Face authentication system using pseudo Zernike moments on wavelet subband

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Abstract: Moments are widely-used feature extractors due to their superior discriminatory power and geometrical invariance. Unfortunately, moments suffer heavy computational load and result long time spending. In viewing of the problem, we proposed a new technique in using moments- apply moments on wavelet subband. In this study, pseudo Zernike moments are selected as feature extractors due to its enhanced feature representation capability. Implementation of moments on wavelet subband affords advantages of performing local-to-global analysis and decomposing image into lower resolution. Experimental results show that this hybrid achieves computational time reduction of 36.23% with enhanced authentication performance.

Keywords: Face authentication system, moments, wavelet

Classification: E019000 Science and engineering for electronics

References

1 Introduction

Javal et al [1] proposed a statistical-based approach, pseudo Zernike moments (PZM) as feature descriptors to face image. Application of moments in signal processing has been a focus in the recent years due to its superior feature representation capability and geometrical invariances [2]. Extracted moment-based features are scaling, rotation and translation invariant. These advantages prompted us for choosing PZM as feature extractor in our system. However, this approach suffers heavy computational burden as the other moments.

In viewing of this limitation, we proposed a new technique in using PZM-apply PZM on wavelet subband. Wavelet transform is able to decompose image into a lower dimensional multiresolution representation, which grants a compact hierarchical framework for interpreting the image information. Thus, PZM only works on lower dimensional subband of $8 \times 10$ pixels, instead of on the original image with dimension $61 \times 73$ pixels. Fig. 1 illustrates the overview of the proposed system- WPZM.

![Fig. 1. Overview of WPZM scheme.](image)

2 Wavelet transform

The wavelet decomposition of a signal $f(x)$ can be obtained by convolution of signal with a family of real orthonormal basis, $\psi_{a,b}(x)$ [3],

$$\langle W_\psi f(x) \rangle (a,b) = |a|^{-\frac{1}{2}} \int_\mathbb{R} f(x) \psi \left( \frac{x - b}{a} \right) dx \quad f(x) \in L^2(\mathbb{R})$$

(1)

where $a, b \in \mathbb{R}, a \neq 0$ are the dilation parameter and the translation parameter respectively. The basis function $\psi_{a,b}(x)$ is obtained through translation and dilation of a kernel function $\psi(x)$ known as mother wavelet as defined below:

$$\psi_{a,b}(x) = 2^{-a/2}\psi(2^{-a}x - b)$$

(2)

The mother wavelet $\psi(x)$ can be constructed from a scaling function, $\phi(x)$. The scaling function $\phi(x)$ satisfies the following two-scale difference equation

$$\phi(x) = \sqrt{2} \sum_{n} h(n) \phi(2x - n)$$

(3)
where \( h(n) \) is the impulse response of a discrete filter which has to meet several conditions for the set of basis wavelet functions to be orthonormal and unique [3]. The scaling function \( \phi(x) \) is related to the mother wavelet \( \psi(x) \) via

\[
\psi(x) = \sqrt{2} \sum g(n) \phi(2x - n) \tag{4}
\]

The coefficients of the filter \( g(n) \) are conveniently extracted from filter \( h(n) \) from the following relation

\[
g(n) = (-1)^n h(1 - n) \tag{5}
\]

For 2D signal such as image, there exists an algorithm similar to the one-dimensional case for two dimensional wavelets and scaling functions obtained from one-dimensional ones by tensorial product. This kind of two-dimensional wavelet transform leads to a decomposition of approximation coefficients at level \( j \) in four components: the approximations at level \( j \), \( L_j \), and the details in three orientations (horizontal, vertical and diagonal), \( D_{j\text{vertical}}, D_{j\text{horizontal}} \) and \( D_{j\text{diagonal}} \):

\[
L_j(m, n) = [H_x * [H_y * L_{j-1}]_{|2,1}|_{1,2}(m, n) \tag{6}
\]

\[
D_{j\text{vertical}}(m, n) = [H_x * [G_y * L_{j-1}]_{|2,1}|_{1,2}(m, n) \tag{7}
\]

\[
D_{j\text{horizontal}}(m, n) = [G_x * [H_y * L_{j-1}]_{|2,1}|_{1,2}(m, n) \tag{8}
\]

\[
D_{j\text{diagonal}}(m, n) = [G_x * [G_y * L_{j-1}]_{|2,1}|_{1,2}(m, n) \tag{9}
\]

where \(*\) denotes the convolution operator, \([2,1] (\downarrow1,2)\) subsampling along the columns (rows), \( H \) and \( G \) are a low pass and bandpass filter, respectively.

3 Pseudo Zernike moments

The two-dimensional pseudo Zernike Moments of order \( p \) with repetition \( q \) of approximation subband, \( L_j(r, \theta) \), are defined as [2, 4]:

\[
PZ_{pq} = \frac{p + 1}{\pi} \int_0^{2\pi} \int_0^1 V_{pq}(r, \theta) L_j(r, \theta) r dr d\theta \tag{10}
\]

where Zernike polynomials \( V_{pq}(r, \theta) \) are defined as:

\[
V_{pq}(r, \theta) = R_{pq}(r)e^{-jq\theta}; \quad j = \sqrt{-1} \tag{11}
\]

and \( r = \sqrt{x^2 + y^2}, \theta = \tan^{-1}\left(\frac{y}{x}\right) \), \(-1 < x, y < 1\)

The real-valued radial polynomials is defined as:

\[
R_{pq}(r) = \sum_{s=0}^{p-|q|} (-1)^s \frac{(2p + 1 - s)!}{s!(p + |q| + 1 - s)!(p - |q| - s)!} r^{p-s} \tag{12}
\]

and \( 0 \leq |q| \leq p, \quad p \geq 0 \)

Since it is easier to work with real functions, \( PZ_{pq} \) is often split into its real and imaginary parts, \( PZ_{pq}^c \), \( PZ_{pq}^s \) as given below [2]:

\[
PZ_{pq}^c = \frac{2(p + 1)}{\pi} \int_0^{2\pi} \int_0^1 R_{pq}(r) \cos(q\theta) L_j(r, \theta) r dr d\theta \tag{13}
\]

\[
PZ_{pq}^s = \frac{2(p + 1)}{\pi} \int_0^{2\pi} \int_0^1 R_{pq}(r) \sin(q\theta) L_j(r, \theta) r dr d\theta \tag{14}
\]
\[
PZ_{pq}^4 = \frac{2(p + 1)}{\pi} \int_0^1 \int_0^1 R_{pq}(r) \sin(q\theta) L_j(r, \theta) r dr d\theta
\]

where \( p \geq 0 \), \( q > 0 \).

4 Experiment

Experiments were conducted using Essex University Face Database [5]. 100 face classes with 10 samples for each class were used in this study. For each class, the first, third, fifth, seventh and ninth sample were used for testing and the rest of five for training. These images were varying in position, rotation, scaling, lighting and facial expression (open/close eyes, smiling/not smiling). The region of interest is cropped into a 61 \times 73 pixel rectangle that encloses the eye brows and lower lips and then converted to 16-bit, see Fig. 1.

Commonly, subband image containing the highest energy distribution will contribute significant features about the image. Therefore, approximation subband, \( L_j \), which possesses most of the energy content, is selected upon \( D_j \)'s for facial structure representation [6]. However, the performance of \( L_j \) in preserving energy of facial image is depended on the chosen wavelet basis. Thus, moments of order 9 of PZM are adopted with different wavelet filters (Haar, Daubechies and Symmlet) with different decomposition levels on face database in order to select the best wavelet basis. Although an image can still be further decomposed into much lower resolution, we stop at the third level decomposition. This is based on the rationale that too fine resolution of the image will contain too little useful information for the recognition task.

5 Results and discussions

Fig. 2 shows the comparative result of WPZM scheme with different wavelet bases and decomposition levels. From the figure, wavelet basis with Symmlet orthonormal wavelet filter order 5, level 3 performs the best verification rate with False Accept Rate (FAR) = 4.79%, False Reject Rate (FRR) = 4.76% and Total Success Rate (TSR) = 95.21%. Besides, we can observe that the performance of the majority of the wavelet filters with decomposition level 3 is poorer than the result provided by decomposition level 1 and 2. This indicates that the excessive down sampling process gets rid of the line feature structures of the coarser images; and this downgrades the discriminatory power of the WPZM features.

By using the chosen wavelet basis, which is Symmlet 5 with decomposition level 3, the verification rate of four subbands at level 3 is indicated in Table I together with that of solely-PZM scheme. The table reveals that approximation subband, \( L_3 \), gives a prime result, yet the other frequency subbands perform unsatisfying performance rate in WPZM scheme. This shows that high frequency subbands are inadequate feature descriptors because none of them can flawlessly describe the print structure of the face image due to their low energy content. High frequency subbands are also sensitive to image vari-
tion due to its high pass feature that tends to comprise noise. On the other hand, the low frequency subband, $L_j$, is the smoothed version of original image and it can capture the features that insensitive to small distortion but significant in representing the face identity. From the table, our proposed method demonstrates better verification rate compared to solely-PZM-based approach and shows a reduction of 36.23% in the computational time.

**Fig. 2.** Comparative result of WPZM scheme using different wavelet bases.

**Table I.** Performance comparison on subbands.

<table>
<thead>
<tr>
<th>Method</th>
<th>Subband</th>
<th>FAR (%)</th>
<th>FRR (%)</th>
<th>TSR (%)</th>
<th>Computational time, (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WPZM, the proposed system</td>
<td>$L_3$</td>
<td>4.79</td>
<td>4.76</td>
<td>95.21</td>
<td>0.3590</td>
</tr>
<tr>
<td></td>
<td>$D_{3vertical}$</td>
<td>23.06</td>
<td>23.40</td>
<td>76.94</td>
<td>0.3590</td>
</tr>
<tr>
<td></td>
<td>$D_{3horizontal}$</td>
<td>21.42</td>
<td>21.12</td>
<td>78.59</td>
<td>0.3750</td>
</tr>
<tr>
<td></td>
<td>$D_{3diagonal}$</td>
<td>34.01</td>
<td>33.92</td>
<td>65.99</td>
<td>0.3600</td>
</tr>
<tr>
<td>Solely-PZM scheme</td>
<td></td>
<td>6.54</td>
<td>6.64</td>
<td>93.46</td>
<td>0.5630</td>
</tr>
</tbody>
</table>

6 Conclusion

A new technique by using pseudo Zernike moments on wavelet subbands has been presented in this paper in order to reduce the moment computational time while preserving the authentication performance. Face images are input into wavelet transform for decomposition before pseudo Zernike moments computation. The wavelet analysis not only produces lower dimensional multiresolution representation that alleviates heavy computational load, but also generates noise and minor distortion insusceptible face wavelet-based templates. Thus, the hybrid wavelet transform and pseudo Zernike moments is
able to accomplish superior performance and achieves better verification rate of 95.21% with a reduction of 36.23% in computational time.

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