



Maximum Value of the Symmetrical Diagonal Matrix Based Two-Dimensional Eigenfaces for Facial Recognition on the Variant Lighting and Expressions

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Abstract: This research proposed a new approach to recognize face image under various lighting expression. The Proposed method is started by generating of the Left Diagonal Matrix (LDM) and the Right Diagonal Matrix (RDM). Subsequently, the dimensionality reduction is conducted by using Two- Dimensional Eigenface of the LDM and the RDM. The results of dimensionality reduction are selected the maximum value based on the corresponding features. Finally, the geometric similarity measurement model is carried out to obtain the recognition rate. The proposed method was evaluated using three different facial image databases, which are the YALE, the ORL and the UoB face image databases. Two until six column features were used to measure the similarity between the training and the testing sets. Experimental results revealed that the proposed method produced 92.2%, 94%, and 94.7% recognition rate for the YALE, the ORL, and the UoB face image databases respectively. The proposed method was also compared to the other methods. On the ORL face image database, the comparison results show that the proposed method outperformed to the Eigenface, the Fisherface, and the Laplacianfaces but not for O-Laplacianfaces and Two-Dimensional Principal Component Analysis method. On the YALE and the UoB face image databases, the proposed method outperformed to the other appearance methods which are the Eigenface, the Fisherface, the Laplacianfaces, the O-Laplacianfaces and Two-Dimensional Principal Component Analysis methods.

Keywords: Dimensionality Reduction, the Left Diagonal Matrix, the Right Diagonal Matrix, Two-Dimensional Eigenface.

1. Introduction

In many computational processes, the large dimensionality made the significant problem in data mining process, biomedical technique, and face recognition [1-6]. Principally, dimensionality reduction is used to obtain the main features of an object, so that computation time of the similarity measurement can be significantly reduced. Many methods have been developed to overcome high dimensionality, such as the Principal Component Analysis well-known as PCA [7-8], Linear Discriminant Analysis [7], Kernel PCA [9-10], Linear Preserving Projection or Laplacianfaces [11-12], Gabor Wavelet [13], and Two-Dimensional Fisherface [14-15]. One of the most common and the oldest methods to extract the features is PCA. It can obtain the features by projecting the original training sets into the new spaces, which are the eigenvectors. It also guarantees to gains the dominant features, when training sets applied is the linear space. In many real world applications, it almost never acquires that the training sets in the linear subspace form. However, the feature extraction results of PCA are affected by training samples used. If some training sets used are more than the image dimensionality, than PCA cannot efficiently work. The improvement of PCA is Two-Dimensional Principal Component Analysis well-known as 2D-PCA [1]. 2D-PCA also has been improved that known as the Diagonal 2D-PCA. It uses the results of spanning the covariance onto the diagonal matrix as features. It is not necessary to convert the training sets into the one-dimensional vector for spanning the features, so it does not depend on the training sets.

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In this research, Selection of the maximum values of the left and the right of the symmetrical diagonal matrix was proposed. To obtain the main features and to reduce the dimension and computation time, Two-Dimensional Principal Component Analysis was proposed to extract it. The proposed method ensured the features applied are the maximum value of the dominant features of the corresponding features.

The rest of this paper was organized into four sections. the second section explains the weakness of one-dimensional of appearance methods. The third part presents the proposed method. The series of the proposed method are also presented in this part, which are the Left Diagonal Matrix or LDM, the Right Diagonal Matrix or RDM, Two-Dimensional Eigenface of the LDM, Two-Dimensional Eigenface of the RDM, selection of the maximum value of the LDM and the RDM features, and similarity measurement. Fourthly, experimental results are explained and followed by analysis. Finally, conclusions are written In the fifth section.

2. The Weakness of One-Dimensional of Appearance Methods.

In the biometrics field, there are three method models to extract the main features of an object, i.e. appearance-based, features-based, and hybrid-based. An appearance-based method extracted an object based on its vision. An object is viewed as space that consists of the features. Two crucial problems on an appearance-based method, which are high dimensional measured and computational time consumed. Principal Component Analysis (PCA or 1D-PCA) is the simplest method based on an object appearance [16-19]. Considering the training sets consists of C classes, for each class has m image poses. If the height and width of image training sets are H and W , then the image dimension n states the multiplication results between H and W ($n=H*W$), in many cases $n \gg C*m$. PCA can efficiently work, when the value of $n \gg C*m$. It means that, if the number of training sets is more than the image dimension than PCA cannot efficiently perform. However, it is not behaved on the One-Dimensional Linear Discriminant Analysis (LDA or 1D-LDA). Class number of the training sets affected the main features used. If training classes are less than the image dimensional, the LDA can optimally extract the features.

The One-Dimensional Locality Preserving Projection or well-known as the LPP or 1D-LPP is the development results of 1D-PCA based on appearance method. LPP is a classical technique of the linear mapping. It projected the training sets of the variance maximum in the linear space. LPP was performed to improve the PCA by creating a graph that corresponded to the neighborhood of the training sets. It exploits the Kernel Hilbert Spaces to produce the data points as the mapping results. However, it has also a weakness, when the training sets used are more than the image dimensionality. Regarding the above explanation, the maximum value of the Symmetrical Diagonal Matrix Based Two-Dimensional Eigenfaces is proposed to extract the main features of facial images. Similarly also occurred in the other methods based on an appearance, such as the Discriminative Sparsity Preserving, Local Discriminant Embedding, and neighborhood preserving embedding.

3. Proposed Method

In this research, the method for facial recognition on the various lighting expression with six stages was proposed. The proposed approach combines Left Diagonal Matrix (LDM), generate the Right Diagonal Matrix (RDM), and Two-Dimensional Eigenface. Specifically, the proposed method is started with producing of the Left Diagonal Matrix (LDM), creating of the Right Diagonal Matrix (RDM). Two-Dimensional Eigenface of the LDM, Two-Dimensional Eigenface of the RDM, selection of the maximum value of the LDM features and the LRM features, calculation the Eigenvalue and Eigenvector, Eigenvalue descending sorting, followed by the corresponding Eigenvector, and similarity measurement as described in Figure 1. It illustrated that the training sets as image input must be transformed into the LDM and the RDM. These matrixes are utilized to obtain the maximum values of the LDM and the RDM, the maximum covariance of the LDM and the RDM, and calculate Two-Dimensional of Eigenvalues and Eigenvectors. Furthermore, sorted decreasingly the Eigenvalues and followed

by corresponding Eigenvectors. Moreover, feature weights of the training sets are computed based on the maximum value of the LDM and the RDM, and the Eigenvector. The testing sets are built by generating of the LDM and the RDM. The maximum values of them and the Eigenvector of the training sets are utilized to obtain the feature weights of the testing sets. The last process is the similarity measurements.

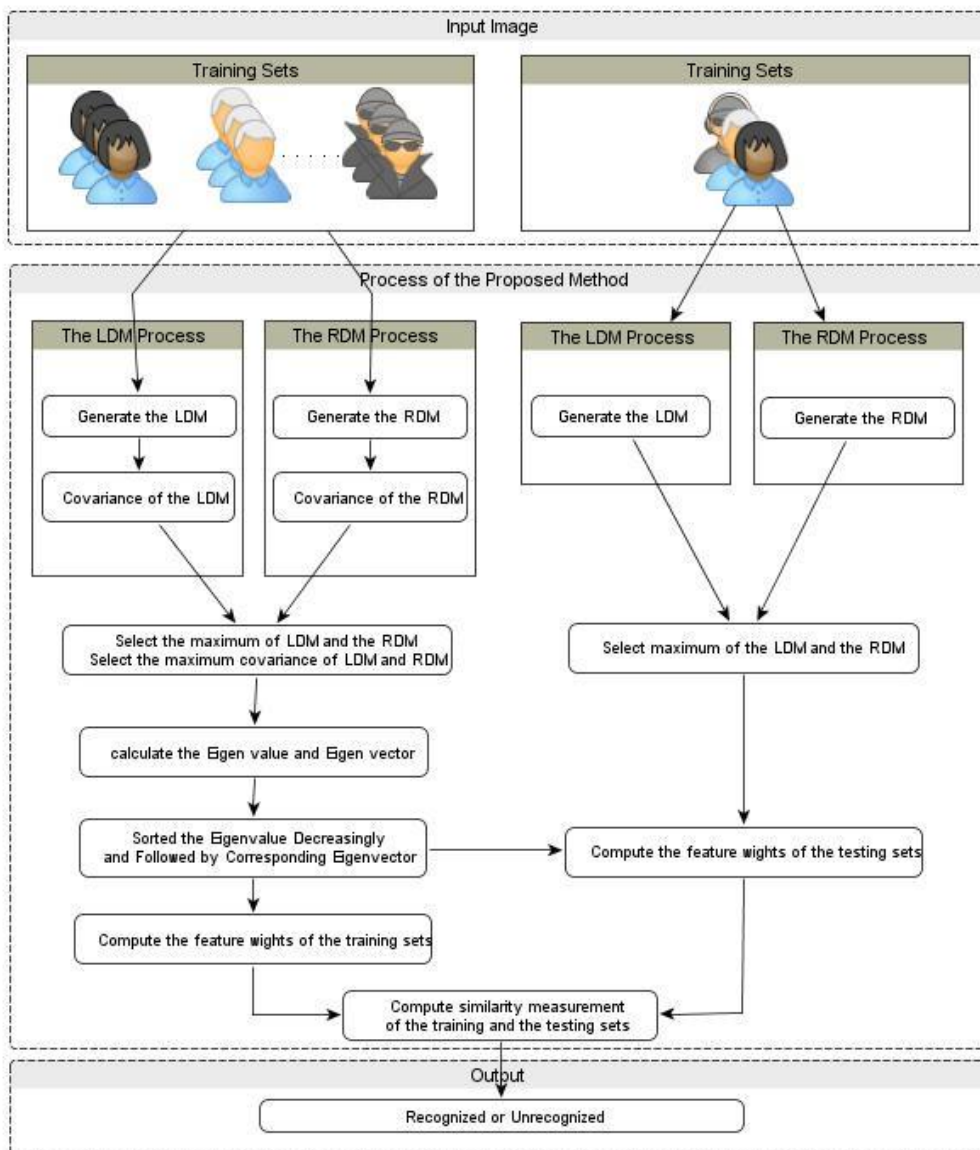


Figure 1. Frame Work of the Proposed Method

A. Generate the Left Diagonal Matrix (LDM)

As seen in Figure 1, the first step of the proposed approach is to generate the LDM. Facial image input is transformed into the left diagonal matrix (LDM). Consider, Equation (1) states the facial image as follows

$$f(x, y) = \begin{pmatrix} f_{1,1} & f_{1,2} & f_{1,3} & \cdots & f_{1,w} \\ f_{2,1} & f_{2,2} & f_{2,3} & \cdots & f_{2,w} \\ f_{3,1} & f_{3,2} & f_{3,3} & \cdots & f_{3,w} \\ f_{4,1} & f_{4,2} & f_{4,3} & \cdots & f_{4,w} \\ f_{5,1} & f_{5,2} & f_{5,3} & \cdots & f_{5,w} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{h,1} & f_{h,2} & f_{h,3} & \cdots & f_{h,w} \end{pmatrix} \quad (1)$$

Three steps to obtain the LDM. The first step, Equation (1) is duplicated and placed under it as written in Equation (2).

$$f_2(x, y) = \begin{pmatrix} f_{1,1} & f_{1,2} & f_{1,3} & \cdots & f_{1,w} \\ f_{2,1} & f_{2,2} & f_{2,3} & \cdots & f_{2,w} \\ f_{3,1} & f_{3,2} & f_{3,3} & \cdots & f_{3,w} \\ f_{4,1} & f_{4,2} & f_{4,3} & \cdots & f_{4,w} \\ f_{5,1} & f_{5,2} & f_{5,3} & \cdots & f_{5,w} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{h,1} & f_{h,2} & f_{h,3} & \cdots & f_{h,w} \\ f_{1,1} & f_{1,2} & f_{1,3} & \cdots & f_{1,w} \\ f_{2,1} & f_{2,2} & f_{2,3} & \cdots & f_{2,w} \\ f_{3,1} & f_{3,2} & f_{3,3} & \cdots & f_{3,w} \\ f_{4,1} & f_{4,2} & f_{4,3} & \cdots & f_{4,w} \\ f_{5,1} & f_{5,2} & f_{5,3} & \cdots & f_{5,w} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{h,1} & f_{h,2} & f_{h,3} & \cdots & f_{h,w} \end{pmatrix} \quad (2)$$

It can be shown that the matrix height has twice the height of Equation (1). The second step, index of the Equation (2) is changed so that its index is increasingly ordered. It is carried out to simplify an explanation of the proposed approach. The last process of the LDM is to replace the matrix value from the first until the w^{th} column. The first column of the LDM is amended by replacing the first column of Equation (3) from the first until the h^{th} rows. The second column of the LDM is filled by the second column of Equation (3) from the second until the $(h+1)^{\text{th}}$ rows. The third column of LDM is replaced by the third column of Equation (3) from the third until the $(h+2)^{\text{th}}$ rows. The same process must be conducted until the w^{th} column, the w^{th} column of the LDM is replaced by the last column of Equation (3) from the w^{th} until the $(w+h-1)^{\text{th}}$ rows. The results of the LDM matrix value can be seen in Equation (4)

$$f_3(x, y) = \begin{pmatrix} f_{1,1} & f_{1,2} & f_{1,3} & \cdots & f_{1,w} \\ f_{2,1} & f_{2,2} & f_{2,3} & \cdots & f_{2,w} \\ f_{3,1} & f_{3,2} & f_{3,3} & \cdots & f_{3,w} \\ f_{4,1} & f_{4,2} & f_{4,3} & \cdots & f_{4,w} \\ f_{5,1} & f_{5,2} & f_{5,3} & \cdots & f_{5,w} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ f_{h,1} & f_{h,2} & f_{h,3} & \cdots & f_{h,w} \\ f_{h+1,1} & f_{h+1,2} & f_{h+1,3} & \cdots & f_{h+1,w} \\ f_{h+2,1} & f_{h+2,2} & f_{h+2,3} & \cdots & f_{h+2,w} \\ f_{h+3,1} & f_{h+3,2} & f_{h+3,3} & \cdots & f_{h+3,w} \\ f_{h+4,1} & f_{h+4,2} & f_{h+4,3} & \cdots & f_{h+4,w} \\ f_{h+5,1} & f_{h+5,2} & f_{h+5,3} & \cdots & f_{h+5,w} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{2h,1} & f_{2h,2} & f_{2h,3} & \cdots & f_{2h,w} \end{pmatrix} \quad (3)$$

$$f_4(x, y) = \begin{pmatrix} f_{1,1} & f_{2,2} & f_{3,3} & \cdots & f_{w,w} \\ f_{2,1} & f_{3,2} & f_{4,3} & \cdots & f_{w+1,w} \\ f_{3,1} & f_{4,2} & f_{5,3} & \cdots & f_{w+2,w} \\ f_{4,1} & f_{5,2} & f_{6,3} & \cdots & f_{w+3,w} \\ f_{5,1} & f_{6,2} & f_{6,3} & \cdots & f_{w+4,w} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{h,1} & f_{h+1,2} & f_{h+2,3} & \cdots & f_{w+h-1,w} \end{pmatrix} \quad (4)$$

The LDM generation can be illustrated in Figure 2. Suppose, an original image has width 5 and height 7, it is duplicated and composed under an original image. To simplify it, the result of image duplication is changed the index. The last process is put the element value from the left to the right diagonal. The left diagonal matrix has the same size with an original image.

B. Generate the RDM

The second stage of the proposed approach is to transform the original image into the RDM. The RDM generation has the same process with the LDM generation. The difference is to change only column element position. The first process of the RDM generation conducts column position shifting of the Equation (1), and Equation (5) is the results of the stage

$$g_1(x, y) = \begin{pmatrix} f_{1,w} & f_{1,w-1} & f_{1,w-2} & \cdots & f_{1,1} \\ f_{2,w} & f_{2,w-1} & f_{2,w-2} & \cdots & f_{2,1} \\ f_{3,w} & f_{3,w-1} & f_{3,w-2} & \cdots & f_{3,1} \\ f_{4,w} & f_{4,w-1} & f_{4,w-2} & \cdots & f_{4,1} \\ f_{5,w} & f_{5,w-1} & f_{5,w-2} & \cdots & f_{5,1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{h,w} & f_{h,w-1} & f_{h,w-2} & \cdots & f_{h,1} \end{pmatrix} \quad (5)$$

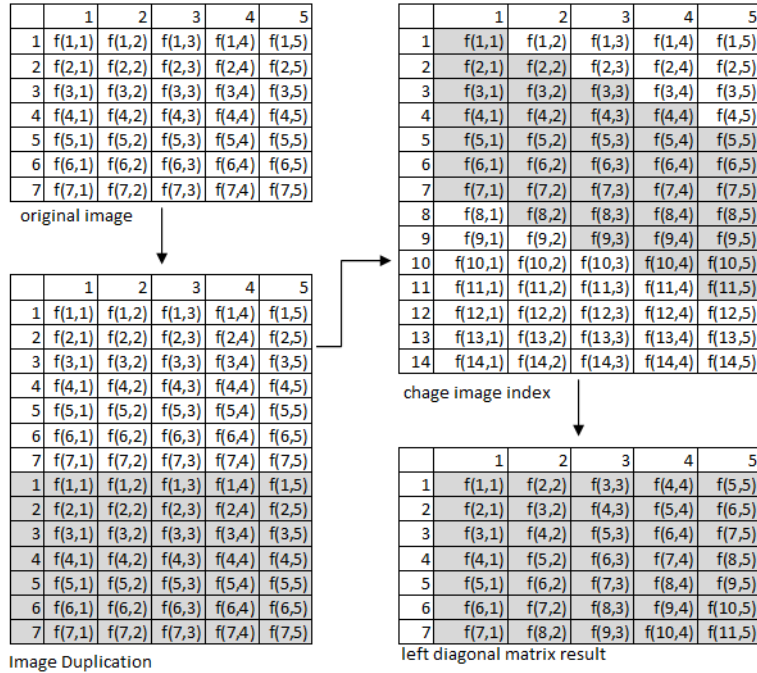


Figure 2. Representation of the LDM Generation

The second step of the RDM is to duplicate the matrix of Equation (5) and to compose it under the last row of Equation (5) as seen in Equation (6)

$$g_2(x, y) = \begin{pmatrix} f_{1,w} & f_{1,w-1} & f_{1,w-2} & \cdots & f_{1,1} \\ f_{2,w} & f_{2,w-1} & f_{2,w-2} & \cdots & f_{2,1} \\ f_{3,w} & f_{3,w-1} & f_{3,w-2} & \cdots & f_{3,1} \\ f_{4,w} & f_{4,w-1} & f_{4,w-2} & \cdots & f_{4,1} \\ f_{5,w} & f_{5,w-1} & f_{5,w-2} & \cdots & f_{5,1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{h,w} & f_{h,w-1} & f_{h,w-2} & \cdots & f_{h,1} \\ f_{1,w} & f_{1,w-1} & f_{1,w-2} & \cdots & f_{1,1} \\ f_{2,w} & f_{2,w-1} & f_{2,w-2} & \cdots & f_{2,1} \\ f_{3,w} & f_{3,w-1} & f_{3,w-2} & \cdots & f_{3,1} \\ f_{4,w} & f_{4,w-1} & f_{4,w-2} & \cdots & f_{4,1} \\ f_{5,w} & f_{5,w-1} & f_{5,w-2} & \cdots & f_{5,1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{h,w} & f_{h,w-1} & f_{h,w-2} & \cdots & f_{h,1} \end{pmatrix} \quad (6)$$

The third step is to change matrix element index. It is conducted to explain clearly the next process. Equation (7) is the index change results

$$g_3(x, y) = \begin{pmatrix} f_{1,w} & f_{1,w-1} & f_{1,w-2} & \cdots & f_{1,1} \\ f_{2,w} & f_{2,w-1} & f_{2,w-2} & \cdots & f_{2,1} \\ f_{3,w} & f_{3,w-1} & f_{3,w-2} & \cdots & f_{3,1} \\ f_{4,w} & f_{4,w-1} & f_{4,w-2} & \cdots & f_{4,1} \\ f_{5,w} & f_{5,w-1} & f_{5,w-2} & \cdots & f_{5,1} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ f_{h,w} & f_{h,w-1} & f_{h,w-2} & \cdots & f_{h,1} \\ f_{h+1,w} & f_{h+1,w-1} & f_{h+1,w-2} & \cdots & f_{h+1,1} \\ f_{h+2,w} & f_{h+2,w-1} & f_{h+2,w-2} & \cdots & f_{h+2,1} \\ f_{h+3,w} & f_{h+3,w-1} & f_{h+3,w-2} & \cdots & f_{h+3,1} \\ f_{h+4,w} & f_{h+4,w-1} & f_{h+4,w-2} & \cdots & f_{h+4,1} \\ f_{h+5,w} & f_{h+5,w-1} & f_{h+5,w-2} & \cdots & f_{h+5,1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{2h,w} & f_{2h,w-1} & f_{2h,w-2} & \cdots & f_{2h,1} \end{pmatrix} \quad (7)$$

The first column of the RDM can be achieved by placing in the first column of Equation (7) from the first until the h rows. The second row of the RDM can be built by putting the second column of Equation (7) from the second until the $(h+1)$ rows. The third column of the RDM can be performed by moving from the third until the $(h+2)$ in Equation (7). The fourth until the w th column can be conducted in the same way with the previous process. Equation (8) is the RDM generation results

$$g_4(x, y) = \begin{pmatrix} f_{1,w} & f_{2,w-1} & f_{3,w-2} & \cdots & f_{w,1} \\ f_{2,w} & f_{3,w-1} & f_{4,w-2} & \cdots & f_{w+1,1} \\ f_{3,w} & f_{4,w-1} & f_{5,w-2} & \cdots & f_{w+2,1} \\ f_{4,w} & f_{5,w-1} & f_{6,w-2} & \cdots & f_{w+3,1} \\ f_{5,w} & f_{6,w-1} & f_{7,w-2} & \cdots & f_{w+4,1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{h,w} & f_{h+1,w-1} & f_{h+2,w-2} & \cdots & f_{w+h-1,1} \end{pmatrix} \quad (8)$$

C. Two-Dimensional Eigenface of the LDM

The original facial image was changed into Equation (4) and (8), for both the training and testing sets. The third stage of the proposed approach is to extract the facial image features by using Two-Dimensional Principal Component Analysis or well-known as Two-Dimensional Eigenfaces. It has ensured that amount of the training sets does not affect the performance of the feature extraction process. It is different from One-Dimensional Principal Component Analysis. Two-Dimensional Eigenfaces method does not require the transformation process the input image into single row or column. The first process of Two-Dimensional Eigenfaces is to compute the average of the training sets as shown in Equation (9)

$$\mu_f(x, y) = \frac{\sum_{c=1}^n \sum_{p=1}^m f_{c,p}(x, y)}{n * m} \quad (9)$$

The result of Equation (9) will be applied to compute the zero mean and covariance. They can be written in Equation (10) and (11)

$$Z_f(x, y) = \sum_{c=1}^n \sum_{p=1}^m (f_{c,p}(x, y) - \mu_f(x, y)) \quad (10)$$

$$C_f(x, y) = \sum_{c=1}^n \sum_{p=1}^m (f_{c,p}(x, y) - \mu_f(x, y)) * \left(\sum_{c=1}^n \sum_{p=1}^m (f_{c,p}(x, y) - \mu_f(x, y)) \right)^T \quad (11)$$

D. Two-Dimensional Eigenface of the RDM

The principal component of LDM has been calculated by using Equation (4). The calculation results of LDM are $\mu_f(x,y)$, $Z_f(x,y)$, $C_f(x,y)$, λ and A , whereas the principal component of the RDM is reckoned by using Equation (8). Average of the RDM can be computed by using Equation (12)

$$\mu_g(x, y) = \frac{\sum_{c=1}^n \sum_{p=1}^m g_{c,p}(x, y)}{n * m} \quad (12)$$

The result of Equation (12) is applied to compute the zero mean and variance. They can be written in the following equation

$$Z_g(x, y) = \sum_{c=1}^n \sum_{p=1}^m (g_{c,p}(x, y) - \mu_g(x, y)) \quad (13)$$

$$C_g(x, y) = \sum_{c=1}^n \sum_{p=1}^m (g_{c,p}(x, y) - \mu_g(x, y)) * \left(\sum_{c=1}^n \sum_{p=1}^m (g_{c,p}(x, y) - \mu_g(x, y)) \right)^T \quad (14)$$

E. Selection of the maximum value of the LDM and LRM features

The Covariance matrix of the LDM and the RDM was gained from the Equation (11) and (14), their results are chosen to acquire the maximum values as follows

$$C(x, y) = \arg \max(C_f(x, y), C_g(x, y)) \quad (15)$$

The result of Equation (15) is used to calculate the Eigenvalue (λ) and Eigenvector (A) as follows

$$(C(x, y) - \lambda I)X = 0 \quad (16)$$

The results of Equation (16) are the Eigenvalues and Eigenvectors. Furthermore the Eigenvalue is decreasingly ordered, and followed by the columns of Eigenvector. In this case, the Eigenvalues gained are $\lambda_1 > \lambda_2 > \lambda_3 > \lambda_4 > \dots > \lambda_w$ and the Eigenvectors produced are $A_1, A_2, A_3, A_4, \dots, A_w$ corresponding to the Eigenvalues. The Eigenvectors represented the characteristics of a facial image. In two-dimensional appearance based, the Eigenvector has the same size with the training or testing sets. They are used to obtain the feature weights, for both the training and the testing sets. Furthermore, the image testing feature weights are compared to the training feature weights. The results of characteristic equation as mentioned in Equation (16) were used to calculate the weights of the training (W) and the testing sets (Y) as follows

$$W = \arg \max(f_4(x, y), g_4(x, y)) * \Lambda \quad (17)$$

$$Y = \arg \max(f_{Test}(x, y), g_{Test}(x, y)) * \Lambda \quad (18)$$

In this case, f_{Test} and g_{Test} represent the Left and the Right Diagonal Matrix of the testing sets.

Figure 3 consists of two rows and four columns. The first column is the original image, whereas the second, the third, and the last column are the left, the right, and the maximum diagonal matrix respectively.



Figure 3. Facial Image Representation for an Original Image, the Left Diagonal, the Right Diagonal and their Maximum Values

F. Similarity Measurement Based on Geometrical Model

In this research, four similarity measurements based on geometrical approach are applied, which are the Euclidian Distance, Manhattan, Canberra, and Chebyshev. In this research, $W_{i,j}$ represents the weight of the training sets image features, whereas the testing sets image features is symbolized with $Y_{i,j}$. The similarity measurements of the Euclidian Distance, Manhattan, Canberra and Chebyshev are delineated by d_{Ed} , d_{Mh} , d_{Cb} , d_{Cs} respectively as displayed in the following equation

$$d_{Ed} = \sum_{i=1}^h \sum_{j=1}^k \|W_{i,j} - Y_{i,j}\| \quad (19)$$

$$d_{Mh} = \sum_{i=1}^h \sum_{j=1}^k |W_{i,j} - Y_{i,j}| \quad (20)$$

$$d_{Cb} = \frac{\sum_{i=1}^h \sum_{j=1}^k |W_{i,j} - Y_{i,j}|}{\sum_{i=1}^h \sum_{j=1}^k (|W_{i,j}| + |Y_{i,j}|)} \quad (21)$$

$$d_{Cs} = \sum_{i=1}^h \sum_{j=1}^k \max(W_{i,j} - Y_{i,j}) \quad (22)$$

In this case h represents row size of features, it has the same size with the height of the training or the testing set images, whereas k states number of column features.

4. Experimental Results and Analysis of the Proposed Method

In this research, three databases were employed to evaluate the proposed method, which is the YALE [20], ORL [21] and University of Bern [22] face image databases. Four scenarios were conducted to evaluate the proposed method, which are two, three, four, and five images as the training sets. For each scenario, 6-Folds Cross Validation were randomly conducted. For each Fold Cross Validation, four similarity measurement methods were performed to obtain the percentage of accuracy, which are the Euclidian Distance, Manhattan, Canberra, and Chebyshev as mentioned in Equation (19), (20), (21), and (22). The experimental results are also compared to the other methods, which are the Principal Component Analysis is as well-known as Eigenfaces (1D-PCA), Fisherface (1D-Fisherface), Laplacianfaces or Locality Preserving Projection (1D-LPP), Orthogonal Laplacianfaces or O-Laplacianfaces or Orthogonal Locality Preserving Projection (1D-OLPP), and Two Dimensional-Principal Component Analysis (2D-PCA).

The training results, two until six column features were utilized to determine the similarity between the training and the testing sets. Column features taken are corresponding to the largest of the Eigenvalues. The eigenvectors are used to obtain the weight of the images, for both the training and testing sets. The weight of the training and testing sets are compared to decide the best result.

A. The YALE Face Image Database

The YALE face image database consists of six expressions, three lighting models, and two accessories. Six expressions are happy, normal, sad, surprised, wink and sleepy. Three lighting models are center light, right light, and left light. Two accessories are using glasses and no glasses. The number of persons employed is fifteen. Total face images used are one hundred and sixty-five [20]. For each image have 104x136 pixels for width and height. Figure 4 shows that YALE face image database samples from the different persons and expressions. Experimental results showed that the recognition rate is influenced by some the training sets used (Table 1). The highest recognition rate is 92.2%. It is obtained by using Canberra with five Eigenface features. For each method, the more the training sets used, the higher recognition rate achieved. It shows that the number of features used has affected the results of similarity measurement. The different case of the Canberra method, the recognition rate using two face images is greater than three face images. It has also occurred on Euclidian Distance and Manhattan when using four and five face images. The experimental results can be displayed in Table 1. The decreasing of the recognition rate is caused by similarity features obtained from the different people. The lighting of the face image on the testing sets has also affected misclassification.



Figure 4. Image Samples of YALE Face Image Database [20]

The proposed method was also compared to the other methods as displayed in Table 2. The results of the proposed method outperformed to the other methods, which are Eigenfaces, Fisherface, Laplacianfaces, O-Laplacianfaces, and 2D-PCA for all scenarios. On the YALE face image database shows that the proposed method can work efficiently for all scenarios. The comparison results displayed that 2D-PCA was better than the proposed method when using three and four training sets, but the proposed method obtained higher accuracy than 2D-PCA when two and five images were used as the training sets. The proposed method also gained higher recognition rate than Eigenface, Fisherface, Laplacianfaces, and O-Laplacianfaces for all scenarios as stated in Table 2.

Table 1. Performance of Proposed Method on the YALE Face Image Database

Training Sets Used	Recognition Rate (%)				Maximum
	Euclidian Distance	Manhattan	Canberra	Chebichev	
2	70	72.5	82.5	66.7	82.5
3	77.5	77.5	79.2	75.8	79.2
4	85.7	85.7	88.6	80.9	88.6
5	84.4	84.4	92.2	83.3	92.2

Table 2. Performance Comparisons on the YALE Face Image Database

Training Sets Used	Recognition Rate (%)					Proposed Method
	1D-PCA	1D-Fisherface	1D-LPP	1D-OLPP	2D-PCA	
2	43.5	45.7	56.5	55.7	79.6	82.5
3	48.9	64.5	68.5	70.1	84.3	79.2
4	52.2	72.7	74.6	77.3	90.4	88.6
5	57.8	77.5	78.3	82.1	91.8	92.2

B. The ORL Face Image Database

The second experiment is conducted on the ORL face image database. The Olivetti Research Laboratory is well-known as the ORL face image database. The facial image database is made by AT&T from Cambridge University. The ORL captured the facial image of forty persons. For each person was captured ten times from the different poses and lightings [21]. The original images have 112 and 92 pixels for height and width. Figure 5 depicts the sample of the ORL face image.

In this research, two until six features are utilized to measure the similarity between the training and the testing sets. The experimental results on the ORL face image database are shown in Table 3. The maximum performance of the proposed method is 75.3%, 88.6%, 92.1%, and 94% for two, three, four, and five training sets respectively. The same trend has also occurred on Euclidian Distance, Manhattan, Canberra, and Chebyshev methods. For each similarity measurement method, the more the face image training used, the more recognition achieved. It shows that the number of training sets has affected the recognition rate. The comparison results to the other methods show that the proposed method outperformed to Eigenfaces, Fisherface, and Laplacianfaces. The O-Laplacianfaces procured higher accuracy than the proposed method, except the second scenario, it produced the same recognition rate as demonstrated in Table 4. The 2D-PCA also produced higher recognition rate for three and four images sets, but not for two and five images as the training sets.



Figure 5. Image Samples of the ORL Face Image Database [21]

Table 3. Performance of Proposed Method on the ORL Face Image Database

Training Sets Used	Recognition Rate (%)				Maximum
	Euclidian Distance	Manhattan	Canberra	Chebyshev	
2	75.3	74.7	72.2	75	75.3
3	88.8	87.9	84.6	82.9	88.6
4	92.1	91.7	86.3	91.3	92.1
5	94	93.5	89	93.5	94

Table 4. Performance Comparisons on the ORL Face Image Database

Training Sets Used	Recognition Rate (%)					Proposed Method
	1D-PCA	1D-Fisherface	1D-LPP	1D-OLPP	2D-PCA	
2	66.3	71.1	76.1	79.6	79.9	75.3
3	75.4	84.2	86.6	88.6	88.9	88.6
4	82	89.5	90.4	94.1	93.9	92.1
5	85.9	92.3	93.2	96.3	95.6	94

C. The University of Bern Face Image Database

The University of Bern face image database is well-known as UoB face image database. It captured 30 people with 512x342 pixels. The UoB face image database has expression small different and four frontal poses, which are left, right, top and bottom. In this research, the UoB face image database has been resized into 140 for height and 120 for width pixels. Figure 6 shows that the UoB face image sample from two different persons [22]. Detail results of the experimental results can be seen in Table 5. Experimental results produce the maximum recognition rate 94.7%. The increasing of recognition rate has depended on the training sets used. The increasing of training sets has produced directly proportional recognition rate for Euclidian Distance, Manhattan, Canberra and Chebyshev methods as seen in Table 5. Fault on the Similarity Measurement is caused by the image testing more resemble another image. Resembles between image testing and image matching result has produced the smaller distance value than other image training sets. The proposed method was compared to the other methods. The comparison results indicated that 2D-PCA outperformed to the other methods for all scenario as shown in Table 6. If it is compared to the proposed method, it produced higher recognition rate when using three and four images, but not for two and five images as the

training sets. The proposed method obtained better accuracy than Eigenface, Fisherface, Laplacianfaces, and O-Laplacianfaces.



Figure 6. Image Samples of UoB Face Image Database [22]

Table 5. Performance of Proposed Method on the UoB Face Image Database

Training Sets Used	Recognition Rate (%)				Maximum
	Euclidian Distance	Manhattan	Canberra	Chebisev	
2	70.8	70	72.9	66.3	72.9
3	73.8	74.3	75.7	69.1	75.7
4	85	85	89.4	81.1	89.4
5	94	92.7	94.7	90	94.7

Table 6. Performance Comparisons on the UoB Face Image Database

Training Sets Used	Recognition Rate (%)					
	1D-PCA	1D-Fisherface	1D-LPP	1D-OLPP	2D-PCA	Proposed Method
2	66.3	66.7	67.5	63.3	71.2	72.9
3	71.5	71.4	71.9	66.2	78.7	75.7
4	83.3	81.7	86.7	77.2	93.4	89.4
5	92	91.3	90	89.3	93.9	94.7

The investigation results showed that the facial images using accessories such as spectacles are harder to be recognized than without accessories. It occurred on the YALE and the UoB face image databases. On the ORL face image database, the image poses with the front view are easier recognized than image poses with other sides. They produced the feature weights more similar to another class than own class, so they were hard to be recognized. Figure 7 displayed the facial images are hard to be recognized. It consists of three rows. The first row is false recognition on the face image Yale database. The second and the third rows represent false recognition on the ORL and the UoB face image databases

The LDM shifts the location of the upper left on the lower left side. It means that the LDM tried to search the optimal projective of the object by the left diagonal shifting. It is also conducted to maintain the rows and columns information. In contrast, it also occurs in the RDM transforms the lower right on the upper right side. It is conducted to integrate rows and columns information of the original images. Selection of the maximum value between the LDM and RDM is carried out to obtain the information block of the object so that the information features can be preserved and reduced the loss information. The similar case also occurs in the selection of the maximum values of the covariance of the LDM and RDM.

Principally, it is conducted to obtain, extract, preserve and combine the information structure for both rows and columns. The more information structure obtained, the better objects are represented, so the image will be easier to be recognized. Because of the above explanation, the proposed method outperform to the other methods.



Figure 7, Facial images which are hard to be recognized (The first, second, and third rows are false detection on the YALE, ORL, and UoB face image databases respectively)

5. Conclusions

In this research, the proposed method has produced high recognition rate on the ORL, YALE, and UoB face image databases. On the ORL face image database, the proposed method outperformed to the Eigenface, Fisherface, and Laplacianfaces methods, but not for the O-Laplacianfaces and 2D-PCA. On the YALE and the UoB face image databases, the proposed method outperformed to the other methods, such as Eigenfaces, Fisherface, Laplacianfaces, O-Laplacianfaces and Two-Dimensional Principal Component Analysis for all scenarios. The proposed method, combination of the LDM, RDM, and 2D-PCA can extract, preserve, and integrate the rows and columns information structure. The recognition rate is proportional to the training sets used. The maximum recognition rate on the YALE, the ORL, and the UoB face image databases are 94.7%, 94%, and 92.2% respectively. The recognition rate is directly proportional to the training features used.

6. References

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