M-BAND WAVELETS APPLICATION TO PALMPRINT RECOGNITION BASED ON TEXTURE FEATURES

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ABSTRACT

In this paper, a new texture feature set based on M-band wavelet analysis is proposed for online Palmprint identification. First, the central part of a palm was decomposed by M-band wavelets transformation, then, 1-norm energy was extracted out as our features, at last, the candidate was found by matching process. The presented experimental results demonstrate the validity of our approach.

Keywords: Multiband Wavelet, Palmprint, Texture

1 INTRODUCTION

Computer-aided personal identification has received considerable attentions for its promising perspective in various security systems, which is based on biometric features of many human body parts, e.g., fingers, hands, feet, faces, etc. Compared with other biometrics features (e.g., fingerprint), palmprint has many advantages, e.g., low resolution, low cost, non-intrusion and unique, stable features, etc., thus it is very useful for personal identification [1].

Palmprint can provide rich biometric information, e.g., geometry features, texture features, line features and datum points. Point features are composed by delta point and minutiae, which can be extracted from high-resolution palmprint images and appropriate for offline palmprint identification [2]. The system based on geometry features measures a hand's shape and finger's length, however, it is very difficult to get high recognition accuracy. Lines features are included by principal lines, wrinkles and ridges. Principal lines can be extracted from low-resolution palmprint images using stack filters and improved template matching. Since there exists similarity in palmprint principal lines of different people, principal lines are only feasible for rough classification in online palmprint identification. Winkles play an important role in palmprint identification, however, it is very difficult for winkles to extract. It is a good way to apply texture analysis to palmprint identification [3]. It has been proved that textures including all the lines and points are very useful for detailed identification. [2] discussed offline palmprint identification, [3] applied TEM, FPS and GF to online palmprint recognition successfully.

Recently, several texture analysis methods have been developed based on different texture features, e.g., the spatial gray-level dependence matrices (SGLDM), the Fourier power spectrum (FPS), the Law's texture energy measures (TEM)[3], Multiresolution fractal feature (MF), Gaussian Marcov Random Fields (GMRFs), Gabor Filters (GF) and Wavelet Transform (WT)[4] and M-band wavelets(MWT)[5], etc.

From experimental results, we know that by the features based on the second-order statistics (e.g., SGLSM) we can get high accuracy but it needs more computational cost. The TEM is computationally simple, however, it has lower accuracy because of its sensitivity to noise. The Gabor filter has good performance for feature extraction, however, the extraction is time consuming and sensitive to non-linear distortions and rotations. WT energy, measured by the average wavelet coefficient magnitude, has the characteristics of multiresolution, but some texture information would be lost when an image is decomposed using 2-D wavelet. In this paper, a new feature based on M-band wavelet transformation is proposed to improve the accuracy and efficiency of identification. In M-band wavelet analysis, a signal is decomposed through projecting it onto a family of functions, which are generated from a signal wavelet basis via dilations and translations. A MBW texture set based on M-band wavelet and l-norm texture energy is used as feature in this paper.

Unlike standard 2-band wavelets decomposition, more subbands can be obtained by M-band wavelet decomposition. There are many mid-frequency subbands, which are important to texture analysis. In [5], texture analysis was discussed using 3-band bi-orthogonal wavelet. Recently, Malay K.Kundu and Mausumi Acharyya[6] used M-band wavelet for texture segmentation for real life image analysis. 4-band wavelet was used to segment the document image in [7]. However, to our knowledge, there has not existed such kind of work to apply M-band wavelet to palmprint application.

This paper is organized as follows. A scheme for palmprint identification is presented in Section 2. M-band wavelet decomposition of an images and texture features extraction are discussed in Section 3. Palmprint matching and experimental results are shown in Sections 4 and 5, respectively. Finally, conclusions in section 6 review our method in this paper.

2. M-BAND WAVELET TRANSFORM

Based on multiresolution analysis, Mallat [8] put forward a pyramid algorithm for decomposition and perfectly reconstruction to 2-band wavelet. Similarly, we generalize this idea to M-band wavelets.

Let integer $M \geq 2$, and Laurent polynomials $\{H_j, 1 \leq j \leq M\}$, satisfied

1. $H_1(1) = 1$ and $H_j(1) = 0$, for all $2 \leq j \leq M$;

2. $\sum_{l=0}^{M-1} H_i(zW^l) H_j(z^{-1}W^{-l}) = \delta_{i,j}$, for all $1 \leq i, j \leq M$ and $z \neq 0$.

Where W denote M^{th} unit root $W = \exp(-2i\pi / M)$. The template of filter $H_{i,j}(x,y), 1 \leq i, j \leq M$, are defined as

$$H_{i,j}(x,y) = H_i(x) H_j(y), 1 \leq i, j \leq M .$$

By M-band wavelet transformation, an image can be decomposed into M*M subbands in different channels. In this paper, we choose M=4 and the Laurent polynomials for filter template as follows:

$$H_1(z)=\frac{1}{4}(1+\sqrt{2}\cos\lambda)(1+z^7)+\frac{1}{4}(1-\sqrt{2}\sin\lambda)(z+z^6) \\ +\frac{1}{4}(1+\sqrt{2}\sin\lambda)(z^2+z^5)+\frac{1}{4}(1-\sqrt{2}\cos\lambda)(z^3+z^4) \tag{1}$$

$$H_2(z)=\frac{-1}{4}(1-\sqrt{2}\sin\lambda)(1-z^7)-\frac{1}{4}(1+\sqrt{2}\cos\lambda)(z-z^6) \\ +\frac{1}{4}(1-\sqrt{2}\cos\lambda)(z^2-z^5)+\frac{1}{4}(1+\sqrt{2}\sin\lambda)(z^3-z^4) \tag{2}$$

$$H_3(z)=\frac{-1}{4}(1-\sqrt{2}\sin\lambda)(1+z^7)+\frac{1}{4}(1+\sqrt{2}\cos\lambda)(z+z^6) \\ +\frac{1}{4}(1-\sqrt{2}\cos\lambda)(z^2+z^5)-\frac{1}{4}(1+\sqrt{2}\sin\lambda)(z^3+z^4) \tag{3}$$

$$H_4(z)=\frac{1}{4}(1+\sqrt{2}\cos\lambda)(1-z^7)-\frac{1}{4}(1-\sqrt{2}\sin\lambda)(z-z^6) \\ +\frac{1}{4}(1+\sqrt{2}\sin\lambda)(z^2-z^5)-\frac{1}{4}(1-\sqrt{2}\cos\lambda)(z^3-z^4) \tag{4}$$

Where the parameter λ runs from 0 to 2π. Especially, the proposed M-band wavelet is 4-band Harr wavelet when $\lambda = 0.75\pi$ and the M-band wavelet coefficient is the same as one presented in [6] when $\lambda = 0.8547\pi$.

3. PROPOSED TEXTURE FEATURES

In this section, l-norm energy was extracted out as our features. Fig 1 shows a palmprint image, from which we can find the following characters of palmprint images, such as lower resolution; lower contrast; translation, rotation and stretch between different samples and stronger noise.

Obviously, these characters above will bring us many difficulties in palmprint identification. In the following, our motivation is to develop a texture based palmprint identification scheme, in which these aspects above are concerned.

Fig.1 an online palmprint

In this paper, we always assume that the central part of the palm has been localized or normalized[3]. The preprocessing of localization or normalization can reduce the influence of translation, rotation as shown in Fig.2. It's well known that texture can be characterized by their energies and their gray-level dependence matrice (SGLDM). The central part of a palm after decomposed by a HARR wavelet was shown in Fig.3.

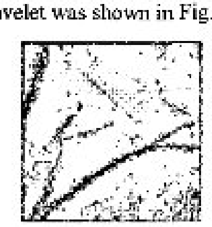


Fig.2 A palm's central part

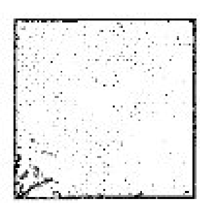


Fig.3 Decomposed by HARR wavelet

Now we present our algorithm steps:

Step 1. Decomposition the central part image based on M-band wavelet

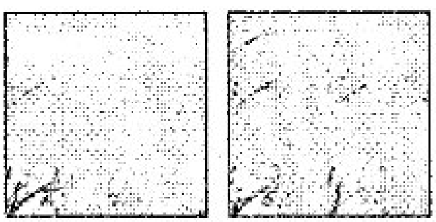
The palmprint image is first decomposed into $M \times M$ channels using an M-band wavelet with down sampling. In this paper, an 4-band wavelet is used and 16 decomposition channels as discussed in Section 2 are obtained. Thus the image is decomposed into 16 subbands and 16 features can be computed. The frequency bands corresponding to decomposition filters are shown in Fig.4,

H41	H42	H43	H44
H31	H32	H33	H34
H21	H22	H23	H24
H11	H12	H13	H14

Fig.4 16 Frequency Subbands

where H11 is a low frequency subband, the other 15 subbands are mid or high frequency subbands. In Fig.4, H12~H14 contain the horizontal direction information, H21, H31, H41 contain the vertical direction information, H22 H33 H44 contain the diagonal direction information, H12 ,H23, H34 contain the horizontal-diagonal direction, and H21, H32, H43 contain the vertical-diagonal direction information.

In order to enhance the high frequency subband for texture analysis, the parameter λ is taken as 0.1*pi, and the decomposition result is shown in Fig.5-. For comparison, we show the decomposition result in Fig.5-A where λ =0.75*pi, and the decomposition result in Fig.5-B where λ =0.1*pi. We can find that the smaller λ is, the bigger the coefficients in higher frequency subbands are.



A: λ = 0.75*pi B: λ = 0.1*pi

Fig.5 4-Band wavelet decomposition with different λ

Step2 . Feature Extraction

The 15 high frequency subbands and one low frequency subband are used to calculate the averaged $l_1 - norm$ energy and their variation, then a 32-D features vector is obtained.

The average deviation energy measurement is defined as:

$$E(i,j) = \frac{1}{(2n+1)^2} \sum_{k=i-n}^{i+n} \sum_{l=j-n}^{j+n} | x(k,l) - m(i,j) | \quad (5)$$

where $x(k,l)$ is the filtered image, $m(i,j)$ is the average value of $x(k,l)$ in a $(2n+1) \times (2n+1)$ window.

The averaged $l_1 - norm$ energy for each channel can be calculated as

$$E_n = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} | E_n(i,j) | \quad , \quad n = 1,2,\cdots,16 \quad (6)$$

The other 16 features are included by the variances of each channel , which can be calculated as:

$$\delta_n = \frac{1}{M * N} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - E_n)^2 \quad n = 17,18,...,32 \quad (7)$$

Step 3. Matching and Searching

It is well known that if the palm comes from one 99 persons, the palmprints, especial their central parts, must be similar to each other. Palmprint identification means matching the captured sample using all the samples in database to find out the candidate palmprints. The distance between two feature sets should be calculated for Feature matching. Accuracy and efficiency are two important aspects for the palmprint identification.

In our experiments, the 32-D features are defined by

$$Q = [q_i, i = 1,...,32] \quad (8)$$

where q_1---q_{16} are the averaged $l_1 - norm$ energies for each of 16 subbands. q_{17}—q_{32} are the variation of wavelet coefficient for each of 16 channels.

Suppose that $Q = [q_1, \ldots \; q_{32}]$ stands for the features in database, $Q' = [q'_1, \ldots \; q'_{32}]$ stands for the features of a captured sample. The two distances between Q and Q' can be obtained,

$$D_1 = \sqrt{\sum_{i=17}^{32} (q'_i - q_i)^2} \quad (9)$$

$$D_2 = \sqrt{\sum_{i=1}^{16} (q'_i - q_i)^2} \quad (10)$$

If (D1<50.0 and D2<180.0), 6 resulted image's file names are returned as our candidates according to the distance in an ascending order.

4 EXPERIMENTAL RESULTS

In this section, we have several experiments to test our method. We captured 480 palmprint images by the same device. All of these images are come from the right hands of 80 different persons. 6 samples are taken for each person, in which 3 samples are used to set up the database and the other 3 samples are used for testing the recognition rate. The size of each original image is 320×240. The gray-level of these original images is 256 and the size of the central part of a palm is 128×128. The size of each subband is 32×32.

The correct recognition implies that for each sample in the testing set, the matched images are from the same palm in the database. The correct recognition rate and the incorrect recognition rate are defined as follows:.

$$\text{The correct rate} = \frac{\text{numbers of correctly recognized images}}{\text{the number of testing samples}};$$

$$\text{The incorrect rate} = 1 - \frac{\text{numbers of incorrectly recognized images}}{\text{the number of testing samples}};$$

The testing results are in Table 3. Among the 240 samples, there are eight samples miss-recognized, where λ = 0.75*pi. Thus the correct recognition rate is about 96.7%. However, if λ is taken as 0.1*pi, the correct recognition rate is 99.2%.

λ	Samples	Right	Wrong	right Rate
0.75*pi	240	232	8	96.7%
0.1*pi	240	238	2	99.2%

Table 3 Recognition rate with different λ

Furthermore, we use other images e.g. offline palmprint and Brodatz texture images to test our method.

Experimental results show that this method is also suitable for texture analysis of the other kinds of images such as Offline palmprint images and Bondry texture images.

5 CONCLUSIONS

In this paper, based on M-Band wavelet transformation, a new online palmprint identification method and a texture-based feature extraction method are proposed.

Compared with the existing feature sets e.g. spatial gray-level dependence matrices, the Law's texture energy, the Fourier power spectrum, the Gabor filter and the 2-band wavelet transformation, the texture features based on M-band wavelet transform can provide more subbands with rich texture features, which are more appropriate for online Palmprint identification, as well as Brodatz texture images. The experimental results show that both efficiency and accuracy have been improved when the parameter λ = 0.1*pi.

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