A Face Recognition Algorithm Using a Fusion Method Based on Adaboost Bidirectional 2DLDA

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Abstract

A challenge for face recognition is variation, such as due to lighting or facial expression differences. To solve this problem, we fuse bidirectional two-dimensional linear discriminant analysis (2DLDA) feature by adaboost technique and propose a novel recognition method called AB2DLDA in this paper. This method can perform well with small number of samples. In this paper, firstly we analyze complementarity for vertical direction of 2DLDA and horizontal direction of E2DLDA. Then we use adaboost to design a classifier, which improves recognition performance by fusing 2DLDA and E2DLDA. Finally, our method is tested on AR face databases. Experimental results show that our method functions with good recognition accuracy and robustness.

Keywords: Face Recognition, Adaboost, Bidirectional Two-Dimensional Linear Discriminant Analysis

1. Introduction

LDA (Linear Discriminant Analysis) is a universal algorithm in pattern recognition [1, 2]. It minimizes element’s distance in one class and maximizes distance between different classes. Then LDA obtains the best classified result by the best mapping direction. Though LDA is widely used in pattern recognition, it cannot solve two problems in face recognition. One is facial variation by variation of lighting and facial expression; another is problem of small sample size [3, 4]. The variation leads to complex non-convex distribution in face image. It makes decrease of recognition performance algorithms which are based on surface. There are many ways to study in non-convex [5-7] and Boosting algorithm is shown higher stabilization. This algorithm is constructed by machine learning theory and simply realized.

Small sample problem is another important problem in face recognition. In fact, when samples’ number is too small to feature dimensionality, the large distance of different samples will make dispersion matrix singular and distance measure invalid. Therefore, LDA cannot find best mapping direction. Nowadays, the main kinds of methods to solve small sample problem are shown below.

a. Regularized Discriminant Analysis [8]. This method uses disturbance to make dispersion matrix nonsingular.

b. Subspace of Low Dimensionality.

These methods decrease dimensionality of sample space. The representative methods are FisherFaces, LDA based on QR decomposition [9], Null space LDA [10, 11], Random subspace LDA [12, 13], et al.

c. LDA in two dimensionality image matrix directly.

These methods decrease dimensionality of sample space. The representative methods are FisherFaces, LDA based on QR decomposition [9], Null space LDA [10, 11], Random subspace LDA [12, 13], et al.

Nowadays, studies in face recognition are also based on LDA. In this paper, we find a new method in face recognition. Our method is based on two dimensionality LDA method. This is because 2DLDA avoids small sample problem and estimate more accurate dispersion matrix both in one class and between different classes than one dimensionality methods. Firstly, we analyze the algorithm of 2DLDA and E2DLDA in some extent. Secondly, by fuse features of 2DLDA and E2DLDA by Adaboost, we give AB2DLDA algorithm. Finally, some experiments are executed to validate our algorithm. The experiments validate effectiveness, robustness and speed of our algorithm.
2. AB2DLDAlgorithm

2.1 2DLDA and E2DLDA

To set \( X = \{X_1, X_2, \ldots, X_i, \ldots, X_L\} \), \( L \) is number of sample classes, \( X_i \) is sample set of class \( i \), \( L_i \) is number of sample \( i \). \( \bar{X} \) is average value of all samples, \( \bar{X}_i \) is average value of class \( i \). 

We use \( P_{2DLDA} \) to describe the best mapping direction of 2DLDA in formula (1).

\[
P_{2DLDA} = \arg \max_w \frac{W^T S^L_w W}{W^T S^L_b W}
\]

Then we use \( S^L_w = \sum_{i=1}^{L} \sum_{j=1}^{L_i} \frac{1}{N} (X_{i,j} - \bar{X}_i)(X_{i,j} - \bar{X}_i)^T \) to describe dispersion matrix in one class and \( S^L_b = \sum_{i=1}^{L} \sum_{j=1}^{L_i} \frac{1}{N} (X_i - \bar{X})(X_i - \bar{X})^T \) to describe dispersion matrix between different classes.

When \( V \) is eigenvalue matrix and \( U \) is eigenvector matrix of \( S^L_w^{-1} S^L_b \), we set \( V = \{V_1, V_2, \ldots, V_i, \ldots, V_m\} \) for \( i = 1, 2, \ldots, m \), \( U = \{U_1, U_2, \ldots, U_i, \ldots, U_m\} \) for \( i = 1, 2, \ldots, m \). Then when we set \( d \) to describe dimensionality reduction parameters, we rank \( V \) with descending order and find \( d \) eigenvectors \( \{U_1, U_2, \ldots, U_d\} \) which are corresponding \( d \) larger eigenvalue \( \{V_1, V_2, \ldots, V_d\} \). The eigenvectors \( \{U_1, U_2, \ldots, U_d\} \) is best mapping direction. The \( d \) is always valued by contribution rate. Experience threshold is valued larger than 90%.

Similarly, we use \( P_{E2DLDA} \) to describe the best mapping direction of E2DLDA in formula (2).

\[
P_{E2DLDA} = \arg \max_w \frac{W^T S^L_w W}{W^T S^L_b W}
\]

Then \( S^L_w = \sum_{i=1}^{L} \sum_{j=1}^{L_i} \frac{1}{N} (X_{i,j} - \bar{X}_i)^T (X_{i,j} - \bar{X}_i) \) is defined to dispersion matrix in one class and \( S^L_b = \sum_{i=1}^{L} \frac{L_i}{N} (X_i - \bar{X})^T (X_i - \bar{X}) \) is defined to dispersion matrix between different classes.
2.2 Process of AB2DLDA

To set training database \( X \), set of sample type \( Y = \{1, \ldots, L\} \), misclassification set of sample \( B = \{(X_{i,j,l}) : l \in Y, l \neq i\} \), initial classification weight of sample \( Z_i(X_{i,j,l}) = \frac{1}{|B|} = \frac{1}{N(L-1)} \).

For \( t = 1, \ldots, T \)

Step 1. To update error distribution of sample \( D_t(Z) \) and pairwise error distribution \( PD_t \).

\[ D_t = \sum_{i=1}^{L} Z_i(X_{i,j,l}) \]

\[ PD_t = \begin{cases} \frac{1}{2} \left( \sum_{i=1}^{L} Z_i(X_{i,j,l}) + \sum_{j=1}^{L} Z_i(X_{i,j,l}) \right) & \text{otherwise} \\ 0 & (p,q) : p, q \in Y \end{cases} \]

Step 2. To set \( t = 1 \) for the first iteration, to obtain \( R_t \subset X \) by select \( r \) samples from each class, otherwise, to obtain \( R_t \subset X \) by select \( r \) misclassification samples from each class of \( D_t \).

Step 3. To extract LDA features and obtain classifier \( C_t \) by use \( D_t, PD_t \) and \( R_t \). To avoid similar classifier, dispersion matrixes in one class and between different classes of LDA are redefined.

\[ \hat{S}_{ij}^L = \sum_{p=1}^{L} \phi_p \phi_p^T \]

\[ \hat{S}_{ij}^R = \sum_{p=1}^{L} \phi_p \phi_p^T \]

\[ \hat{S}_{ij}^L = \frac{1}{N} \sum_{i=1}^{L} \sum_{j=1}^{L} D_t(X_{i,j})(X_{i,j} - \bar{X}_i)(X_{i,j} - \bar{X}_i)^T \]

\[ \hat{S}_{ij}^R = \frac{1}{N} \sum_{i=1}^{L} \sum_{j=1}^{L} D_t(X_{i,j})(X_{i,j} - \bar{X}_i)^T(X_{i,j} - \bar{X}_i) \]

Step 4. To obtain iteration loss \( E_t \) and present weight of classifier \( \beta_t \).

\[ E_t = \frac{1}{2} \sum_{(X_{i,j,l}) \in B} Z_i(X_{i,j,l})(1 - h_t(X_{i,j,i}) + h_t(X_{i,j,l})) \]

\[ \beta_t = \frac{E_t}{1 - E_t} \]

Step 5. To update \( Z_t \).

\[ Z_{t+1}(X_{i,j,l}) = \begin{cases} \alpha Z_t(X_{i,j,l}) & \text{if } (1 - h_t(X_{i,j,i}) + h_t(X_{i,j,l})) \geq 1 \\ Z_t(X_{i,j,l}) & \text{else} \end{cases} \]

\[ \alpha > 1 \] is a constant.

Step 6. To unified \( Z_t \).

\[ Z_{t+1}(X_{i,j,l}) = \frac{Z_{t+1}(X_{i,j,l})}{\sum_{(X_{i,j,l}) \in B} Z_{t+1}(X_{i,j,l})} \]
Finally, we obtain strong classifier

\[
C(x) = \arg \max_{i \in Y} \sum_{t=1}^{r} \left( \log \frac{1}{\beta_t} \right) C_t(x, t)
\]

3. Experiment Result

3.1 Face Database

We use AR [18] to experiment.

![Ar database images](image)

Figure 1. AR database (a & d: normal, b & e: smile, c & f: anger, g & j: left lighting, h & k: right lighting, i & l: bilaterally lighting)

In this paper, we use faces of 121 persons in AR database. There are 12 samples of a person with expression and lighting variety. Total number of training images is 1452. We divide AR_E to two parts by time. In figure 1, images a-c are from AR_E1 and d-f are from AR_E2. We also divide AR_L to two parts by time. Images g-i are from AR_L1 and j-l are from AR_L2 in figure 1.

Before experiment, all samples are processed initially. We equalize grey level and zoom them to the same size 48×66. In our experiment, we use leave-one-out in cross validation method because some objects may not be selected in training database. So the experiment result will be shown great accurate in our test of recognition performance, stability and robustness when we use leave-one-out method. All experiment contains five parts.

a. Experiment of expression variety,

b. Experiment of lighting variety,

c. Experiment of both expression and lighting variety,

d. Analysis of recognition performance overall,

e. Validation of theorem 1. In other words, we validate correctness of AB2DLDA.

3.2 Expression Variety

The average recognition results of AR_E is shown in table 1. Then we show average recognition rate by different K and R in figure 2.
Table 1. Comparison of recognition rate of different algorithms with expression variety

<table>
<thead>
<tr>
<th>Database</th>
<th>Algorithm</th>
<th>E1</th>
<th>E2</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>FisherFaces</td>
<td>58.40</td>
<td>64.46</td>
<td>61.43</td>
</tr>
<tr>
<td></td>
<td>2DLDA</td>
<td>95.59</td>
<td>94.50</td>
<td>95.04</td>
</tr>
<tr>
<td></td>
<td>E2DLDA</td>
<td>95.60</td>
<td>96.42</td>
<td>96.01</td>
</tr>
<tr>
<td></td>
<td>B2DLDA</td>
<td>95.04</td>
<td>94.77</td>
<td>94.90</td>
</tr>
<tr>
<td></td>
<td>(2D)LDA</td>
<td>96.14</td>
<td>95.04</td>
<td>95.59</td>
</tr>
<tr>
<td></td>
<td>R=3</td>
<td>97.25</td>
<td>97.52</td>
<td>97.38</td>
</tr>
<tr>
<td></td>
<td>R=4</td>
<td>96.97</td>
<td>96.69</td>
<td>96.83</td>
</tr>
</tbody>
</table>

Figure 2. Recognition rate of AB2DLDA with expression variety. R is sampling number of each kind of sample.

In Table 1 and Figure 4, we find that expression variety makes great negative effect in the vertical direction. But there is enough information in the horizontal direction. So we find E2DLDA shows better result than 2DLDA. Then we can see that AB2DLDA is always shows better result than other algorithms. It is because our algorithm has more discriminant information. We can see there is better result when K is larger. This is tendency of AB2DLDA.

3.3 Lighting Variety

We show average recognition result of CAL_L and AR_L in Table 2. Then we show average recognition rate by different K and R in Figure 3.

Table 2. Comparison of recognition rate of different algorithms with lighting variety

<table>
<thead>
<tr>
<th>Database</th>
<th>Algorithm</th>
<th>L1</th>
<th>L2</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>FisherFaces</td>
<td>68.6</td>
<td>68.6</td>
<td>68.6</td>
</tr>
<tr>
<td></td>
<td>2DLDA</td>
<td>81.54</td>
<td>83.75</td>
<td>82.64</td>
</tr>
<tr>
<td></td>
<td>E2DLDA</td>
<td>86.78</td>
<td>86.23</td>
<td>86.5</td>
</tr>
<tr>
<td></td>
<td>B2DLDA</td>
<td>79.89</td>
<td>79.89</td>
<td>79.89</td>
</tr>
<tr>
<td></td>
<td>(2D)LDA</td>
<td>76.31</td>
<td>77.41</td>
<td>76.86</td>
</tr>
<tr>
<td></td>
<td>R=3</td>
<td>92.84</td>
<td>95.87</td>
<td>94.35</td>
</tr>
<tr>
<td></td>
<td>R=4</td>
<td>92.56</td>
<td>94.49</td>
<td>93.52</td>
</tr>
</tbody>
</table>
We find that complementarity of 2DLDA and E2DLDA shows obvious by lighting variety. For example, recognition result of 2DLDA is better than E2DLDA in AR_L, because there is great shade change by horizontal lighting from one side. In this case, nearly all row information is affected negatively. But there are half column information persisted because half of one image nearly intact. So 2DLDA and AB2DLDA shows their advantage.

3.4 Both expression and lighting variety

We show average recognition result of CAL and AR with both expression and lighting variety in table 3. Then we show average recognition rate by different K and R in figure 4.

Table 3. Comparison of recognition rate of different algorithms with both expression and lighting variety

<table>
<thead>
<tr>
<th>Database</th>
<th>Algorithm</th>
<th>E</th>
<th>L</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FisherFaces</td>
<td>59.78</td>
<td>75.21</td>
<td>67.49</td>
</tr>
<tr>
<td></td>
<td>2DLDA</td>
<td>86.5</td>
<td>93.66</td>
<td>90.08</td>
</tr>
<tr>
<td></td>
<td>E2DLDA</td>
<td>91.18</td>
<td>84.02</td>
<td>87.6</td>
</tr>
<tr>
<td>AR</td>
<td>B2DLDA</td>
<td>85.95</td>
<td>93.66</td>
<td>89.81</td>
</tr>
<tr>
<td>AR</td>
<td>$(2D)^2$LDA</td>
<td>84.57</td>
<td>93.11</td>
<td>88.84</td>
</tr>
<tr>
<td></td>
<td>AB2DLDA</td>
<td>R=3</td>
<td>93.94</td>
<td>95.04</td>
</tr>
<tr>
<td></td>
<td>AB2DLDA</td>
<td>R=4</td>
<td>93.66</td>
<td>96.69</td>
</tr>
</tbody>
</table>

![Figure 3](image3.png)

**Figure 3.** Recognition rate of AB2DLDA with lighting variety. R is sampling number of each kind of sample.

We find that complementarity of 2DLDA and E2DLDA shows obvious by lighting variety. For example, recognition result of 2DLDA is better than E2DLDA in AR_L, because there is great shade change by horizontal lighting from one side. In this case, nearly all row information is affected negatively. But there are half column information persisted because half of one image nearly intact. So 2DLDA and AB2DLDA shows their advantage.

![Figure 4](image4.png)

**Figure 4.** Recognition rate of AB2DLDA with both expression and lighting variety. R is sampling number of each kind of sample.
Experiment result in this part is consistent to the above two results. Our algorithm shows better result than 2DLDA and E2DLDA with lighting variety. In table 3, we find that only AB2DLDA makes rate more than 80% with lighting variety in CAL. This means AB2DLDA shows better performance and stability than other algorithms. Then we can see that recognition rate of expression variety is better than lighting variety in all algorithms. It is to say that lighting variety is also a different area to study in future.

3.5 Analysis of recognition performance overall

We show average recognition result of AR with overall samples in table 4. We find that AB2DLDA shows better result than 2DLDA and E2DLDA by overall samples with both expression and lighting variety. To compare with B2DLDA and (2D)2LDA, AB2DLDA improve performance because it obtains more information by complementarity of 2DLDA and E2DLDA.

<table>
<thead>
<tr>
<th>Database</th>
<th>Algorithm</th>
<th>E</th>
<th>L</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>FisherFaces</td>
<td>60.88</td>
<td>70.80</td>
<td>65.84</td>
</tr>
<tr>
<td></td>
<td>2DLDA</td>
<td>92.2</td>
<td>86.32</td>
<td>89.26</td>
</tr>
<tr>
<td></td>
<td>E2DLDA</td>
<td>94.4</td>
<td>85.68</td>
<td>90.04</td>
</tr>
<tr>
<td></td>
<td>B2DLDA</td>
<td>91.92</td>
<td>84.48</td>
<td>88.2</td>
</tr>
<tr>
<td></td>
<td>(2D)²LDA</td>
<td>91.92</td>
<td>82.28</td>
<td>87.1</td>
</tr>
<tr>
<td></td>
<td>AB2DLDA S=3</td>
<td>95.96</td>
<td>94.58</td>
<td>95.27</td>
</tr>
<tr>
<td></td>
<td>AB2DLDA S=4</td>
<td>95.78</td>
<td>94.58</td>
<td>95.18</td>
</tr>
</tbody>
</table>

4. Conclusion

2DLDA uses discriminant information in vertical direction and E2DLDA uses discriminant information in horizontal direction. We observe that the information in these two directions shows consistency and complementarity. We improve the pattern recognition performance by fusing the discriminant information in both vertical and horizontal directions. The experiments show that the new algorithm can achieve better recognition performance.

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