# Performance Analysis of Modified Nearest Feature Line Method in a 3-D Face Recognition System with Various Numbers of Objects

Lina[1], Benyamin Kusumoputro[2]

[1]Faculty of Information Technology, Tarumanagara University,
Jl. Letjen S.Parman 1, Jakarta 11440, INDONESIA
[2]Faculty of Computer Science, University of Indonesia
Depok Campus 16424, INDONESIA
email: lina@tarumanagara.ac.id, kusumo@cs.ui.ac.id

***Abstract*—Authors have developed a novel method for achieving higher recognition capability of a 3-D face recognition system based on feature line method. This method, which is called the Modified Nearest Feature Line, is used as a classifier and it is combined with our developed Subspace Karhunen-Loeve transformation method as a feature extraction subsystem to build a 3-D face recognition system. In this paper, the authors evaluate and analyze the performance of this Modified Nearest Feature Line method for recognizing 3-D face images with various numbers of objects. As recognition rates were usually decreased by increasing the number of objects that are necessary to be recognized, the performance of M-NFL method, in its recognition rate, is evaluated and compared with that of the conventional NFL method. Experimental results show that the use of various numbers of objects influenced the recognition rates of both systems. However, the slopes of the decrement values using M-NFL method were lower than NFL method. It is also shown that in every same number of objects to be recognized, M-NFL method could always give a high recognition rate than the NFL method, with up to 20% in recognition rate difference value.**

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

## I. 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, lighting, etc. It is argued in [2,3] that 3-D recognition can also be accomplished by 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 base method, image feature base 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 with various numbers of objects. The developed system consists of two main processes, a feature extraction subsystem and a face classification subsystem. In the features extraction subsystem, a feature space is developed based on transforming every face image in the spatial domain as a vector in the feature space, by using the Karhunen-Loeve transformation (K-LT) [4].

In order to increase the recognition rate of the developed system, authors have introduced the K-LTFullspace method and K-LTSubspace1 method as transformation procedures [4,5]. In K-LTFullspace all trained images are transformed into only one eigenspace, while in K-LTSubspace1, these model images from every viewpoint positions are transformed into every sub-eigenspace. Our previous research has shown that the use of K-LTSubspace1 technique has demonstrated a higher estimation rate compare with that of the use of the K-LTFullspace technique [4-6]. However, the K-LTSubspace1 algorithm has a drawback on its decision phase of the classifier subsystem, in which the decision of the classification process is only based on ‘near’ or ‘far’ of the calculated distance to a zero value that may alternate case by case and could not exactly determined. Based on those results, we propose another K-LTSubspace technique, which is called K-LTSubspace2 in [1]. In K-LTSubspace2, model images from every two nearest viewpoint positions are transformed into one sub-eigenspace. Based on our experimental results such in [1,4,5,6], the recognition rates of the system using K-LTSubspace2 were higher than that of using K-LTFullspace and K-LTSubspace1 as its transformation method. Thus, in this paper we use the K-LTSubspace2 as the transformation method in the feature extraction subsystem.

The diagram of our developed 3-D face recognition system is illustrated in Figure 1.

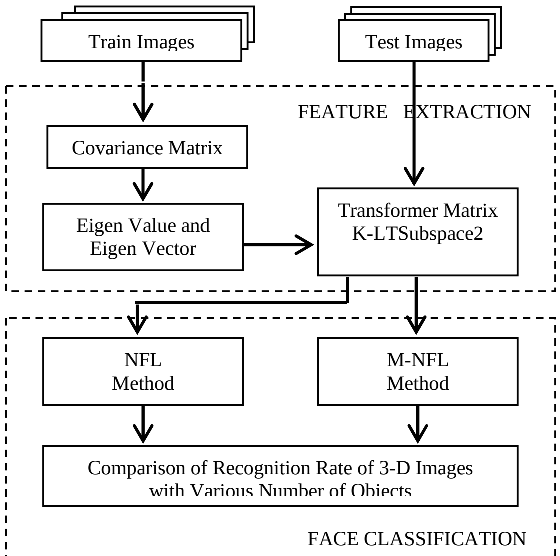



**Figure 1. 3-D Face Recognition System Diagram**

## II. Feature Space Forming Process Using K-LTSubspace2

The Karhunen-Loeve (K-L) transform 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 consequences, the computation cost of the system will be reduced also.

In this paper, we use the K-LTSubspace2 in which a model 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, train images with $deg^o$ and $(deg+t)^o$ viewpoint position are transformed into one class, which is the $(deg, deg+t)^o$ class. While the train images with $(deg+t)^o$ and $(deg+2t)^o$ of viewpoint position are transformed into another class $(deg+t, deg+2t)^o$, and the process is continued for the other training images with other viewpoint positions. In its application of the system, an unknown face of the test images will be represented as feature points in every available multiple eigenspaces that have been formed in the training phase.

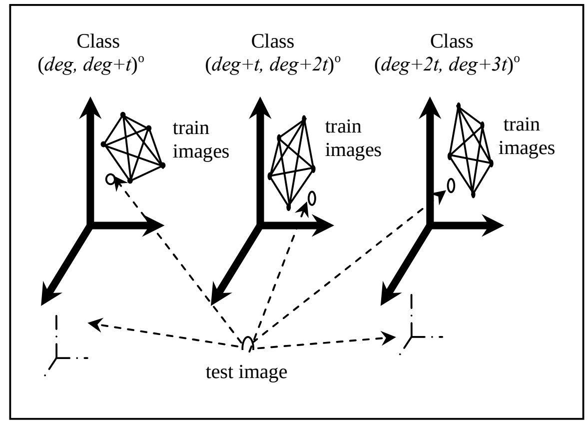



**Figure 2. The Forming Process of the Sub-eigenspaces using K-LTSubspace2**

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

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

From this covariance matrix, we can derive a set of $\lambda_{x_N}$ 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, $\lambda_1 > \lambda_2 > \ldots > \lambda_m$, 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.

## III. Face Classification Process Using M-NFL Method

After transforming the images with K-LTSubspace2 into its eigenspaces domain, do a generalization process by connecting all feature points in the same class. The straight line between two feature points is called the feature line [9]. The aim of this process is we can have more information of feature variations of an object. Hopefully, with more information of feature variations, the recognition rate of the 3-D face recognition system will be increased. Illustration of the forming process of feature lines is shown in Figure 3 and Figure 4.

Based on Figure 3, in the conventional NFL method, the feature lines that can be formed are $\overline{y_1y_2}$ , $\overline{y_1y_3}$ , and $\overline{y_2y_3}$ , which means that for each class in NFL method, we have:

$$G_c = H_c(H_c - 1)/2 \tag{5}$$

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

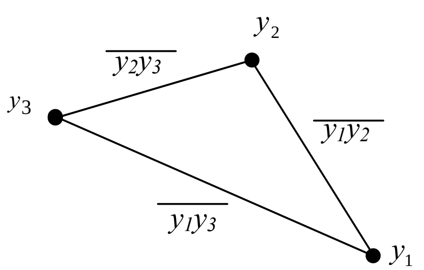



**Figure 3. The process of forming the feature lines using NFL method**

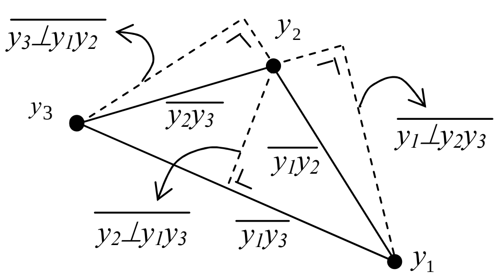



**Figure 4. The process of forming the feature lines using M-NFL method**

Meanwhile, in our developed M-NFL method, we add more feature lines by projecting each feature point to all available feature lines. As illustrated in Figure 4, the feature lines 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 adding the feature lines above, with $H_c$ denotes number of feature points and $G_c$ denotes number of feature lines, the total number of feature lines in this M-NFL method can be calculated through:

$$G_c = H_c(H_c - 1)^2 / 2 \tag{6}$$

In the classification process of an unlearned face image with unknown viewpoint, it is necessary to firstly transformed this point of image in its spatial domain into a point of the unknown image in its eigenspace domain as a point of $y$. Then projected this unknown viewpoint image, $y$, in the eigen domain to all of the available feature lines as a point of $p$ using:

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

with $\gamma$ as a position parameter of the projection point $p$ to $y_1$. We can calculate $\gamma$ by using dot product from 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 class.

The test image is then be clustered into a class that has the minimum distance, as a distance comparison of the test point $y$ to all of the available lines in the entire class. 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 $y_2$. If $y_1$ and $y_2$ belong to the different object, and if $\gamma \leq \frac{1}{2} d(y_1, y_2)$, then $y$ will be recognized as the same object as $y_1$. Otherwise, $y$ will be recognized as the same object as $y_2$.

## IV. Results and Analysis

In our developed 3-D face recognition system, we implemented the system to recognize a real face images of Indonesian people with different viewpoint positions, its expressions, and modify the number of objects. The experimental system used four, six, and eight objects of face images with different expressions, such as normal, smile, angry, and laugh, which are taken from different viewpoints ranging from $-90^o$ until $+90^o$. Examples of face images that are used in the experiments are shown in Figure 5.

Testing of this system is conducted to recognize an image that has totally different viewpoints with that of the trained images. The recognition rate of the developed system is also examined by recognizing various face images within different numbers of objects. As recognition rate is usually used to evaluate the performance characteristics of a recognition system, we calculate the recognition rate of M-NFL method and then compare it with that of NFL method. 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 properly of these data sets.

The recognition rate of the 3-D face recognition system to recognize unlearned images with unknown viewpoints using various Data Set within various numbers of objects, with its different classification methods, are depicted in Table 2, Table 3, and Table 4, respectively.

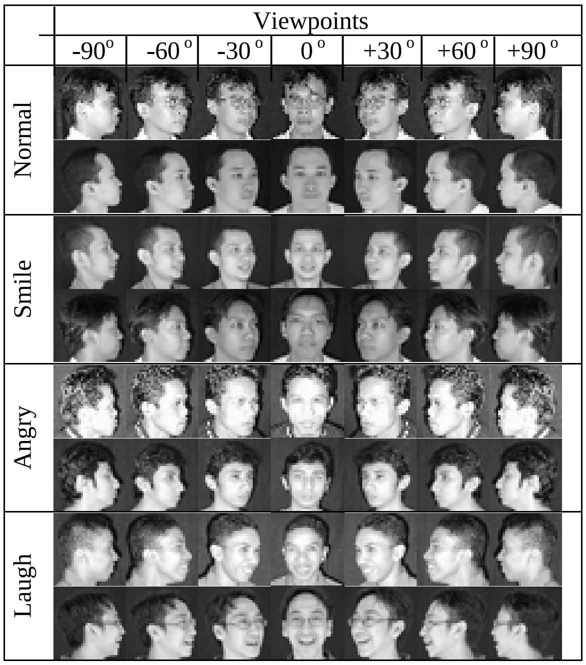



**Figure 5. Example of images which are used in the experiments**

Table 2 shows the recognition rate of the developed system using the K-LTSubspace2 with different classifier methods, i.e. NFL and M-NFL methods, for recognizing images in all three Data Set within four objects. 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 the K-LTSubspace2 with NFL and M-NFL methods for recognizing images in all three Data Set within six objects. 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 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 K-LTSubspace2 with NFL and M-NFL for 4 objects**

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

Table 4 shows the recognition rate of the 3-D face recognition system using the K-LTSubspace2 with NFL and M-NFL methods for recognizing images in all three Data Set within eight objects. 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 percentage to its testing percentage 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 Data Set 3 within four objects, with the highest of 92.31% for NFL method and could be increased up to 100% for M-NFL method. However, when the system is used to recognize images in all three Data Set within six and eight objects, the NFL method could not give a satisfactory result; the highest recognition rate is only 76.6% for recognizing images in six objects and only 75% for recognizing images in eight objects.

Meanwhile, our developed M-NFL method still could give a high recognition rate of the developed system, with the highest is 97.12% for recognizing images in six objects and is 95.67% for recognizing images in eight objects.

**Table 3. Recognition rate of 3-D face recognition system using K-LTSubspace2 with NFL and M-NFL for 6 objects**

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

**Table 4. Recognition rate of 3-D face recognition system using K-LTSubspace2 with NFL and M-NFL for 8 objects**

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

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 objects. 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 objects that being recognized.

However, when NFL method is used as a classifier, the slope of this decreasing recognition rate is higher than that of when M-NFL method is used. For all of the used Data Sets, the M-NFL method always has a lower slope of decrement; and the recognition rate differences between those two methods were always increased along with the increment number of objects.

**Figure 6. Comparison of recognition rate using various numbers of objects in DataSet 1**

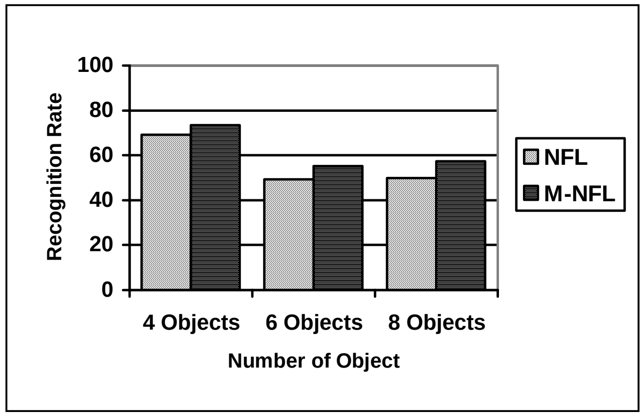



**Figure 7. Comparison of recognition rate using various numbers of objects in DataSet 2**

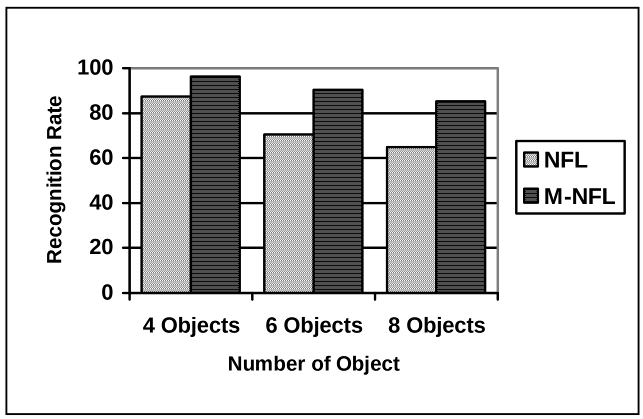
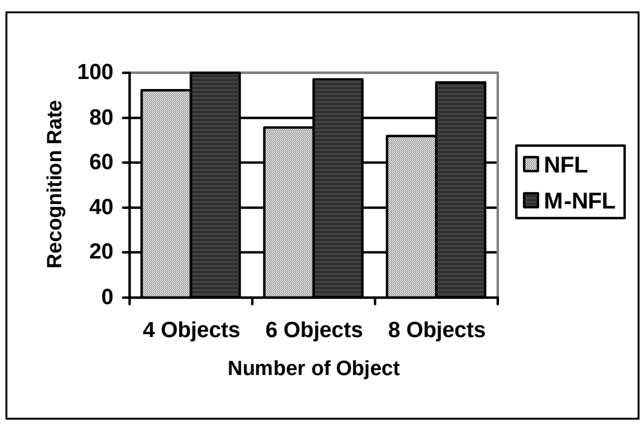



**Figure 8. Comparison of recognition rate using various numbers of objects in DataSet 3**



The recognition rate difference for Data Set 1 is 4.33% for 4 objects, changes to 5.77% for 6 objects and finally up to 7.69% for 8 objects. This phenomenon is also happened when using Data Set 2, with recognition rate difference is 8.75% for 4 objects, and is 19.87% for 6 objects and up to 20.43% for 8 objects. When using Data Set 3, the recognition rate difference is 7.69% for 4 objects, and is 21.48% for 6 objects and up to 23.79% for 8 objects.

## V. Conclusion

Our 3-D face recognition system is developed based on K-LTSubspace2 technique as a feature extraction subsystem and M-NFL method as a pattern classifier. This system could recognize various unlearned face images with unknown viewpoints, which are different from 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 within various numbers of objects used in experiments, our proposed M-NFL method could always give a higher recognition rate than the NFL method. The use of various numbers of objects has influenced the recognition rates of the system. For both M-NFL and NFL methods, the recognition rates were decreased along with the increment number of objects that are necessary to be recognized by the system. 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 Datasets within every various numbers of objects. 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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