Abstract

Various techniques in analyzing palmprint have been proposed but to the best of our knowledge, none has been studied on the selection and division of the region-of-interest (ROI). Previous methods were always applied only to a fixed size square region chosen as the central part of the palm, which were then divided into square blocks for extraction of local features. In this paper, we proposed a new method in locating and segmenting the ROI for palmprint analysis, where the selected region varies with the size of the palm. Instead of square blocks, the region is divided into sectors of elliptical half-rings, which are less affected by misalignment due to rotational error. More importantly, our arrangement of the feature vectors ensures that only features extracted from the same spatial region of two aligned palms will be compared with each other. Encouraging results obtained favor the use of this method in the future development of palmprint analysis techniques.

1. Introduction

Biometrics, identification of a person by his/her physiological or behavioral characteristics, has become increasingly prevalent in modern identification and verification systems [1][2]. Of all the biometrics studied, palmprint has an advantage over other biometrics such as voice and face recognition where uniqueness between people is doubtful [3] or fingerprint and iris pattern where high-resolution images are required (e.g. over 400 dpi). Palmprints are unique between people and relatively low-resolution images will suffice (less than 100 dpi) [4][5]. However, there is a major shortfall in the previous algorithms. That is they only utilize a fixed area of a palm for identification regardless of the actual palm size. Obviously, a lot of information has been overlooked. Figure 1 illustrates this shortfall. Two palms are captured from the same distance and with the same resolution. A fixed size region-of-interest (ROI) (red dotted square) is considered to be small on large palms.

In this paper, we propose a new method in palmprint identification that allows the ROI in analyzing a palm image to vary with the actual palm size (see Figure 1, blue solid square). In the following sections, related work in the study of palmprint is presented in Section 2. Section 3 provides the details of our proposed method. Section 4 discusses the experimental setup with the results shown in Section 5. Section 6 concludes the major findings and contributions of this paper.

2. Related Work

The studies of palmprints were first carried out on inked palmprint images [6]. Not only that the image collection process is tedious and unrealistic, the hollowed central part of the palm is often missing. With the advance of technology, inkless palmprint images can now be captured, by either scanning technologies or CCD cameras. Palm images captured by CCD cameras, which is the technology used in this study, are of lower resolution but in turn required less processing time.

Apart from utilizing the structural properties of palmprint [6][7], other typical features that have been studied include: fuzzy directional element energy features, adopted from Chinese characters recognition algorithms [8]; features in Fourier space [9]; eigen features retained after performing dimensionality reduction by Karhunen-Loeve transform [10] or Fisher’s linear discriminant [11]; and, statistical features obtained by texture analysis using Gabor filters [4] or wavelets transform [5][12].
In all these previous studies, subjects are required to place their hands on a contact surface. Some even fixed subjects’ hand posture by pegs [4]. Features are only extracted from a fixed size square block of the central part of the palm. Since palm size varies greatly amongst people, using only a fixed size palm region on all palmprints actually neglects a lot of distinctive and unique information on the other parts of the palmprint. This shortfall is significantly relevant when the size of the palmprint is large (see Figure 1).

We therefore proposed a new method in dividing and arranging the features extracted from palmprint such that the utilization region of the palmprint is greatly increased and more features can be extracted. A wavelet-based technique is chosen to analyze palmprints, i.e. by the simple Haar wavelet transform, which has been demonstrated to produce the best results amongst various wavelet transforms [5]. It is noted that the proposed method can be easily integrated into other feature extraction algorithms examined in previous studies.

3. Methodology

In the new approach we proposed, palmprint is identified by the total energy level in sectors of elliptical half-rings of the palm image. The proposed algorithm allows the extracted palm region to vary proportionally with palm size. At the same time, it can cope with slight variations in the extracted region within a person, i.e. even when two feature vectors were extracted from different palm sizes of the same individual (due to the extent of stretching of the hand), the feature vectors are still comparable. Details of the algorithm is as follows:

3.1. Identify hand image from background

The setting of our system is such that we employ a contact-less capturing system that works without pegs. The background of the image is relatively uniform and is of a relatively low intensity when compared to the hand image. Using the statistical information of the background and that of the rest of the pixels, the algorithm estimates an adaptive threshold to segment the image of the hand from the background. Pixels with intensity above the threshold are considered to be part of the hand image.

3.2. Locate region-of-interest

Maximum palm area is extracted from the binary image of the hand. To ensure the extracted palm region has minimal rotation and translation error, the algorithm identifies gaps-between-fingers and uses them as reference points to align the image. By leveling the gap between the index finger (IF) and the middle finger (MF), and that between the MF and the ring finger (RF), images of the palm are aligned rotationally. Since the gap between MF and RF is usually the most robust point amongst the three gaps, it is used as the reference point to eliminate translation error (see Figure 2).

The maximum square region that can fit in the selected palm area is chosen as the ROI. The square region is horizontally centered on the axis running through the gap between MF and RF. In addition, since the ROI will be divided into non-overlapping elliptical half-rings, the size of the region must be divisible by the width of each elliptical layer (50 pixels in this study) (see Figure 3).

3.3. Feature extraction

Preprocessing of palm images is necessary to minimize variations in palm images of the same individual. Firstly, a 2-D lowpass filter is applied to the image. The result is subtracted from the image to minimize the non-uniform illumination effect on projecting a 3-D object onto a 2-D image. Secondly, a Gaussian window is used to smooth out the image since Haar wavelet, due to its rectangular wave nature, is sensitive to noise.
A 1-level decomposition of the image by the Haar wavelet is carried out. For each of the three detail images obtained, i.e. image consisting of the horizontal, vertical and diagonal details, a smoothing mask is applied to remove noise. It was found that most of the low frequency components are attributable to the redness underneath the skin and should preferably be excluded from features for identification. Thus, pixels with frequency values within one standard deviation are set to zero. Values of the rest of the pixels are projected onto a logarithm scale so as to minimize the absolute differences in the magnitude of the frequency components between two images. That is,

\[
I(x_i, y_i) = \begin{cases} 
0, & \text{if } |I(x_i, y_i)| \leq \text{std}(I(x, y)) \\
\ln( |I(x_i, y_i)| - \text{std}(I(x, y)) + 1 ), & \text{otherwise}
\end{cases}
\]  

where \(I(x_i, y_i)\) is the frequency value in a detail image.

Finally, a 3x3 operation mask in the form of a ring is applied to enhance connectivity and to thicken the detected palm lines. The processed image is shown in Figure 4.

3.4. Feature vector construction

Each of the detail images is divided into non-overlapping elliptical half-rings. The ellipses are all centered at the same point, with the area of them increasing by a factor of 4, i.e. the major and minor axis of an ellipse doubles that of its immediate inner one. Each ring is separated into a different number of sectors. The innermost ellipse is divided into 3 sectors, while moving out from it, each outer ring will have 2 more sectors than its inner layer (see Figure 5(a)).

Mean energy level of each sector, i.e. the total absolute sum of the frequency components divided by the number of pixels in each sector, is used to construct the feature vector. Arrangement of the feature vector is such that energy levels of an inner layer, for all the three detail images, precede those of an outer layer (see Figure 5(b)). The arrangement ensures that when two feature vectors of unequal length are compared to each other, point-wise comparison of them is actually comparing features in the same spatial region of the two different palm images.

3.5. Matching score calculation

Since the palm images under process are divided into elliptical half-rings of same widths regardless of the size of the original image, different palm sizes will result in feature vectors of different lengths. Due to the possibility of having variations in the extent the hand is stretched, the resultant maximum palm area may vary within the same subject. Therefore, the distance measure used must be able to fairly compare two feature vectors with unequal dimension.

The score is calculated as the mean of the absolute difference between two feature vectors. If \(\text{feature}_{Vi}\) represents a feature vector of \(N_i\) elements, the score between two images is given as:

\[
\text{Score}(i, j) = \frac{\sum_{n=1}^{\min(N_i, N_j)} | \text{feature}_{Vi}(n) - \text{feature}_{Vj}(n) |}{\min(N_i, N_j)}
\]  

4. Experimental setup

We have captured hand images from 170 individuals, whose age ranges from 16 to above 50. Approximately 60% are female and 90% are Chinese. Hand images are captured with resolution of 1280x960 (in pixels) and 8-bit colors. Ten images each of the left and right hand of 170 individuals were captured to form a database of 340 subjects (right hands are flipped around the vertical axis and stored as another subject).

Unlike previous studies in palmprint identification, where subjects are required to place their hands on a contact surface with their hand posture fixed by pegs [4], our study employed a contact-less capturing system that
works without pegs. Subjects were merely asked to place their hands flat on a soft surface with the palm facing skyward, with their fingers kept apart and not touching each other. A CCD camera kept at a fixed distance above the table was used to capture the complete hand image. The setup avoids the need of frequent cleaning of the contact surface in order to maintain a high quality of the captured image in a contact device and offers a convenient and comfortable setting for the users.

Using the database, experiments on identification and verification are carried out. For identification, 10-fold and 2-fold cross-validation methods are employed together with the one-nearest-neighbor (1-NN) classifier. For verification, each image is compared with the rest of the images, resulting in 15,300 genuine scores and 5,778,300 imposter scores.

The performance of the proposed algorithm will be compared to algorithms found in previous studies (e.g. [5]), where fixed size square region was used and the region is divided into non-overlapping square blocks. Testing was performed using MATLAB 6.1 on a Pentium IV 1,500MHz processor with 256MB RAM.

5. Results

The average time of processing an image and constructing its corresponding feature vector using the proposed method is slower than the previous algorithm by 0.6±0.7 seconds but the average number of features per image is less by 20±40 features.

For 10-fold 1-NN classification, the proposed method has an accuracy of 99.6%. For 2-fold classification, the accuracy dropped to 97.9%. Results shows that the proposed method performs better than the previous algorithm, which only achieve 99.3% and 97.1% in 10-fold and 2-fold classification respectively.

Equal error rate for the new method and the previous methods are 4.6% and 7.0% respectively. A summary of the comparison is presented in Table 1.

### Table 1. Comparison of Performance

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<tr>
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<tbody>
<tr>
<td>10-Fold 1-NN</td>
<td>99.6 %</td>
<td>99.3%</td>
</tr>
<tr>
<td>2-Fold 1-NN</td>
<td>97.9 %</td>
<td>97.1%</td>
</tr>
<tr>
<td>EER</td>
<td>4.6%</td>
<td>7.0%</td>
</tr>
<tr>
<td>Avg. Proc. Time</td>
<td>2.5±0.6 sec</td>
<td>1.9±0.4 sec</td>
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<tr>
<td>Avg. Vec. Len.</td>
<td>172±40</td>
<td>192</td>
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6. Conclusion

This paper proposes a new method in selecting and dividing the ROI for analysis of palmprint. The new method utilizes the maximum palm region of a person to attain feature extraction. More importantly, it can cope with slight variations, in terms of rotation, translation, and size difference, in images captured from the same person. Feature vectors are arranged such that point-wise comparison is matching features from the same spatial region of two different palms. Results are promising, with accuracy as high as 99.6% when 9 captures of each subject were used for training in a database of 340 subjects. Even when only 5 images were used, the level of accuracy can still be retained at 97.9%. For verification, the new method achieves an equal error rate of 4.6%, as compared to 7.0% where features are only extracted from non-overlapping square blocks of a fixed size square region of the palm.

7. Acknowledgement

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8. References