FACE RECOGNITION RESEARCH BASED ON ANTI-SYMMETRICAL WAVELET AND EIGENFACE

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Abstract:
In this paper, a new human face recognition method based on anti-symmetrical biorthogonal wavelet transformation (ASBWT) and eigenface was proposed. First the anti-symmetrical biorthogonal wavelet is chosen to degrade the face image dimension, meanwhile complete the process of face location and segmentation; And then human face is reverted through the face space of Eigenface, the traditional average human face is replaced in the within-class scatter matrix. This within-class scatter matrix is used to calculate within-class and between-class distance proportion as a rule function, calculate the twice eigenface through Discrete Karhunen-Loeve Transform (DKLT), and use Singular Value Decomposition (SVD) method to calculate the eigenvector. Finally we compute the weights and classify the face images. The results show that the proposed method has higher recognition rate and more robust than the traditional eigenface analysis method.

Keywords:
Face recognition; Anti-symmetrical biorthogonal wavelet; Eigenface; SVD

1. Introduction

Eigenface is a significant research direction with immense attraction and challenge in Pattern Recognition domain. Reliable and robust face recognition system has broad application prospects. Facial variation makes face recognition is so difficult, as age growth, pose variety, illumination changes and difference of collection facilities will make face images different. Face recognition method with high accuracy rate and strong adaptability is pursued by people all the time. Currently, face recognition methods can be mainly divided into two categories: One is geometric features based approaches, which typically extracted a set of facial features from the image, such as eyes, nose etc, used them to classify the face; the other is global or “holistic” approaches, which takes a holistic view of the recognition problem, and holistic feature extraction of face images is adopted in this approach [1][2]. Common global features approaches includes Eigenfaces [3], Fisherfaces [4], complete 2-Dimensional principle component analysis (2-DPCA) [5], wavelet transform analysis [6] and support vector machine (SVM) [7], Probabilistic decision based Neural Networks (PDBNN) [8], and so on. These methods have good recognition rate in certain specific circumstances, whereas the recognition rate may be influenced on the condition changes.

The approach proposed in this paper is to utilize wavelet transforms for face location and segmentation. The anti-symmetrical biorthogonal wavelet was chose to degrade the face image dimension for it inheres good character as bases; then perform discrete Karhunen-Loeve Transform [9], revert human face by means of the eigenspace obtained by Eigenface, and subtract them from original face, to substitute for traditional mean human face $\mu_i$ in the within-class scatter matrix $S_w$; adopt SVD (Singular Value Decomposition) method to calculate the eigenvectors of within-class scatter matrix $S_w$, overall scatter matrix $S_o$ and between-class scatter matrix $S_b$ finally use the proportion between the within-class and the between-class distance as a criterion function to acquire the twice eigenface for face images recognition. This method improves the recognition rate and enhances the robustness effectively compared to the classical Eigenfaces method.

2. Theoretical foundation

2.1. ASBWT

Compared with Fourier transform and WFT(windows Fourier transform), wavelet transform has both spatial (or temporal) and frequency dual locality, which is able to implement function or signals Multiscale Analysis through the translation and dilation operation.
Symmetrical biorthogonal wavelet CDF-9-7 is confirmed to be of excellent property on coding compression by abundant research, which makes it be the first choice for American FBI in fingerprint image compression. However, studies indicate that anti-symmetrical biorthogonal wavelet works better than symmetrical biorthogonal wavelet on some aspects of coding compression [10]. Anti-symmetrical biorthogonal wavelet has differential coefficient function, which makes it feasible applying wavelet coefficient to extract image characteristic directly from compression data domain.

Assume that we are already given two pairs of functions \( \{\phi, \psi\}, \{\tilde{\phi}, \tilde{\psi}\} \), where scaling functions \( \phi, \tilde{\phi} \) are used to generate MRA \( \{V_j\} \) and MRA \( \{	ilde{V}_j\} \), respectively, and the other two functions \( \psi, \tilde{\psi} \) to generate corresponding complementary space respectively. If their inner product satisfy the condition as follows.

\[
\begin{align*}
\langle \phi(x - l), \tilde{\phi}(x - m) \rangle &= \delta_{l,m} \\
\langle \phi(x - l), \psi(x - m) \rangle &= 0 \\
\langle \psi(x - l), \tilde{\psi}(x - m) \rangle &= 0 \\
\langle \psi(x - l), \tilde{\psi}(x - m) \rangle &= \delta_{l,m}
\end{align*}
\]

Then we call the two pairs of functions dual biorthogonal wavelet. Apply two-dimensional biorthogonal wavelet to process human face frequency domain decomposition, four areas are derived: horizontal and vertical low frequency information (LL) called approximation component; horizontal high frequency (High Pass); horizontal low frequency and vertical high frequency information (HL); both horizontal and vertical are high frequency information (HH).

2.2. Eigenfaces

Human faces recognition based on Eigenfaces is first proposed by Turk and Pentland of MIT Media laboratory [3][11]. Considering Eigenfaces is not sensitive to rotation of certain angle and has good robustness, and which is a relatively mature recognition technique by now, FaceIT chose Eigenfaces as its recognition technique[12]. FaceIT from Visionics is a famous commercial product of automatic face recognition system.

Eigenfaces apply KL(Karhunen - Loeve) transform theory to original facial images with the purpose of finding a set of biorthogonal vectors, which best account for the distribution of face images within the entire image space. These vectors construct a new face space that is the so-called eigenfaces, which remains the basic information of facial images, and minimizes the mean-square error, achieving the goal of degrading dimension.

Assume that we apply DKLT transform to the sequence of \( n \) facial images \( z_1, z_2, \ldots, z_K \), and \( \overline{z} \) represents the mean value of the \( n \) images, the overall scatter matrix \( S_t \) which is used to be a generated matrix can be defined as (ignoring quotienty):

\[
S_t = \sum_{i=1}^{K} (z_i - \overline{z})(z_i - \overline{z})^T \in \mathbb{R}^{K \times K}.
\]

Then we can calculate normalization eigenvector \( u_i \), namely eigenface, through \( S_t \) ( \( S_t \) is positive definite matrix), and dimension of \( u_i \) is \( K - 1 \). We can also use between-class scatter matrix \( S_b \) as generated matrix for DKLT transform:

\[
S_b = \sum_{i=1}^{M} (\overline{m}_i - \overline{z})(\overline{m}_i - \overline{z})^T \in \mathbb{R}^{K \times K},
\]

\( \overline{m}_i \) is the mean vector for the \( i \)th person in the training image database, and \( M \) is the number of the people in the training image database. The dimension of eigenface calculated by \( S_b \) is \( M - 1 \). Replacing the overall scatter matrix \( S_t \) by between-class scatter matrix \( S_b \) can reduce calculation a lot, because the complexity of K-L transform is in proportion to the number of rows of the generated matrix, in other words it related with the number and dimension of the face vector.

Use between- and within-class distance proportion to construct criterion function as follows.

\[
J(y_i) = \frac{u_i^T S_b u_i}{u_i^T S_w u_i} = \frac{u_i^T S_b u_i}{\lambda_i}
\]

The within-class scatter matrix can be expressed as follows.

\[
S_w = \sum_{i=1}^{C} \sum_{j=1}^{N_i} (X_{ij} - \mu_i)(X_{ij} - \mu_i)^T
\]

In the formula(5), \( C \) is the number of people in the training sample set, \( N_i \) is the number of training samples for the \( i \)th person, each sample \( X_{ij} \) is the vector (dimension is \( j \) ) of the \( i \)th person’s facial image after
extending, \( \mu_i \) is the mean image of the ith person’s facial image samples. Calculate the corresponding eigenvalue \( \lambda_i \) and eigenvector \( u_i \) \((i = 1, 2, \ldots)\) by processing DKLT on \( S_n \). Then we can obtain \( J(y_i) \) by (4). Choose vectors corresponding with the former bigger values of \( J(y_i) \) as the transform matrix, which promises a good result.

When the dimension \( n \) of eigenvectors of pattern samples is far bigger than the number of training samples \( K \), it is difficult to calculate eigenvalues and eigenvectors of \( \Sigma \) directly. In this situation, we may choose SVD [13] to solve the problem. Singular value vector has good algebraic and geometrical invariance, such as stability, displacement invariance, and changing in proportion to corresponding image luminance, transposition invariance, and so on.

After calculating eigenvector \( u_i \) and the corresponding eigenvalue \( \lambda_i \) of Eigenface using criterion function constructed by between- and within-class distance proportion, we can calculate the weight of facial images and confirm clustering center, further more, test classification.

Calculate training images mean for each person, named \( \Gamma_k \), and the training images mean for all people is named \( \Psi \). Assume that the number of assured principal components is \( M1 \), and then the weight vector of the \( K \)-th person is:

\[
w_i = u_i^T (\Gamma_k - \Psi) \quad (i = 1, \ldots, M1)
\]  

(6)

As a result, we project it to the face space expanded by eigenvectors. \( w_i \) is the coordinate of mean image \( \Gamma_k \) for the \( K \)th person in eigenfaces. These weights constitute the weight vector for the \( K \)th person:

\[
\Omega^k = [w_1, w_2, \ldots, w_{M1}]
\]  

(7)

Take advantage of Nearest Neighbor (NN) method to judge image’s adscription sort. The judging function is Euclidean Distance.

\[
d_k = \| (\Omega - \Omega_k) \|^2
\]  

(8)

\( \Omega_k \) is the facial image sample center for the \( K \)th person, then we use the average distance of different images of the same person as primary benchmark threshold, and keep on modifying it from then on. Comparing the smaller \( d_k \) among those \( M \) \( d_i \) with the threshold, if smaller, then range it to the \( K \)th facial image class. If there are more than one \( d_k \) satisfied the condition, keep their information for further recognition.

3. Facial image recognition based on ASBWT and Eigenfaces

In the anti-symmetrical biorthogonal wavelet domain, to detect and locate faces, we can start with defining integral projection function[14]. Image integral projection is defined as follows. Given \( N \times M \) image \( I(x, y) \), horizontal function \( H(y) \) and vertical projection function \( V(x) \) can be defined respectively as:

\[
H(y) = \sum_{x=1}^{N} I(x, y)
\]  

(9)

\[
V(x) = \sum_{y=1}^{M} I(x, y)
\]  

(10)

Because organs like eyes correspond to chopped position in the facial images, it reflects to be edge information, namely maximum value, on the wavelet decomposing quotienty. Therefore, projection function presented above corresponds to different maximum value. Document [13] only provides general conclusions in theory, instead of specific processes. In practical processing, we may encounter many questions, such as several maximum values. Here we give a viable process method. Showing as Figure 1, the first line is the four areas information of facial images segmentation based on anti-symmetrical biorthogonal wavelet in order. Make integral projection on the vertical detail diagram to get integral projection function \( V(x) \) depicted as the curves in the first picture of the second line. There are obviously two peak values, we can set a value, so as to keep those maximum values bigger than it, the coordinates of the extreme point we get are 9 and 39. Intercept the horizontal detail diagram to get vertical bands according to those two extreme values just like the second picture in the second line. Similarly, make the horizontal projection to get \( H(y) \), several apparent maximum values appears and choose the last maximum value to be the mouth location information, then figure out the top boundary and bottom boundary to be 13 and 56 respectively on account of human face structure. Sequentially, a face is to be divided up, looks like the last facial image on the second line.
Original facial images exhibited in Figure 2 shows like Figure 3 after segmentation. Utilize between- and within-class distance proportion to construct criterion function, we can get eigenface vector $t_i$. While calculating between-class scatter matrix $S_w$, we revise formula (5) like below:

$$S_w = \sum_{i=1}^{C} \sum_{j=1}^{N_i} (X_{ij} - \hat{\Phi}_i)(X_{ij} - \hat{\Phi}_i)^T$$  (11)

$\hat{\Phi}_i$ is the ith person’s approximately reconstructed facial images (Figure 4), assume that the ith person’s eigenface vector is $\mu = [\mu_1, \mu_2, \cdots, \mu_M]$, then we can get $\hat{\Phi}_i$ through $\mu$’s pseudo-inverse, as well as through $\mu$ by K-L transform described in this paper.

After calculating twice eigenface information (Figure 5) by using between- and within-class distance proportion to construct criterion function, we can calculate weight and test classification to implement face recognition.

4. Experimental results and analysis

The experiments were performed on the ORL database, which is a popular face database in face recognition research in the international. This database includes 40 people, with 10 images for each person, and comprises 400
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images altogether. The images were taken at different time instances, with different lighting conditions, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the persons in an upright, frontal position, with tolerance for some movement. All of the images are 112 x 92 in size. We chose part of the database, which is chose randomly, as our training image database. Change the number of people for facial image database and the number of images for each person. Compared the performance of method presented in this paper with the classic Eigenfaces, and the correct recognition rate (CRR) obtained by them are reported in Table 1. From the results we know: after adopting the algorithms proposed in this paper, aiming at various facial image database, the recognition rate increases and improves evidently from the classic one. With less images in training set and higher classification recognition rate, recognition rate decreases going with the number of the sorts increasing. The revised algorithms is more stable, but if add images within class, in the case of small sample, recognition rate will decrease instead. The reason may be that the within-class image’s stability reduces the between-class’s difference. If there are many samples, the condition will get improved, that is the recognition rate is more stable. Additionally, the third method in the table is not sensitive to illumination, and apt to the case of big illumination changes, as a result, we get better robustness, without increase of calculation, only one more time of calculation while training, while the recognition speed is the same to the second method.

<table>
<thead>
<tr>
<th>Facial image database</th>
<th>Classical Eigenface (%)</th>
<th>ASBWT and SVD(%)</th>
<th>ASBWT segmentation, and SVD(%)</th>
<th>Eigenface</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 people 2 images for each</td>
<td>91.25</td>
<td>96.25</td>
<td>96.25</td>
<td></td>
</tr>
<tr>
<td>10 people 3 images for each</td>
<td>90.00</td>
<td>94.29</td>
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<tr>
<td>20 people 2 images for each</td>
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<td>87.5</td>
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<td>90.00</td>
<td></td>
</tr>
<tr>
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<td>83.33</td>
<td>84.58</td>
<td></td>
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<tr>
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<td>80.63</td>
<td>81.88</td>
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<tr>
<td>40 people 4 images for each</td>
<td>62.08</td>
<td>82.50</td>
<td>83.33</td>
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</tr>
</tbody>
</table>

5. Conclusions and future work

In this paper, a new method based on anti-symmetrical wavelet and eigenface was presented for human face recognition. Our experimental results have shown that this new method provides higher recognition rate and more robust in human recognition than the traditional eigenface method. Face recognition is a complicated project. In reality, the factors we have to consider are much more complex. To improve the face recognition rate and practicability, there is a big enhancing space for this paper, such as how to make use of wavelet transform areas better, how to exact and segment faces in the complicated background is the next study focus.

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References


