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Arif Muntasa
*Informatics Engineering, Faculty of Engineering, Universitas Trunojoyo, Madura 16912, Indonesia*, arifmuntasa@if.trunojoyo.ac.id

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# The Gaussian Orthogonal Laplacianfaces Modelling in Feature Space for Facial Image Recognition

Arif Muntasa

Informatics Engineering, Faculty of Engineering, Universitas Trunojoyo, Madura 16912, Indonesia

*e-mail: arifmuntasa@if.trunojoyo.ac.id*

## Abstract

Dimensionality reduction based on appearance has been interesting issue on the face image research fields. Eigenface and Fisherface are linear techniques based on full spectral features, for both Eigenface and Fisherface produce global manifold structure. Inability of them in yielding local manifold structure have been solved by Laplacianfaces and further improved by Orthogonal Laplacianfaces, so it can yield orthogonal feature vectors. However, they have also a weakness, when training set samples have non-linear distribution. To overcome this weakness, feature extraction through data mapping from input to feature space using Gaussian kernel function is proposed. To avoid singularity, the Eigenface decomposition is conducted, followed by feature extraction using Orthogonal Laplacianfaces on the feature space, this proposed method is called Kernel Gaussian Orthogonal Laplacianfaces method. Experimental results on the Olivetty Research Laboratory (ORL) and the YALE face image databases show that, the more image feature and training set used, the higher recognition rate achieved. The comparison results show that Kernel Gaussian Orthogonal Laplacianfaces outperformed the other method such as the Eigenface, the Laplacianfaces and the Orthogonal Laplacianfaces.

## Abstrak

**Pemodelan Gaussian Orthogonal Laplacianfaces dalam Ruang Fitur untuk Pengenalan Citra Wajah**. Reduksi dimensi berbasis penampakan telah menjadi isu menarik pada bidang penelitian citra wajah. Eigenface dan Fisherface merupakan teknik linier pada fitur-fitur spectral penuh, baik Eigenface Fisherface menghasilkan struktur manifold global. Ketidakmampuan struktur global dalam menghasilkan struktur manifold lokal telah dapat diselesaikan dengan nenggunakan Laplaciaface dan hasil perbaikannya yaitu Orthogonal Laplacianface, sehingga mampu menghasilkan vektor-vektor fitur orthogonal. Namun, metode tersebut juga mempunyai kelemahan ketika sampel data pelatihan mempunyai distribusi non linier. Untuk mengatasi kelemahan tersebut, diusulkan pemetaan data dari ruang input ke ruang fitur. Untuk menghindari singularity diusulkan dekomposisi Eigenface, diikuti dengan ekstraksi fitur menggunakan Orthogonal Laplacianface pada ruang fitur. Metode usulan ini disebut dengan Kernel Gaussian Orthogonal Laplacianface. Hasil-hasil eksperimen pada citra wajah basis data Olivetty Research Laboratory (ORL) dan YALE menunjukkan bahwa, semakin banyak fitur dan data pelatihan yang digunakan, semakin tinggi tingkat pengenalan yang diperoleh. Hasil perbandingan menunjukkan bahwa metode Kernel Gaussian Orthogonal Laplacianfaces mengungguli metode lain seperti Eigenface, Laplacianface, dan Orthogonal Laplacianface.

*Keywords: dimensionality reduction, gaussian kernel function, laplacianfaces, orthogonal laplacianfaces*

## 1. Introduction

Biomtrics research results have influenced security system development of the bank, the stronghold department and goverment. Fingerprint, face, palm, voice and gait recognition are biometrics field which have been developed by many researchers. Crucial problem on face recognition is high dimension or called curse dimensionality problem. Dimensionality reduction method has been the most used to overcome it. Dimensionality reduction method that have been successfully used by many researchers is Principal Component Analysis (PCA) and its derivative [1-12]. It can reduce the image dimension into a number of training data used [13]. However, it has failed to find the local structure of image, though it was developed by

Yambor et al., that is Linear Discriminant Analysis (LDA) [14]. Both PCA and LDA only able to produce a global manifold structure as the object characteristic, however the local manifold structure is more important than the global manifold structure [15,16]. The inability of PCA and LDA to generate the local manifold structure using Eigen decomposition can be improved by using locality-preserving projection (LPP). LPP is linear technique that yields local manifold structure; it is also known as Laplacianfaces [17]. However, it has a weakness, for both the resultant basis vectors and subspace are not orthonormal [18-20].

The weakness of LPP was improved by the using Orthogonal Laplacianfaces technique [21]. It is built by using the nearest neighbor graphics as an estimation of the local manifold stucture. The results of some researchers show that the Orthogonal Laplacianfaces method is superior to PCA, LDA, and Laplacianfaces. However, it still presents a problem when the data distribution used is nonlinear. Consequently, the Orthogonal Laplacianfaces method cannot overcome complicated structure. Simplifying a complicated structure becomes simpler by conducting the required mapping from the input space to the feature space [4,5,22,23].

In this study, a new approach to feature extraction by reducing the dimension is proposed. It can be counducted by mapping from the input to the feature space, by using Kernel Gaussian function, followed by feature extraction using Orthogonal Laplacianfaces. The remainder of the study is organized as follows: In section 2, the proposed method is explained. To measure similarity, in section 3, we explain the similarity measurement. In section 4, the results of the experiment and analysis are presented for the ORL [24] and the YALE [24] face image databases to demonstrate the robustness of the proposed method. Finally, conclusions are presented in section 5. Kernel Gaussian Orthogonal Laplacianfaces method is used to improve Orthogonal Laplacianfaces. The novelty of proposed method is the feature-extraction process. The proposed method can simplify complicated structures, so that facialfeatures are further separated by mapping from the input to the feature space before feature extraction is conducted.

## 2. Methods

The inability to overcome nonlinear data using the Orthogonal Laplacianfaces method can be overcome by using the feature extraction of orthonormal basis vectors in the feature space. To avoid singularity, it is necessary to conduct initial processing by using Eigenface transformation in the feature space. To separate the distributed nonlinear data and obtain the orthonormal basis vectors with the local manifold structure, transformation of basis vectors from the input into the feature space was used.

We have divided the process into four training stages. The first is mapping from the input to the feature space. Second, the transformation of Eigenface vectors in feature space is conducted to avoid singularity. The third stage, building feature vectors by using Kernel Orthogonal Laplacianfaces is followed by the fourth, building the training face image weight on the feature space. In addition, the testing process was divided into two stages, building the testing face image weight on the feature space and the similarity measurements, as shown in Figure 1.

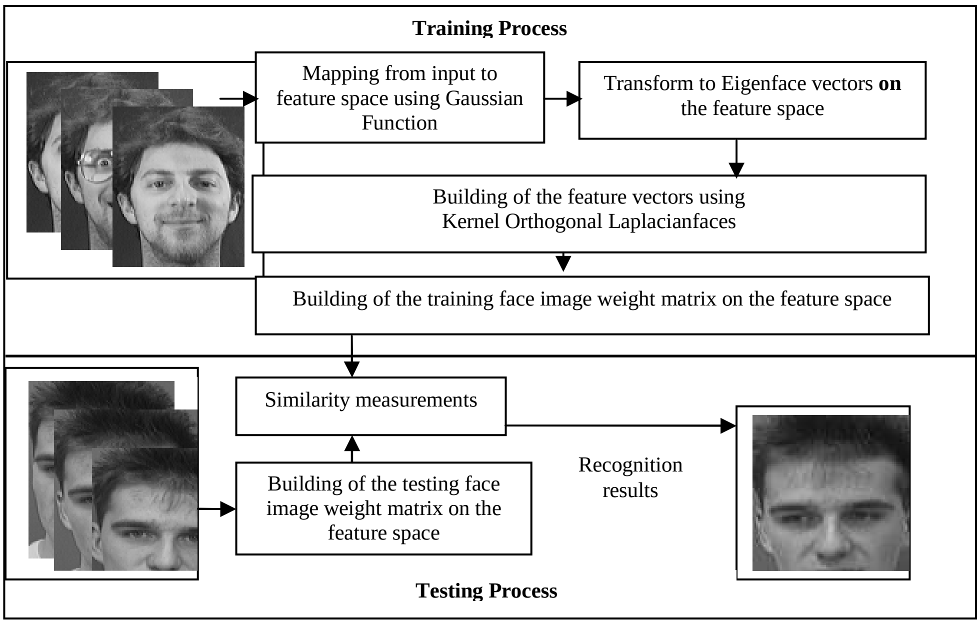



**Figure 1. Proposed Method Framework**

In the training process, the difference between the Kernel Orthogonal Laplacianfaces and Orthogonal Laplacianfaces method is the additional process of mapping from the input to the feature space on the first stage of the Kernel Laplacianfaces method, so that the second, third, and fourth stages also differ from the Orthogonal Laplacianfaces method. In the second stage, a transformation to the Eigenface vector is conducted on the feature space. Similarly, in the last stage, the training face image weight matrix method is conducted on the feature space, whereas in the Orthogonal Laplacianfaces method, all of the processes are conducted on the input space. An additional process of mapping from the input to the feature space on the first stage Kernel Laplacianfaces method it possible to overcome the complicated structure in the training sets.

In the testing process, to achieve the testing face image weight matrix, the Kernel Gaussian Orthogonal Laplacianfaces method also was used to map from the input to the feature space, which is a clear difference from the Orthogonal Laplacianfaces method. The difference between the two processes for both the training and testing is that the Kernel Gaussian Orthogonal Laplacianfaces method can overcome complicated structure, whereas Orthogonal Laplacianfaces cannot.

**Mapping from input to feature space using Gaussian.** Suppose the number of samples used for the training set is $[X_1, X_2, X_3, \ldots, X_m] \in \mathfrak{R}^N$ consists of *c* classes and the dimension of the training set is *r* pixels for image row and *c* pixels for image column, $\forall$ the training set $\mathfrak{R}^{r,c}$ can be transformed in the vector basis $\mathfrak{R}^{1,n}$, where $n=r*c$. Mapping from the input to the feature space can be evaluated by using the following equation

$$\Phi : \Re \rightarrow F \tag{1}$$

$\phi$ *inner product* $\langle\ ,\ \rangle$ can be represented by using *F* or well-known as *reproducing kernel hilbert space* (RKHS). Mathematically, it can be written by using the following equation

$$K(x_i, x_j) = \left\langle \Phi(x_i), \Phi(x_j) \right\rangle \tag{2}$$

*K*(.,.) is the *positive semi-definite* kernel function shown in Table 1. In the study, we used Gaussian Kernel function to map from the input into the feature space as shown in the following equation

$$K(x_i, x_j) = \exp\left(\frac{-\| x_i - x_j \|^2}{\sigma}\right) \tag{3}$$

Mapping from the input to the feature space using the Gaussian Kernel function is done to overcome a complicated structure that cannot be simplified in a linear subspace. The results of mapping from the input to the feature space are used to transform Eigen vectors in the feature space. The feature-extraction process on the input space cannot simplify complicated structure, because feature separation between classes is more difficult achieve.

**Transformation into Eigenface vectors in feature space**. If the result of the covariance matrix determinant is zero, then the Eigen value and the Eigen vector cannot be calculated. To avoid this problem, the Eigenface transformation into the feature space is conducted. The result of mapping by using the kernel trick in Equation (2) yields a linear combination of vectors in the feature space. These vectors are used as the training set in the Eigenface transformation. If the input used is a linear combination in the feature space of $\{\Phi(X_1), \Phi(X_2), \Phi(X_3), \ldots, \Phi(X_m)\}$, the number of the training set is *m* and the image dimension used is *n*, then the average of the training sets in the feature space can be computed as

$$\Phi(\mu_i) = \frac{1}{m}\sum_{j=1}^{m}\Phi(X_{i,j}) \tag{4}$$

In addition, covariance of the feature space can be written by using the following equation:

$$\Phi(c) = \left(\Phi(\mu_i) - \Phi(X_{i,j})\right)\left(\Phi(\mu_i) - \Phi(X_{i,j})\right)^T \tag{5}$$

Based on equation (5), the Eigen value and the Eigen vector in the feature space can be computed as shown in the following equation:

$$\lambda\Lambda = \Phi(c)\Lambda\ . \tag{6}$$

It can be rewritten as in the following equation:

$$\lambda\left\langle \Phi\left(X_j\right), \Lambda \right\rangle = \left\langle \Phi\left(X_j\right), \Phi(c)\Lambda \right\rangle \quad \forall j = 1, \ldots\ldots, m \tag{7}$$

Due to vectors of the feature space is expressed as linear combination vectors of $\{\Phi(X_1), \Phi(X_2), \Phi(X_3), \ldots, \Phi(X_m)\}$, the value of the Eigen vector of the feature space can be computed by using the following equation

$$\Lambda = \sum_{j=1}^{m}\alpha_j \Phi(X_j) \tag{8}$$

If equation (7) is substituted in equation (8), then $\forall j$, $j=1..m$ produces equation

$$\lambda\sum_{j=1}^{m}\alpha_j \Phi(X_j)\Phi^t(X_k) = \frac{1}{m}\left[\sum_{i=1}^{m}\alpha_i \Phi(X_i)\right].V \tag{9}$$

In this case $V = [\sum_{j=1}^{m}\Phi(X_j)\Phi^t(X_j)]\Phi^t(X_k)$, so *eigenvector* yielded has *m*x*m* dimension, where $m<<n$ and $\forall\ \Lambda^T$ has *1xm* dimension, that is $\Phi(\Lambda_{PCA})$=[ $\Phi(\Lambda_1)$, $\Phi(\Lambda_2)$, . . . . $\Phi(\Lambda_m)$]. Furthermore, the e*igenvalue* of equation (9) is sorted descending and followed by sorting the corresponding *eigenvector* on the feature space.

**Feature extraction of Kernel Orthogonal Laplacianfaces.** The result of equation (9) is used to build Kernel Orthogonal Laplacianfaces basis vectors. This process is begun by creating the nearest neighborhood graph in the feature space by using the following equation

$$\Phi(W_{ij}) = \begin{cases} e^{-\frac{\|\Phi(x_i)-\Phi(x_j)\|^2}{t}} & \|\Phi(x_i)-\Phi(x_j)\| < \varepsilon \\ 0 & otherwise \end{cases} \quad (10)$$

$\varepsilon > 0$ expresses local *neighborhood* and $t$ is constant value approaching 1 ($t \cong 1$). Objective function in the feature space of the ortogonal laplacianfaces can be expressed by using the following equation

$$\Phi(X)\Phi(L)\Phi(X^T)a = \lambda\Phi(X)\Phi(D)\Phi(X^T)a \quad (11)$$

To get $a_k$, it can be computed the *eigenvector* value in feature space $\Phi(\Lambda_{OL})$ using the following equation

$$M^{(k)} = \{I - \left(\Phi(X)\Phi(D)\Phi(x)^T\right)^{-1} A^{(k-1)}[B^{(k-1)}]^{-1}[A^{(k-1)}]^T\} \left(\Phi(X)\Phi(D)\Phi(x)^T\right)^{-1}\left(\Phi(X)\Phi(L)\Phi(x)^T\right)^{-1} \quad (12)$$

In this case, $A^{(k-1)}$ and $B^{(k-1)}$ can be defined by using the following equation

$$A^{(k-1)} = [a_1, a_2, ............., a_{k-1}] \quad (13)$$

$$B^{(k-1)} = [A^{(k-1)}]^T(\Phi(X)\Phi(D)\Phi(X^T))^{-1}A^{(k-1)} \quad (14)$$

**Face image weight matrix in feature space.** The training face image weight is matrix used as feature on similarity measurements. If the training face image weight on the feature space is represented by using $\phi(\Lambda)$ and it is symbolized by using $\phi(X)$, then the training face image weight on the feature space can be expressed by using the following equation

$$\Phi(\Omega) = \Phi(X_{Training}).\Phi(\Lambda) \quad (15)$$

In this case $\Phi(\Lambda)$ is the multiplication result of the Kernel Eigenface and the Gaussian Kernel Orthogonal Laplacianfaces eigenvector on the feature space as seen the following equation

$$\Phi(\Lambda) = \Phi(\Lambda_{PCA}).\Phi(\Lambda_{OL}) \quad (16)$$

**Building of the testing face image weight matrix on the feature space.** Before similarity measurements process is conducted, it is necessary to compute the new data set as seen in the following equation

$$\Phi(\psi) = \Phi(X_{Testing}) * \Phi(\Lambda) \quad (17)$$

**Similarity measurements using Euclidian distance.** Testing set used will be multiplied with face image weight first. The result of the testing wieght face image will be compared to the training face image weight. In this research, *Euclidian Distance* formula is utilized for similarity measurements as seen in the following equation:

$$d_1(\Phi(\Omega), \Phi(\Psi)) = \sqrt{\sum_{j=1}^{NoF}(\Phi_j(\Omega) - \Phi_j(\Psi))^2} \quad (18)$$

*Nof* represents number of features used, $\Phi(\Omega)$ represents the training weight on the feature space and the testing weight on the feature space is represented by using $\Phi(\psi)$. The recognition rate can be calculated by divide true data calssfication (*Ctrue*) to the number of data used (*S*)

$$T_{Classification} = \frac{CTrue}{S} x100\% \quad (19)$$

## 3. Results and Discussion

To examine proposed method, the Olivetty Research Laboratory (ORL) [14] and the YALE face image databases [18] have been utilized for experiments. In the ORL face image database, forty persons have been used for training and testing sample. For each person have 10 different poses, expression and accessories. Poses owned by each person are left, right, up, and down. Their expressions are eyes open, eyes close, smiling and not smiling, but for accessories, only a small percentage use glasses as an accessory. Face images used for experiment are 400. In this research, image size used is original size, which is 112 pixels x 92 pixels [14]. In Figure 2, example of the ORL face image database for a person with ten different poses, expressions and accessories is shown.

**Experimental results analysis on the ORL face image database.** In this research, we use three testing scenarios as seen in Table 1. For each scenario, we use five, six and seven poses per person as training set and the remainder as testing set. To examine the reliablility of proposed method, we utilized 5 to 50 dimensions as features, based on the greatest Eigen vector. The complete experimental results can be seen in Figure 3. The experimental results indicate that the greater the Eigen vector used is, the higher recognition rate obtained is. The recognition rate maximum using five, six and seven training set can be seen in Table 1, which are 97%, 98.75%, and 99.17% the maximum recognition rate for the 1st, 2nd, and 3rd respectively.

**Figure 2. Sample of the ORL Face Image Database**

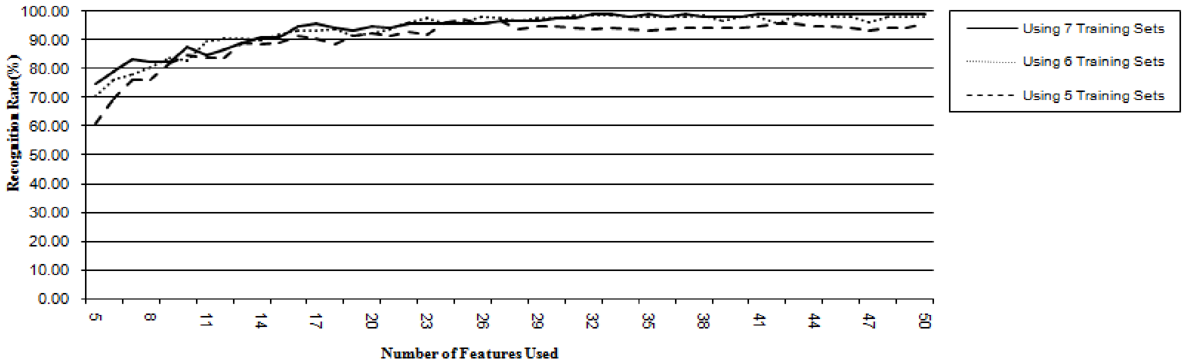



**Figure 3. Experimental Results of Proposed Method on the Olivetty Research Laboratory Face Image Database**

**Table 1. Maximum Recognition Percentage of Proposed Method on the ORL Face Image Database**

| Scenario | Number of Poses for Each Person | Maximum Recognition Rate (%) | Dimension |
|---|---|---|---|
| 1st | 5 | 97.00 | 35 |
| 2nd | 6 | 98.75 | 33 |
| 3rd | 7 | 99.17 | 22 |

The experimental results of the proposed method were compared to the Eigenface, Laplacianfaces, and Orthogonal Laplacianfaces methods, as shown in Figure 4. The recognition rate of the proposed method out performed the other methods for all scenarios, except with Orthogonal Laplacianfaces for seven training sets. In the last scenario using seven poses, the proposed method has the same recognition rate as the Orthogonal Laplacianfaces has, but it outperformed the Eigenface and Laplacianfaces methods. The difference of the testing face image weight smaller than the training face image weight of the different class makes failure of the similarity measurements. Detailed experimental results using five to fifty features from the ORL face image database can be seen in Figure 3. Increasing the number of feature used affected the recognition results. The greater the number of features used, the better the recognition rate obtained were, either using the five, six and seven training sets, although at certain points of the recognition accuracy is degraded.

The increase inaccuracy of the proposed method is significant when compared to the accuracy of both the PCA and Laplacianfaces methods, although it was not significant compared to Appearance Global and Local Structure Fusion method and the Orthogonal Laplacianfaces method, especially when using six and seven poses for each person. However, there were significant differences in the term accuracy between the Kernel Orthogonal Laplacianfaces method and the Orthogonal Laplacianfaces method, when five poses for each person were used as the training process.

**Experimental results analysis on the YALE face image database**. In addition to testing using the ORL face image database, the YALE face image database was also used as experimental data. The YALE face image database has 165 face images. The YALE database has taken 15 persons with 11 variations, different poses, expressions, and lighting, which are left lighting, right lighting, center lighting, normal, smiling, sad, sleepy, surprising, wink, wearing or not wearing glasses as shown in Figure 5. The YALE face image size is 136 pixels for height image and 104 pixels for width image. In the first scenario, five poses for each person were employed for the training set. In the second scenario, we used six poses for each person as the training set and five others as the testing set. The last scenario, seven poses were used as the training set, and four others were used as the testing set. In each scenario, from 5 to 50 dimensions were used as features. In this study, the experimental results show that, for the first, second, and third scenarios, the maximum recognition rate achieved was 95.56%, 96.00%, and 98.33%, respectively, as shown in Table 2. In the first scenario, four images were unrecognized, three because of lighting conditions and one due to a person wearing glasses, so the recognition rate was 95.56%. The effect of accessories on the testing caused the testing set to be unrecognizable, and this was because the training set variants do not data that is similar with the testing set data. The effect of lighting in the testing also caused features of the testing set to be more similar to the data of a different class, thus failing to perform face recognition.

The maximum recognition rate increases proportional to the number of training sets used. Errors in recognition were caused by lighting condition and accessories used.

Table 2 shows that proposed method outperforms the Eigenface, the Laplacianfaces and the Orthogonal Laplacianfaces for all scenarios. The difference of significant results can be seen between the Eigenface, Laplacianfaces and proposed method for all scenarios. The more training set used, the more maximum recognition rate obtained and the less number of dimension found. The more training sets are utilized, the more feature references of each class are also available. The increasingly varied features of the training sets caused the greater the testing set can be recognized. Detail experiments for all scenarios can be seen in Figure 6. The more features used, tends to increase the recognition rate, this is caused by a number of parameters were measured on each face image. The more features used has a tendency of getting close to the facial image class training.

The experimental results on the YALE face image database was also compared to other method, which are Principal Component Analysis (PCA), Laplacianfaces (Locality Preserving Projection/LPP) and Orthogonal Laplacianfaces as seen in Figure 7. Proposed method outperform other method such as PCA, Laplacianfaces and Orthogonal Laplacianfaces for all scenarios.

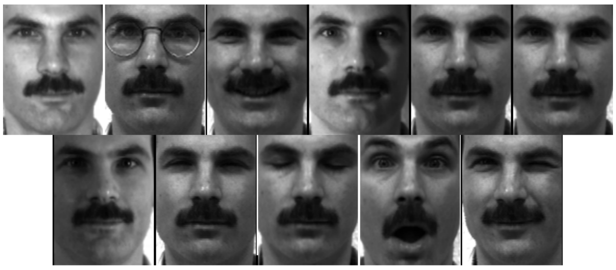
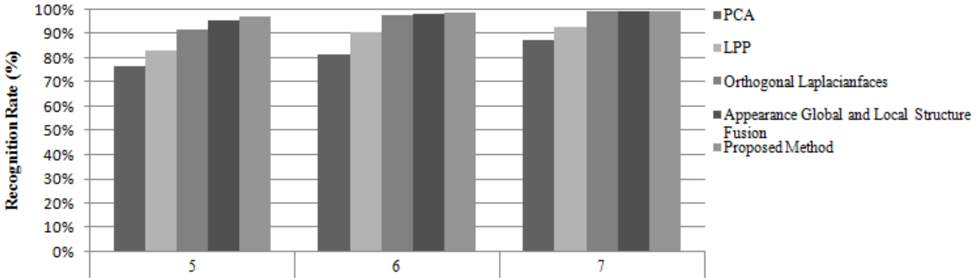


**Figure 5 Sample of the YALE Face Image Database**




| | 5 | 6 | 7 |
|---|---|---|---|
| PCA | 76.50% | 81.25% | 87.50% |
| LPP | 83.00% | 90.63% | 92.50% |
| Orthogonal Laplacianfaces | 91.50% | 97.50% | 99.17% |
| Appearance Global and Local Structure Fusion | 95.50% | 98.13% | 99.17% |
| Proposed Method | 97.00% | 98.75% | 99.17% |

Number of Training Sets

**Figure 4 Comparison of the Recognition Rate on the Olivetty Research Laboratory Face Image Database**

**Table 2. The Maximum Recognition Rate of Proposed Method on the YALE Face Image Database**

| Scenario | Number of Training Sets | The Maximum Recognition Rate (%) | Dimension |
|---|---|---|---|
| 1st | 5 | 95.56 | 25 |
| 2nd | 6 | 96.00 | 17 |
| 3rd | 7 | 98.33 | 8 |

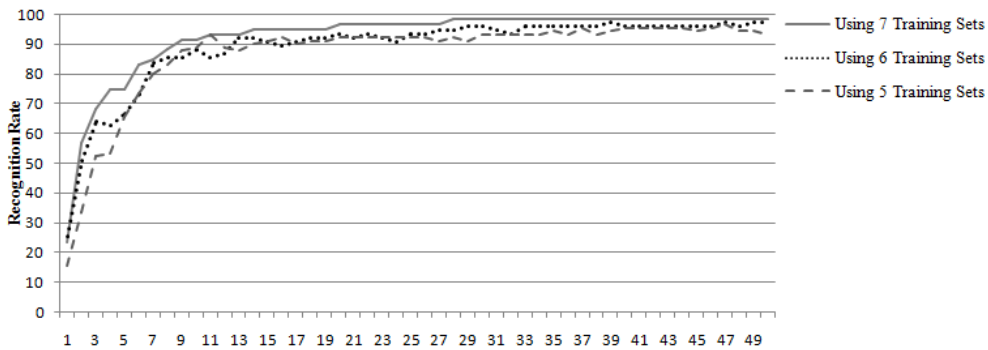
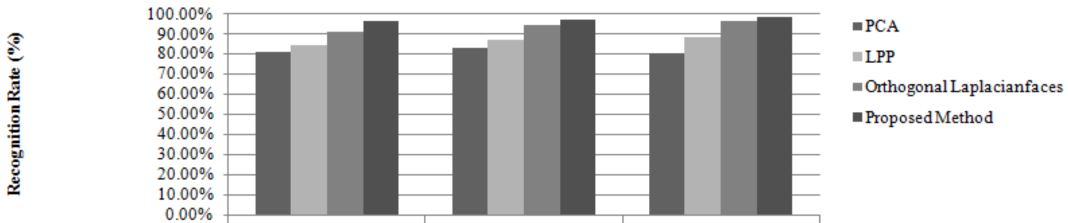



**Figure 6. Experimental Results of Proposed Method on the YALE Face Image Database**




| | 5 | 6 | 7 |
|---|---|---|---|
| PCA | 81.11% | 82.67% | 80.00% |
| LPP | 84.44% | 86.67% | 88.33% |
| Orthogonal Laplacianfaces | 91.11% | 94.67% | 96.67% |
| Proposed Method | 96.67% | 97.33% | 98.33% |

Number of Training Sets

**Figure 7. Comparison of the Recognition Rate on the YALE Face Image Database**

## 4. Conclusions

The proposed method, the Gaussian Orthogonal Laplacianfaces in feature space or well-known as the Kernel Gaussian Orthogonal Laplacianfaces has been able overcome the weakness of the Orthogonal Laplacianfaces method. Two factors has influenced the recognition rate, which are the number of features and the number of training set. The more features used in feature space, the higher recognition rate achieved. Similarly, also occured on the number of training set used.

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