Experimental results shown that the system using *K-LTSubspace2* and *Modified Nearest Feature Line* method could have the highest recognition rate of *99.17%* for unknown face images and could reach *99.62%* if data training included as data testing.

Key words: 3-D face recognition system, Nearest feature line method (*NFL*), Modified nearest feature line method (*M-NFL*), Karhunen-Loeve transformation, Eigenspace representation

1 Introduction

Research and development of a 3-D face recognition system has grown fast along with the increasing demand of reliable automatic user identity recognition system for secure accesses to buildings or services. Classical techniques based on passwords and cards have a certain drawbacks such as forgotten or compromised, lost or stolen, and the system is not able to make difference between a client and the impostor [1]. So researchers suggested methods to recognize users by physiological features such as finger-prints, iris, voice, and face. Basically, a 3-D face recognition system is a detection system to recognize a human face by comparing an image with models that already exist in the database gallery. It is argued that 3-D recognition can be accomplished using linear combinations of as few as four or five 2-D viewpoint images [2][3]. In many implementations of face recognition algorithms, images are taken in a constrained environment with controlled illumination, minimal occlusions of facial structures, uncluttered background [4]. Up to now, successful experiments were achieved only in recognizing the 2-D images with frontal or semi frontal positions.

Two most popular techniques to recognize users by their characteristics are geometric feature based and image feature based. In geometric feature based methods [5][6], facial features are detected and used as descriptors of faces for recognition. In contrast, image feature based methods [7][8][9] generally operate directly on image-based representation. Neural network techniques have been used in the face recognition system [10][11], and the authors have proposed a cylindrical structure of hidden layer neural network [12][13] for face recognition system with various pose positions images.

In this paper, we proposed a new method to develop a higher recognition rate of a 3-D face recognition system using modified Karhunen-Loeve transformation (K-LT) technique and modified feature lines based on *NFL* method [14]. The proposed system consists of a feature extraction subsystem using modified *K-LTSubspace* techniques that defines the feature-spaces, and the recognition subsystem using the developed modified feature line methods for recognizing the unknown face images.

In the feature extraction subsystem, a feature-space is developed based on transforming every face images in the spatial domain as a vector in the feature-space domain [15]. The transformation processes are done by using two types of modified *K-LTSubspace* techniques. Authors have introduced the *K-LTSinglespace* method and *K-LTSubspace* method as transformation procedures [16]. Research in viewpoint estimation system shows that the use of *K-LTSubspace* technique can give a higher estimation rate than the *K-LTSinglespace* technique [15][16]. Based on that, in this paper, we propose another *K-LTSubspace* technique, which is called *K-LTSubspace2*, and define the previous as *K-LTSubspace1*. In *K-LTSubspace1*, model images from every viewpoint position will be transformed into every sub-eigenspace. While in *K-LTSubspace2*, model images from every two nearest viewpoint positions are transformed into one sub-eigenspace.

In the recognition subsystem, we applied our proposed modified feature lines, called *M-NFL* method, and compared its performance with *NFL* method [14]. These methods assume that at least we have two feature points that represents two images in each viewpoint class and we can form a feature line that generalized images which is not exists in the database gallery.

Recognizing the unknown image is done by transforming the image as a point in every sub-eigenspaces and calculating the nearest distance of that point to every feature lines. Detail explanations of these methods will be discussed in the following sections.

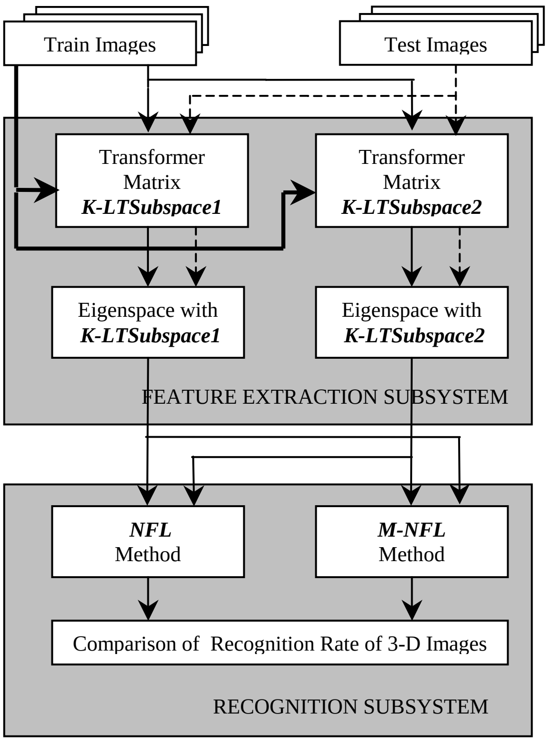

Figure 1. Diagram of the 3-D face recognition system

2 The 3-D Face Recognition System

The input given to this 3-D face recognition system is a number of 2-D images, which are used as model images. The developed Face Recognition System consists of two subsystems, i.e. the feature space subsystem and the recognition subsystem, as can be depicted in Figure 1.

In the feature extraction subsystem, we use the *K-LTSubspace1* and *K-LTSubspace2* as the transformation procedures to form the multiple sub-eigenspaces, which will be explained in the next section. While in the recognition subsystem, the *NFL* and our proposed *M-NFL* method will be used to recognize the testing images.

3 Subspace Karhunen-Loeve Transformation (*K-LTSubspace*)

Probably the most attractive approaches to automatic feature extraction are the linear mappings induced by Karhunen-Loeve transformation and discriminant analysis [17][18]. Karhunen-Loeve transformation means to orthogonalize the extracted feature for the separability process of the pattern classification. The aim of these methods is to optimize pattern representation by selecting features during an initial learning stage [19]. By selecting features and reducing its dimension in the classification process, the computational cost will be decreased but we still have a good recognition rate.

In this paper, as we have mentioned earlier, we proposed the *K-LTSubspace1* and *K-LTSubspace2*. The difference between those methods is only in the forming process of the sub-eigenspaces. Figure 2 represents the forming process of the sub-eigenspaces using *K-LTSubspace1* and Figure 3 represents the forming process of the sub-eigenspaces using *K-LTSubspace2*.

In *K-LTSubspace1*, the entire model images from one viewpoint will be transformed into one sub-eigenspace. So we will have multiple sub-eigenspaces that are related with *n*-viewpoints of images.

In *K-LTSubspace2*, model images from two nearest viewpoints are transformed into one sub-eigenspace. Suppose we have classes of images with a viewpoint of 0^o, 45^o, and 90^o. Then the entire images of iewpoints 0^o and 45^o will be transformed into a $(0\text{--}45)^o$ sub-eigenspace, a $(45\text{--}90)^o$ sub-eigenspace consists of images in viewpoints 45^o and 90^o, and so on.

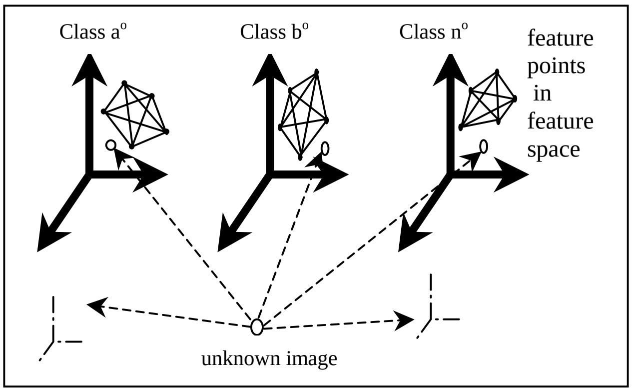

Figure 2. The forming process of the sub-eigenspaces using *K-LTSubspace1*

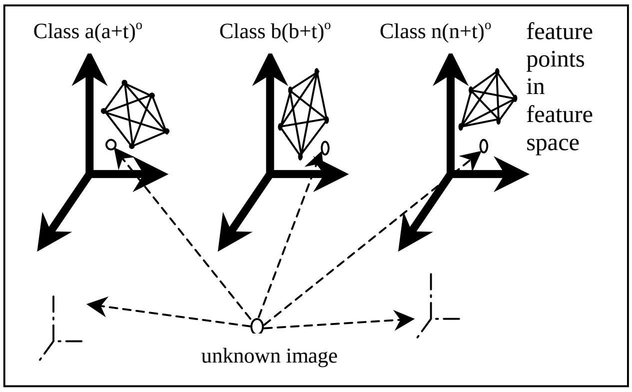

Figure 3. The forming process of the sub-eigenspaces using *K-LTSubspace2*

The same transformation procedure will be applied for both methods. First by forming a base vector of a number of d images in $N = n$ x n dimensions, i.e. $x_N(k)=[x_1\ x_2,...x_d]$, with $k=1,2,...,d$. Then, compute the average vector μ_{x_N} and determine the covariance matrix C_{x_N} through:

$$C_{x_N} = \frac{1}{d}\sum_{k=1}^{d}(x_N(k)-\mu_{x_N})(x_N(k)-\mu_{x_N})^T \quad (2)$$

From this covariance matrix, we can derive the nonnegative eigenvalues (λ_{x_N}) and the orthonormal eigenvectors (e_{x_N}). Then, arrange the eigenvalues in decreasing order and constructed a matrix transformation y_M to map a set of x_N image vectors in eigenspace through:

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

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

$$x_N = e_{x_N}{}^T y_M + \mu_{x_N} \qquad (4)$$

In order to gain an optimal matrix transformation for higher estimation rate, compute the cummulative proportion of eigen values using [14]:

$$\alpha^l = \left(\sum_{i=1}^{l}\lambda_i\right) \Big/ \left(\sum_{j=1}^{m}\lambda_j\right) \qquad (5)$$

Then, recalculate the equations (3) and (4) to compute y_M' and x_N '. In this paper, we used *90%, 95%,* and *99%* of cummulative proportion to optimize the transformation matrix.

4 Modified Feature Lines for Higher Recognition

After transforming the images with *K-LTSubspace* into its eigenspaces domain, we have feature lines that generalize the variation of image points, which can give more information to separate images between classes. In this recognition subsystem, we use the *NFL* method and our proposed *M-NFL* method [15] by calculating the nearest distance between an unknown feature point to its projected point in every feature lines on the sub-eigenspace defined previously. Illustration of the process in forming the feature lines is shown in Figure 4.

Based on Figure 4, in *NFL* method, the feature lines that can be formed are $\overline{y_1 y_2}$, $\overline{y_1 y_3}$, and $\overline{y_2 y_3}$. So, for each class in *NFL* method, we have:

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

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

Meanwhile, the feature lines in *M-NFL* method are $\overline{y_1 y_2}$, $\overline{y_1 y_3}$, $\overline{y_2 y_3}$, $\overline{y_1 \perp y_2 y_3}$, $\overline{y_2 \perp y_1 y_3}$, and $\overline{y_3 \perp y_1 y_2}$. With H_c denotes number of feature points and G_c denotes number of feature lines, we have:

$$G_c = H_c(H_c - 1)^2/2 \qquad (7)$$

These additional feature lines are generated by projecting new lines from every feature points to the other feature lines in each class. Detail explanation of our *M-NFL* method is already explained in the previous paper [15].

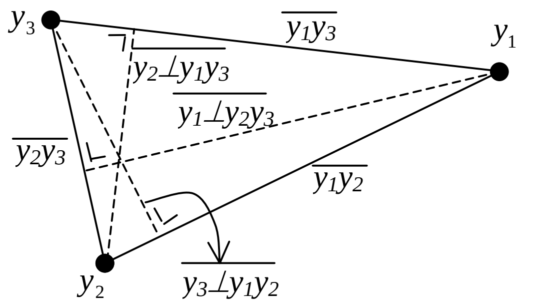

Figure 4. The process of forming the feature lines

The recognition algorithm for both *K-LTSubspace1* and *K-LTSubspace2* methods are as follows:

1. Project the unknown viewpoint image y as point p to all available feature lines using

$$p = y_1 + \gamma(y_2 - y_1) \tag{8}$$

with

$$\gamma = \frac{(y - y_1) \bullet (y_2 - y_1)}{(y_2 - y_1) \bullet (y_2 - y_1)} \tag{9}$$

2. Calculate the distances between y and its projected point p through:

$$d(y, p) = \| y - p \| \tag{10}$$

in every available class.

3. Select the minimum distance from the entire class. Suppose that the minimum distance is determined to be in the line that connecting two points of y_1 and y_2, then:
   a. if y_1 and y_2 belong to the same object, then y will be recognize as the same object as y_1 and y_2
   b. if y_1 and y_2 belong to the different object, then:
      i. if $\gamma \le \frac{1}{2} d(y_1, y_2)$, then y will be recognize as the same object as y_1
      ii. otherwise, y will be recognize as the same object as y_2

The increasing number of feature lines in *M-NFL* hopefully can increase the capability of capturing variations of limited images in the gallery and in the end it can give a higher recognition rate in our 3-D face recognition system.

5 Experimental Result and Analysis

Testing of this 3-D face recognition system are conducted by using images of Indonesian people with various viewpoints and expressions, such as normal, smile, laugh, and angry. Different viewpoints of objects are taken from -90^o until $+90^o$. Part of face images which are used in the experiments are shown in Figure 6.

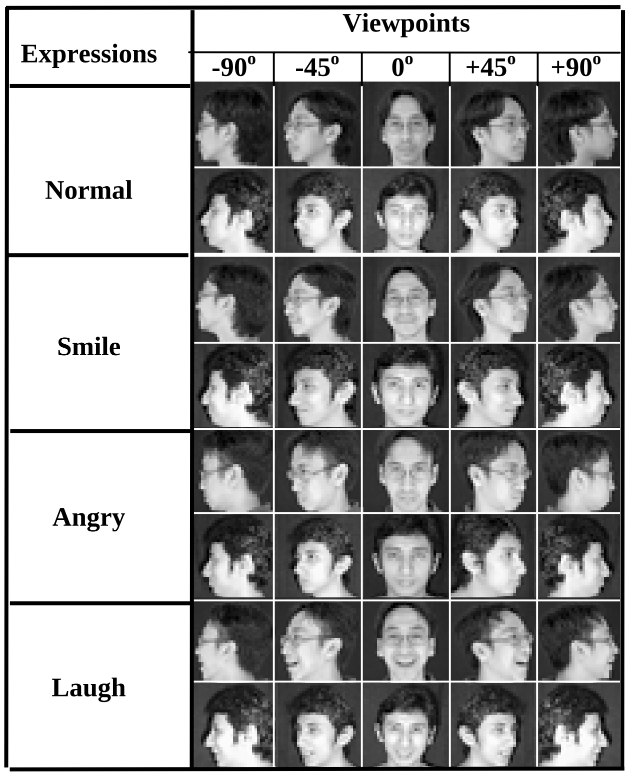

Figure 6. Part of face images which are used in the face recognition system's experiments

Testing images that are used in these experiments are images with unknown viewpoints and also the training 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, *30.8%*: *69.2%*. While *Data Set 2* has *38.5%*: *61.5%*, and *Data Set 3* has *53.8%*: *46.2%*. The different training/testing data conditions are used in order to measure the stability of the recognition rate of this system.

The recognition rate of the 3-D face recognition system using various *Data Set*, transformation techniques, and classification methods can be seen at Table 2, Table 3, Table 4, and *NFL* Table 5. For all results of experiments, we can see that the recognition rates of the system are different when we use different cumulative proportion. The increment of cumulative proportion percentage in the system will increase the recognition rate of the system.

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
Percentage	30.8%	69.2%		
2	20	32	0,45,90, 135,180	15,30,60, 75,105,120, 165
Percentage	38.5%	61.5%		
3	28	24	0,30,60, 90,120, 150, 180	15,45,75, 105,135,165
Percentage	53.8%	46.2%		

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

Data set	Recognition Rate (percentage)		
	90%	**95%**	**99%**
1	40.00%	38.89%	40.56%
1*)	41.54%	40.38%	41.54%
2	76.43%	77.14%	76.43%
2*)	78.85%	77.31%	78.85%
3	76.43%	77.14%	76.43%
3*)	88.85%	90.38%	90.38%

*) *Data Training are included as Data Testing*

Table 2. Recognition rate on 3-D face determination using *K-LTSubspace1* and *NFL* method

Based on Table 2, system used the *K-LTSubspace1* and *NFL* method. The highest recognition rate for *Data Set 1* is *40.56%* with *99%* cumulative proportion. Meanwhile, if training images are included as data testing the highest recognition rate could reach up to *41.54%* with *90%* and *99%* cumulative proportions. In *Data Set 2*, the highest recognition rate is *77.14%* with *95%* cumulative proportion and *78.85%* with *90%* and *99%* cumulative proportions for trained images. While in *Data Set 3*, the highest recognition rate is *77.14%* with *95%* cumulative proportion for images with unknown viewpoints and for trained images could reach *90.38%* with *95%* and *99%* cumulative proportions.

When the system used the *K-LTSubspace1* and *M-NFL* method, as can be seen at Table 3, the highest recognition rate for *Data Set 1* is *40.56%* with *99%* cumulative proportion. Meanwhile, if training images are included as data testing the highest recognition rate could reach up to *43.46%* with *90%* and *99%* cumulative proportions. In *Data Set 2*, the highest recognition rate is *78.57%* with *95%* cumulative proportion for images with unknown viewpoints and *84.62%* with *95%* cumulative proportion for trained images. While in *Data Set 3*, the highest recognition rate is *89.17%* with *95%* and *99%* cumulative proportions for images with unknown viewpoints and for trained images could reach *91.54%* with *95%* cumulative proportion.

Data set	Recognition Rate (percentage)		
	90%	**95%**	**99%**
1	40.00%	39.44%	40.56%
1*)	43.46%	42.69%	43.46%
2	77.14%	78.57%	77.14%
2*)	83.08%	84.62%	83.08%
3	87.50%	89.17%	89.17%
3*)	91.15%	91.54%	91.15%

*) *Data Training are included as Data Testing*

Table 3. Recognition rate on 3-D face determination using *K-LTSubspace1* and *M-NFL* method

Data set	Recognition Rate (percentage)		
	90%	**95%**	**99%**
1	56.11%	56.67%	57.78%
1*)	58.46%	59.62%	59.62%
2	81.43%	84.29%	84.29%
2*)	83.85%	84.62%	84.62%
3	92.50%	92.50%	96.67%
3*)	92.69%	92.69%	97.31%

*) *Data Training are included as Data Testing*

Table 4. Recognition rate on 3-D face determination using *K-LTSubspace2* and *NFL* method

Data set	Recognition Rate (percentage)		
	90%	**95%**	**99%**
1	56.11%	57.22%	59.44%
1*)	61.15%	63.07%	63.46%
2	91.70%	91.43%	90.00%
2*)	95.00%	95.38%	94.62%
3	96.67%	99.17%	98.33%
3*)	98.85%	99.62%	99.23%

*) *Data Training are included as Data Testing*

Table 5. Recognition rate on 3-D face determination using *K-LTSubspace2* and *M-NFL* method

Next, Table 4 shows the recognition rate of the 3-D face recognition system using the *K-LTSubspace2* and *NFL* method. The highest recognition rate for *Data Set 1* is *57.78%* with *99%* cumulative proportion for images with unknown viewpoints. Meanwhile, if training images are included as data testing the highest recognition rate could reach up to *59.62%* with *95%* and *99%* cumulative proportions. In *Data Set 2*, the highest recognition rate is *84.29%* with *95%* and *99%* cumulative proportions for images with unknown viewpoints and *84.62%* with *95%* and *99%* cumulative proportions for trained images. While in *Data Set 3*, the highest recognition rate is *96.67%* with *99%* cumulative proportion for images with unknown viewpoints and for trained images could reach *97.31%* with *99%* cumulative proportion.

When the system used the *K-LTSubspace2* and *M-NFL* method, as can be seen at Table 5, the highest recognition rate for *Data Set 1* is *59.44%* with *99%* cumulative proportion for images with unknown viewpoints. Meanwhile, if training images are included as data testing the highest recognition rate could reach up to *63.46%* with *99%* cumulative proportion. In *Data Set 2*, the highest recognition rate is *91.7%* with *90%* cumulative proportion for images with unknown viewpoints and *95.38%* with *95%* cumulative proportion for trained images. While in *Data Set 3*, the highest recognition rate is *99.17%* with *95%* cumulative proportion for images with unknown viewpoints and for trained images could reach *99.62%* with *95%* cumulative proportion.

Based on Table 2, Table 3, Table 4, and Table 5, we can see that the increment of the training percentage to its testing percentage could increase the recognition rate of the system. Experimental results show that the highest recognition rate of the system is *99,62%* with *95%* cumulative proportion when using the *K-LTSubspace2* and *M-NFL* methods in *Data Set 3*.

Next, Table 6 shows the comparison of percentage classification using *NFL* and *M-NFL* methods when utilized with *K-LTSubspace1*, while Table 7 shows the comparison of percentage classification using *NFL* and *M-NFL* methods when utilized using *K-LTSubspace2*. In those two tables, there are three categories to do the analysis and are shown in three columns. Second column shows the correct classification percentage using *NFL* that is classified correct also by our *M-NFL* method, while the third column shows the percentage of incorrect classification by *NFL* method but classified as correct classification by *M-NFL* method. The fourth column shows the inverse condition of the third column, in which the correct classification *NFL* method is classified as incorrect by *M-NFL* method.

Cumulative Proportions and Data Sets		Classification Percentage		
		Correct NFL - Correct M-NFL	Incorrect NFL - Correct M-NFL	Correct NFL - Incorrect M-NFL
90%	Data#1	40%	0%	0%
	Data#1*)	41.54%	1.92%	0%
	Data#2	75.71%	0.71%	0%
	Data#2*)	78.85%	4.23%	0%
	Data#3	87.50%	0%	0%
	Data#3*)	88.85%	2.30%	0%
95%	Data#1	38.33%	0.56%	0%
	Data#1*)	40.38%	2.31%	0%
	Data#2	75.71%	1.43%	0%
	Data#2*)	77.31%	7.31%	0%
	Data#3	87.50%	0.83%	0.83%
	Data#3*)	90%	1.54%	0.38%
99%	Data#1	40%	0%	0%
	Data#1*)	41.54%	1.92%	0%
	Data#2	75.71%	0.71%	0%
	Data#2*)	78.85%	4.23%	0%
	Data#3	89.17%	0%	0%
	Data#3*)	90.38%	0.77%	0%

*) *Data Training are included as Data Testing*

Table 6. Comparison of *NFL* and *M-NFL* classification in 3-D face recognition system with *K-LTSubspace1*

Cumulative Proportions and Data Sets		Classification Percentage		
		Correct NFL - Correct M-NFL	Incorrect NFL Correct M-NFL	Correct NFL - Incorrect M-NFL
90%	Data#1	50.56%	2.78%	2.78%
	Data#1*)	55.77%	5.38%	2.69%
	Data#2	72.14%	9.29%	0%
	Data#2*)	83.85%	11.15%	0%
	Data#3	86.67%	5%	4.17%
	Data#3*)	92.31%	6.54%	0.38%
95%	Data#1	56.67%	1.11%	0.56%
	Data#1*)	59.24%	3.83%	0.38%
	Data#2	75.71%	7.86%	0.71%
	Data#2*)	84.24%	11.14%	0.38%
	Data#3	85.83%	6.67%	0%
	Data#3*)	92.69%	6.93%	0%
99%	Data#1	51.67%	3.89%	2.22%
	Data#1*)	57.70%	5.76%	1.92%
	Data#2	77.86%	5.71%	0.71%
	Data#2*)	84.24%	10.38%	0.38%
	Data#3	93.33%	2.50%	0.83%
	Data#3*)	96.93%	2.30%	0.38%

*) *Data Training are included as Data Testing*

Table 7. Comparison of *NFL* and *M-NFL* classification in 3-D face recognition system with *K-LTSubspace2*

Based on Table 6, the use of *K-LTSubspace1* makes the percentage classification of correct classification by *NFL* method and correct classification by *M-NFL* method increase along the increment of training/testing paradigm. Also shown that the percentage classification of incorrect classification by *NFL* method but correct classification by *M-NFL* method and correct classification by *NFL* method but incorrect classification by *M-NFL* method are similar. So the recognition rate of 3-D face recognition system with *NFL* method and *M-NFL* method gives the similar results when using the *K-LTSubspace1* as a transformation technique.

Meanwhile, Table 7 shows the use of *K-LTSubspace2* also makes the percentage classification of correct classification by *NFL* method and correct classification by *M-NFL* method increase along the increment of training/testing paradigm. It is also shown on Table 7, that the percentage classification of incorrect classification by *NFL* method but correct classification by *M-NFL* method are higher than the percentage classification of correct classification by *NFL* method but incorrect classification by *M-NFL* method. It means that the use of *K-LTSubspace2* and *M-NFL* method can give a better recognition result than the use of *K-LTSubspace2* and *NFL* method.

6 Conclusions

Our 3-D face recognition system are developed based on a modified *NFL* (*M-NFL*) technique by increasing the number of feature lines without increasing the number of feature points in the eigenspace domain. It can recognize faces with the same viewpoints as the trained images and also recognize images with unknown viewpoints, which are different from the trained ones. Experimental result shows that the 3-D face recognition system using the *K-LTSubspace2* could give a better recognition rate than the *K-LTSubspace1*, because in *K-LTSubspace2* the feature space are formed by the two nearest eigen classes. A better recognition rate could also achieved by using our *M-NFL* technique compared to the *NFL* technique, because the addition of the number of feature lines could capture more information about variations changes among objects. The highest recognition rate of the 3-D face recognition system using *NFL* method is *97.31%* with *99%* cumulative proportion, while it can reach up to *99.62%* with *95%* cumulative proportion when using our *M-NFL* method.

ACKNOWLEDGEMENT

The authors would like to express their gratitude to Ministry of Research and Technology of Indonesia for their support funding of this research through RUT X under contract number 14.06/SK/RUT/2003

References:

[1] S. Ben-Yacoub, Y.Abdeljaoued, and E.Mayoraz, “Fusion of Face and Speech Data for Person Identity Verification”, IEEE Trans.on Neural Network, Vol.10, No.5, 1999, pp. 1065-1074.

[2] S. Ullmann and R. Basri, “Recognition of linear combination of models”,IEEE T.PAMI, Vol.13, No.10, 1991, pp. 992-1007.

[3] T. Poggio and S. Edelman, “A network that learns to recognize three dimensional objects”, Nature, Vol.343, No.6255, 1990, pp. 263-266.

[4] O.de Vel and S.Aeberhard, “Line-Based Face Recognition under Varying Pose”, IEEE T.PAMI, Vol.21, No.10, 1999, pp. 1081-1088.

[5] A.Samal and P.A.Iyengar, “Automatic recognition and analysis of human faces and facial expressions: A survey”, Pattern Recognition, vol 25, 1992, pp.65-77.

[6] R.Brunelli and T.Poggio, “Face Recognition: Features versus templates”, IEEE T.PAMI, Vol 15, 1993, pp.1042-1052.

[7] R. Brunelli and T. Poggio, “Face recognition through geometrical features”, Proceedings of ECCV 92, Santa Margherita Ligure, 1992, pp. 792-800.

[8] M. Kirby and L. Sirovich, “Application of the Karhunen-Loeve procedure for the characterization of human face”, IEEE T.PAMI, Vol.12, No.1, 1990, pp. 103-108.

[9] M. Turk and A. Pertland, “Face recognition using Eigenfaces”, Proc. IEEE CCVP’91, 1991, pp. 586-591.

[10] D.Valentin, H.Abdi, A.J.O.Toole, and G.W.Cottrell, “Connectionist models of face processing: A survey”, Pattern Recognition, vol 27, no.9, 1994, pp.1209-1230.

[11] R.Chellappa, C.L.Wilson, and S.Sirohey, “Human and machine recognition of faces: A survey”, Proc.IEEE, vol 83, 1995, pp.705-740.

[12] B. Kusumoputro, Renny Isharini and A. Murni, “Development of neural network with cylindrical structure of hidden layer and its application in 3-D recognition system”, Proc. IECI CECI-2001, Vol.6, 2001, pp.24-27.

[13] B. Kusumoputro and A. Sulita, “Genetics algorithms in optimization of cylindrical-hidden layer neural network for 3-D object recognition system”, Neural Network World, Vol.10, No. 4, 2000, pp. 631-639.

[14] S.Z. Li and J. Lu, “Face recognition using the nearest feature line method”, IEEE Trans. on Neural Networks, Vol.10, No.2, 1999,pp.439-443.

[15] Lina and B.Kusumoputro, “Determination of 3-D Image Viewpoint Using Modified Nearest Feature Line Method in Its Eigenspace Domain”, WSEAS Transactions on Computers, Issue 1, Vol.2, pp.140-147.

[16] R. Sripomo and B. Kusumoputro, “Pose estimation system of 3D human face using nearest feature lines in its eigenspace representation”, IEEE Proc. of APCCAS, 2002, pp. 241-246.

[17] K.Fukunaga, “Statistical Pattern Recognition”, San Diego, California: Academic Press, 1990.

[18] D.L.Swets and J.Weng, “Using Discriminant Eigenfeatures for Image Retrieval”, IEEE T.PAMI, Vol.18, No.8, 1996, pp. 831-836.

[19]B.Kusumoputro and R.F.Shah, “Three Dimensional Face Recognition System using Nearest Feature Line in Its Eigenspaces Representation”, Proc.ofCECI, 2001,pp.VI20-23