A New Approach: The Local Feature Extraction

Based on the New Regulation of the Locally Preserving Projection

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Abstract

A novelty of the local feature extraction was proposed for face recognition. To optimize the Eigenvalue and Eigenvector, a new regulation has been embedded to the Locally Preserving Projection. The proposed method has reduced computation time to obtain the new subspace of the original of the Locally Preserving Projection. The proposed method has also produced orthogonal basis function matrix. However, orthogonal basis function matrix can reconstruct easier than non-orthogonal function. The proposed method has been evaluated by using three face image databases, they are the University of Bern, the YALE-A, and the ORL face image databases. The experimental results of the proposed method have produced the recognition rate 96% for the University of Bern, 96.19% for the YALE-A and 98% for the ORL facial image databases. The experimental results of the proposed method have produced higher recognition rate than the Principal Component Analysis, the Linear Discriminant Analysis and the Locally Preserving Projection.

Keywords: Locally preserving projection, new regulation, face recognition, and feature extraction

1. Introduction

Recently, the biometric fields are interesting research to be more developed. An appearance method is one of the methods developed to obtain the local or the
global features, such as Graph Embedding method [1], Probability Distribution Functions [2], the Principal Component Analysis [3-4], Sparse Representation [5], the linear Discriminant analysis [6-11], Kernel Direct Discriminant Analysis [12], Orthogonal Discriminant Vector [13], the Laplacianfaces [14], Orthogonal Laplacianfaces [15], and Modified of Two Dimensional-Fisherface [16]. For both the Principal Component Analysis and the linear Discriminant analysis have produced the global features. They only represent the outside of the dominant features. In fact, the local features are also very required to depict the object characteristics. If an object characteristic can be obtained in more detail, than the object can be easier clustered. The local features can be obtained using the Locally Preserving Projection. However, the Locally Preserving Projection has produced the local features, but matrix obtained is non-orthogonal. To determine the constraint of the Locally Preserving Projection, it is need $O(n^2)$ computation time after Eigenvalue and Eigenvector are found.

In this research, the new regulation of the Locally Preserving Projection is proposed to avoid singularity problem, overcome non-orthogonal basis function, and reduce the computation time. To avoid the singularity problem, the Principal Component Analysis as the beginning process was proposed to obtain the new subspace and weight. They will be used as input in the new regulation of the proposed method. To overcome non-orthogonal basis function, the Locally Preserving Projection is added to its transpose and the small value. To reduce the computation time, the constraint can be directly taken from the Eigenvalue and Eigenvector optimization results.

The rest of the paper will be composed as follows. The explanation of Locally Preserving is written in section 2. Section 3 describes the new regulation of the Locally Preserving Projection as the proposed method. The experimental results and discussion are explained in section 4. Finally, the conclusions of the research are written in section 5.

2. Proposed Method

Given a set of images data class $c$ training set, for each class $i$ have $p_i$ images. It means that, number of training set is $m$, where $m$ describes multiplication class ($c$) and sum of $P$ ($\Sigma p_i$). If number of image dimension is $n$, where $n=h\times w$, then the training set can be described as follows

$$
X = \begin{bmatrix}
 f_{1,1}(1,1) & \cdots & f_{1,1}(h-1,1) & \cdots & f_{1,3}(l,1) & \cdots & f_{1,3}(h,w) \\
 f_{1,2}(1,1) & \cdots & f_{1,2}(h-1,1) & \cdots & f_{1,3}(l,1) & \cdots & f_{1,3}(h,w) \\
 \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
 f_{c-1,p_{c-1},1}(1,1) & \cdots & f_{c-1,p_{c-1}}(h-1,1) & \cdots & f_{c-1,p_{c-1}}(l,1) & \cdots & f_{c-1,p_{c-1}}(h,w) \\
 f_{c,p_c}(1,1) & \cdots & f_{c,p_c}(h-1,1) & \cdots & f_{c,p_c}(l,1) & \cdots & f_{c,p_c}(h,w)
\end{bmatrix}
$$

(1)
In this case, training sets has been reshaped into row matrix. If number of training set is \( m \), where \( m \) represents multiplication between \( c \) and \( \sum p_i \), the label matrix is a set of values labeled training sets, which is arranged as a matrix of rows or column. If known \( c \) class training set, for \( i \) each class using the \( p_i \) images, the label matrix \((L)\) can be written using the following matrix

\[
Lb = \begin{bmatrix}
1, & \cdots & 1_{p_1}, & 2, & \cdots & 2_{p_2}, & \cdots, & c, & \cdots, & c_{p_c}
\end{bmatrix}^T
\]  

(2)

In this case

\[
T = \sum_{k=1}^{c} P_i
\]  

(3)

**The New Subspace Projection and the Weight of the Principal Component Analysis**

To overcome the singularity problem and obtain the new subspace, the Locally Preserving Projection method is always started with the Principal Component Analysis process. The results of Eigenvalue \((\lambda)\) and followed Eigenvector \((V)\) are used to obtain new subspace projection and the weight as follows

\[
N^{(PCA)} = X^T \ast V
\]  

(4)

\[
W^{(PCA)} = X \ast N^{(PCA)}
\]  

(5)

**The Affinity Matrix**

For both new subspace projection and the weight will be used to compute of the Locally Preserving Projection. Beside them, the Affinity matrix is also requested. There are five main processes to compute the Affinity matrix as shown in Figure (1)

![Figure 1. The Affinity Matrix Calculation (L)](image-url)
The constant value \( t \) has a range between 0 until 1. To compute the Similarity Matrix \( S \), the training set is calculated the distance using “Euclidian Distance Method”. Calculation is conducted between \( n^\text{th} \) row and \( n^\text{th+1} \) row as follows

\[
S_{i,j} = \begin{cases} 
\frac{\sum_{e} |P_{i,e} - P_{j,e}|^t}{e} & \text{if } i \neq j \\
0 & \text{otherwise}
\end{cases} 
\]  

(6)

The result of an Equation (6) is called as the “Normal Euclidian”. Furthermore, the connectivity matrix \( G \) is necessary to be built. To obtain the value of the connectivity matrix \( G \), an Equation (2) will be used as reference to produce it. The connectivity matrix builds a matrix with element “1”, where the matrix size is equal to the number of image member. If number of images for the first class has \( p_i \) images member, then the connectivity matrix can be seen as follows

\[
G = \begin{bmatrix}
1_{1,1} & 1_{1,2} & \cdots & 1_{1,p_i} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1_{2,1} & 1_{2,2} & \cdots & 1_{2,p_i} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1_{p_i,1} & 1_{p_i,2} & \cdots & 1_{p_i,p_i} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1_{1,1} & 1_{1,2} & \cdots & 1_{1,p_i} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1_{2,1} & 1_{2,2} & \cdots & 1_{2,p_i} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \vdots & \vdots & \ddots & \vdots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1_{p_i,1} & 1_{p_i,2} & \cdots & 1_{p_i,p_i} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \ddots & \vdots & \vdots & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1_{1,1} & \cdots & 1_{1,p_i} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & \ddots & \vdots & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1_{p_i,1} & \cdots & 1_{p_i,p_i}
\end{bmatrix}
\]  

(7)

The results of the Equation (6) and (7) are used to calculate the Heat Kernel matrix \( H \), where the Kernel Matrix is the results of dot product multiplication between the Normal Euclidian \( S \) and the connectivity matrix.

\[
H = G \bullet S_{i,j}
\]  

(8)

The result of Equation (8) will be selected the maximum values, the result of the maximum values selection is called as Affinity matrix as shown in the following equation

\[
L = \max(H, H')
\]  

(9)
A New regulation of the Locally Preserving Projection

The training sets, new subspace and the weight of the Principal Component Analysis, an Affinity matrix, as seen in Equation (4), (5), and (9) are used as input of the proposed method, which is the “New Regulation of Locally Preserving Projection”. The result of the Affinity matrix as seen the Equation (9) is summed based on row. Mathematically, sum of the Affinity matrix can be written as follows.

\[ D_i = \sum_{j=1}^{m} L_{i,j} \]  

(10)

For both the value of the Affinity Matrix \((D)\) and the diagonal matrix \((L)\) are symmetric and positive semi-definite. It shows that the value of \(X^*L^*X^T\) and \(X^*D^*X^T\) are also symmetric and positive semi-definite. In this research, to obtain the dominant features, the values of Eigenvector can be obtained by optimizing the \(a^*\) as seen in the following equation.

\[
a^* = \arg \max \left( \frac{(X^T * D * X) + (X^T * D * X)^T \bullet + \zeta)}{(X^T * L * X) + (X^T * L * X)^T \bullet + \zeta} \right)
\]  

(11)

The result of Equation (12) are the Eigenvalue \((\lambda^{(R_{LPP})})\) and Eigenvector \((V^{(R_{LPP})})\). The Eigenvalue must be sorted decreasingly and followed by corresponding of the Eigenvector. The Eigenvectors \((V^{(R_{LPP})})\) are used to obtain the new subspace \((N^{(R_{LPP})})\) and the new weight of the proposed method \((W^{(R_{LPP})})\) as follows.

![Figure 2. New Regulation of Locally Preserving Projection Process](image-url)
To evaluate the proposed method, four similarity measurements method were used, namely Euclidian Distance, Manhattan, Canberra, and Chebyshev.

The modification results of the Locally Preserving Projection as seen in Equation (11) has produced symmetric and positive semi-definite matrix. The generated features as seen Equation (13) can separate object better than the original method, which is the Locally Preserving Projection. The proposed method did not need iteration process to obtain the projection matrix as the dominant features. It is need \( O(n^2) \) to obtain new regulation of the constraint of the Locally Preserving Projection and \( O(n^3) \) to obtain its transpose. Total time complexity is \( 2O(n^2) \). It is equivalent to \( O(n^3) \).

### 3. Experimental Results and Discussions

In this research, three face image databases were used to evaluate performance of the proposed method, which are the ORL, the YALE, and the University of Bern face image databases. For each face image databases have been evaluated using the proposed method, which are two, three, four and five for the University of Bern, the YALE and the ORL face image database.

**The Proposed Method Experimental Results on the University of Bern Face Image Database**

The University of Bern has captured thirty persons, for each person has 10 different poses. The face image has 512 pixels for height and 342 pixels for width. In this experiment, the image has been change the size into 140 pixels for height and 120 pixels for width [17].

![Figure 3. The University of Bern Face Image Database [17]](image)

Four scenarios has been conducted by using the University of Bern face image database, which are using two, three, four and five training sets as show in Figure...
4. To reduce computation time, the proposed method uses ten until thirty features for similarity measurements. In Figure 4a shows that the maximum recognition rate is 79.58%. The best recognition rate occurred when it uses thirty features.

The experimental results using three training sets produce higher recognition rate than using two training sets. It can be shown that the maximum recognition results obtained is 86.67%, when it uses thirty features as seen in Figure 4b.

The similar pattern is also occurred, when experimental using four and five training sets as seen in Figure 4c and 4d. The maximum recognition rates obtained are 93.89% for four training sets and 98% for five training sets. The best recognition is obtained when it uses thirty features for four training sets and twenty seven features for five training sets.

Figure 4. Recognition Results on the University of Bern Face Image Database Using 2 (a), 3 (b), 4 (c), and 5 (d) Training Sets of the proposed Method.

The Proposed Method Experimental Results on the YALE-A Face Image Database

The YALE-A face image database is also used to evaluate the performance of the proposed method. The YALE has 165 images [18]. They are captured from fifteen persons, for each person has 15 pose. The image height and width are 136 and 104 pixels. The image sample of YALE-A can be seen in Figure (5).
The experimental results can be shown in Figure 6. Figure 6a shows the experimental results using two training sets. The best recognition rate is occurred when using fifteen features, which is 82.96%. In this case, addition of the features cannot increase the recognition rate. Figure 6b displayed the experimental results using three training sets. The maximum recognition rate has occurred when using fourteen and fifteen features, which is 85.83%. The maximum recognition rate obtained using three training sets is higher than using two training sets. It shows that number of the training sets has effect to the recognition rate.

The similar condition is also occurred when using four training sets. The maximum recognition rate obtained is 96.19% as seen in Figure 6c. A significant increase has occurred when the number of training set is four training sets. The difference of the recognition results between three and four training sets is 10.36%. It means the dominant features of the more training sets will produce the more recognition rate. The experimental results using five training sets have produced the lower recognition than using four training sets, though it is not significant. The maximum recognition rate for five training sets is 95.56% as seen in Figure 6d, whereas for five training sets is 96.19%. It shows that the difference is 0.63%.

Figure 6. Recognition Results on the YALE-A Face Image Database Using 2 (a), 3 (b), 4 (c), and 5 (d) Training Sets of the proposed Method
The Proposed Method Experimental Results on the ORL Face Image Database

The last training set to evaluate the robustness of the proposed method is the ORL face image database (see Figure 7). It has captured forty persons, for each person was captured with the different expressions, lighting, and times [19]. It shows that the ORL face image database has at least 400 data experiment. As like the previous scenario, the ORL face image database is dividing into two parts, which are the training and testing set. Four scenarios have been conducted to verify the proposed method. The recognition rate for each scenario can be seen in Figure 8.

![Figure 7. Sample of the ORL Face Image Database [19]](image_url)

![Figure 8. Recognition Results on the ORL Face Image Database Using 2 (a), 3 (b), 4 (c), and 5 (d) Training Sets of the proposed Method](image_url)

The usage of the training sets from two until five show that, the recognition rate increases with the number of training set used. The maximum recognition rates
obtained are 81.56%, 91.07%, 95.41% and 96% for two, three, four and five the training sets respectively. Recognition rate tends to increase proportional to the number of training sets used. The similarity results are also occurred when using three, four and five the training sets. The significant difference of the recognition rate has occurred when using two and three the training sets (9.51%). But the difference of the recognition rate between four and five training sets is only 0.59%.

**Discussions and Comparing to Other Method**

Beside the features, the training set also influence to the recognition rate. The recognition rate is increase when the number of features is also increase. It can be seen the increasingly recognition, when the number of dominant features are also increased. The recognition rate is almost excellent when using five training sets. It is occurred when thirty features are used.

The best recognition rate on the University of Bern, the YALE-A, and the ORL face databases are 96%, 96.19% and 98% respectively as seen in Figure 9. The proposed method has showed that the local features can represent the characteristics in detail, so that they can work efficiently. The low dimensionality has been taken to evaluate the proposed method. The recognition results show that the proposed method has produced the higher recognition on the low dimensionality. Table 1 describes the features that are not used in the measurement of similarity. As can be conducted in the experimental, the proposed method only used five until thirty features in the similarity measurements. It shows that the number of features used is very little, but it can produce the higher recognition rate. The training computation time of the proposed method can be seen in Table 2. The average of computation time is 0.05 second for each training image set.

<table>
<thead>
<tr>
<th>Training Set Used</th>
<th>UB Number of Images Training</th>
<th>Features are not Used</th>
<th>YALE Number of Images Training</th>
<th>Features are not Used</th>
<th>ORL Number of Images Training</th>
<th>Features are not Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>60</td>
<td>30-55</td>
<td>30</td>
<td>0-25</td>
<td>80</td>
<td>50-75</td>
</tr>
<tr>
<td>3</td>
<td>90</td>
<td>60-85</td>
<td>45</td>
<td>15-40</td>
<td>120</td>
<td>90-115</td>
</tr>
<tr>
<td>4</td>
<td>120</td>
<td>90-115</td>
<td>60</td>
<td>30-55</td>
<td>160</td>
<td>130-155</td>
</tr>
<tr>
<td>5</td>
<td>150</td>
<td>120-135</td>
<td>75</td>
<td>45-70</td>
<td>200</td>
<td>170-195</td>
</tr>
</tbody>
</table>
Table 2. The Average of Computation Time of the Proposed Method

<table>
<thead>
<tr>
<th>Training Set Used</th>
<th>Number of Images Training</th>
<th>Average Number of Comp. Time (Second)</th>
<th>Number of Images Training</th>
<th>Average Number of Comp. Time (Second)</th>
<th>Number of Images Training</th>
<th>Average Number of Comp. Time (Second)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>60</td>
<td>0.05</td>
<td>30</td>
<td>0.06</td>
<td>80</td>
<td>0.05</td>
</tr>
<tr>
<td>3</td>
<td>90</td>
<td>0.04</td>
<td>45</td>
<td>0.06</td>
<td>120</td>
<td>0.05</td>
</tr>
<tr>
<td>4</td>
<td>120</td>
<td>0.04</td>
<td>60</td>
<td>0.05</td>
<td>160</td>
<td>0.05</td>
</tr>
<tr>
<td>5</td>
<td>150</td>
<td>0.03</td>
<td>75</td>
<td>0.06</td>
<td>200</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Figure 9 is the comparison result between the proposed methods and other methods. The comparison results on the University of Bern face image database shows that, the proposed method outperformed to other methods, such as the Eigenface, Fisherface, Laplacianfaces, and Orthogonal Laplacianfaces. The similar results are also occurred on the YALE-A face image database. The proposed method is also better than other methods.

On the ORL face image database, the Orthogonal Laplacianfaces has obtained better recognition rate than the proposed method when using five training sets only. But the proposed method has produced better recognition rate than other methods for all training sets, except using five training sets.

Figure 9. The Comparison Results between the Proposed Method and Other Methods, (a) Using the University of Bern Face Image Database. (b) Using the YALE-A Face Image Database. (c) Using the ORL Face Image Database.
5. Conclusions

The proposed method has been proven to represent a new space that can be used as a feature for face recognition on three databases. The local features can produce the higher recognition than global features, such as the Principal Component Analysis and Linear Discriminant Analysis. The proposed method has demonstrated with lower dimensional, but it has been able to produce high accuracy. The experimental results have proven, the recognition rate depend on two factors. The first is the number of training sets and the second as the number of features used for similarity measurements. The more the training sets and features used, the higher recognition rate obtained and vice versa.

References


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