Fingerprint Matching Based on Directional Image Constructed Using Expanded Haar Wavelet Transform

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Abstract

In this paper, a directional image for a fingerprint obtained from an expanded second stage Haar wavelet transform is presented. This directional image will represent the orientation pattern that later on will be used for fingerprint matching so that the real owner can be identified. To construct the directional image, we first perform a second stage Haar wavelet transform on a fingerprint. Due to the limitation of the Haar wavelet, we use the expanded version of it instead so that a better directional image can be obtained. Next, we quantize the directional image into a few grey-level values that represent a range of angle orientations. We then smooth the image using an averaging filter. Based on this image we then perform the matching process based on the minimum square error (MSE) criteria.

1. Introduction

Biometrics is the science of identifying individuals by a particular physical characteristic such as voice, eye colour, fingerprints, height, facial appearance, iris texture or signature [1]. Fingerprinting has been used for identification of individuals since the late 19th century and it has been discovered that every individual has different fingerprints, even identical twins. This is why fingerprint was arguably as the most popular biometric among others.

Fingerprints are actually the ridge and furrow patterns on the tip of a finger [2]. In a fingerprint, its pattern is related to the direction of the ridges. A lot of research has been done transforming the fingerprint image into a directional fingerprint image to classify and match the fingerprint [3], [4]. In this work wavelet transform is applied in constructing the directional image that represents the orientation pattern for a given fingerprint. Figure 1 shows the flow process of the overall matching process presented in this paper. There are three processes involved. The first step is transforming the original image using the wavelet transform. The mid-range frequency results from the wavelet transform are then used to obtain an estimate the orientation of the fingerprint ridges. In order to obtain a smooth directional image Prewitt edge operator is applied. Lastly, the directional image is smoothed to get a better directional image.
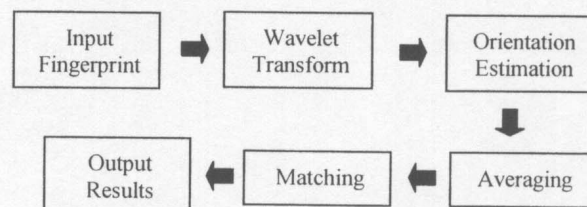

Figure 1 Flow chart of the overall matching process

This paper is organized as follows: Section 2 explains the reasons of using the Haar wavelet transform. It is in this section that the expanded Haar wavelet will be presented. The estimation of the ridges orientation will be given in section 3 while the matching process is explained in section 4. Experimental results are given in section 5 and section 6 concludes the paper.

2. Wavelet Transform

In our work, we firstly applied wavelet transform onto the fingerprint image. It is well understood that when an image undergoes a wavelet transform then the resulting image will have 4 components viz. approximation level (low frequency), horizontal and vertical details (mid-range frequencies) and diagonal details (high frequency).

2.1. Haar Wavelet

In our approach we have decided to use the Haar wavelet transform. There are many popular wavelet families being used in different applications such as Daubechies wavelets, Mexican Hat wavelets and Morlet wavelets. These wavelets have the advantage of giving better resolution for smoothly changing time series. However, they have the disadvantage of being more computationally expensive than the Haar wavelets. We

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make use of the Haar wavelet transform because of the following reasons:

- It is conceptually simple.
- It is fast.
- It is memory efficient, since it can be calculated in   place without a temporary array.

However, the Haar wavelet has its limitation, which can be a problem. Since the Haar wavelet transform performs an average and difference on a pair of values and then shifts over by two values and calculates another average and difference on the next pair, it cannot detect if a big change takes place from an odd index value to an even index value [6]. For an example, lets consider a one-dimensional signal that has 24 elements as shown in the Figure 2. In the figure, there is a large drop between elements 6 and 7, and a large rise between elements 11 and 12. After the first stage wavelet transform, results for the high frequency computation is shown in Figure 3. Only the large drop between elements 6 and 7 is detected. Large rise between elements 11 and 12 is not detected because the change is from an odd element to an even element.
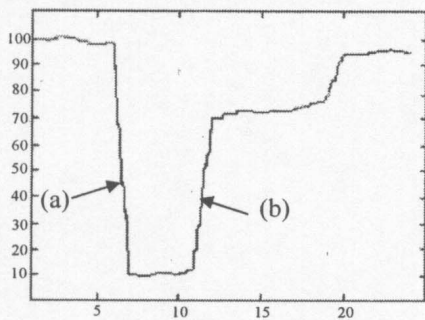

Figure 2 One-dimensional signal with 24 elements; (a) large drop between elements 6 and 7, (b) large rise between elements 11 and 12
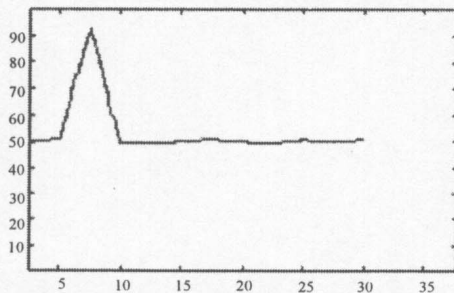

Figure 3 High pass filter of signal in Figure 2 using Haar coefficient

This problem can be corrected by expanding the filter coefficients into a length of three instead of two as in the original Haar wavelet transform. Thus, the coefficients for

the high pass filter become $\begin{bmatrix} \frac{1}{2} & 0 & -\frac{1}{2} \end{bmatrix}$. These coefficients will do the same operation as with the original Haar coefficient where it computes the difference for the high pass filter. Likewise the new expanded low pass filter coefficient will become $\begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}$ so that it can still act as a low pass filter. Results for the high frequency computation using the new coefficients is shown in Figure 4. Now the large drop between elements 11 and 12 is detected as well as the rise between elements 6 and 7.
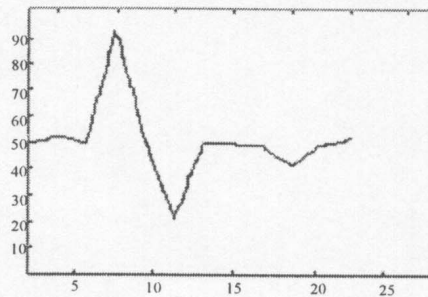

Figure 4 High pass filter of signal in Figure 2 using expanded Haar coefficient

Notice that this expanded filter looks very similar to the gradient-based edge detector. One that is almost similar to the expanded filters is the Prewitt gradient filter. These filters are specified by:

$$[h]_x = [A]^T[B] = \frac{1}{3}\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \quad (1)$$

$$[h]_y = [B]^T[A] = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \quad (2)$$

where h_x and h_y estimate the gradient in the horizontal and vertical directions respectively. We can also rewrite these operators using two separable vectors as shown above. In these two equations, vector A is the low pass filter coefficient while vector B is the high pass filter coefficient. Using the expanded Haar coefficients, the horizontal detail and the vertical detail becomes:

$$[h]_x = [A]^T[B] = \frac{1}{6}\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \quad (3)$$

$$[h]_y = [B]^T[A] = \frac{1}{6}\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \quad (4)$$

Note that the difference lies only on the scaling factor and these two filters will give identical result when equation 5 is employed for estimating the orientation of the ridge. Hence, we make use of this expanded Haar wavelet for the second stage transform so that we would not 'miss' any significant changes in the ridges. The computation for the first stage transform, however, would still be based on the original Haar wavelet. The reason being is because we are interested only in the approximation (low frequency) component of the image and thus the use of the expanded version is not needed for the 1st stage decomposition.

Figure 5b and 5c show the results of the second stage directional image using the original Haar wavelet and the expanded Haar wavelet respectively. It is clear from the figure that the directional image obtained using the original Haar wavelet contains many jagged lines, which is an indication that many important orientations are missing. On the other hand, the result obtained using the expanded Haar wavelet (Figure 5c) exhibits a smoother transition between grey levels. The process of constructing the estimated orientation as shown in Figure 5b and 5c will be explained in the next section.
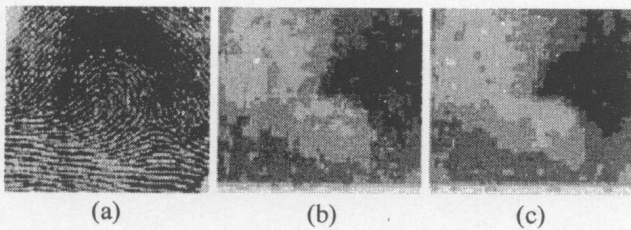

(a)   (b)   (c)

Figure 5 Comparison of the directional image; (a) Input image (b) Using original Haar wavelet (c) Using expanded Haar wavelet.

3. Ridge Orientation Estimation

The directional image is an image whereby every single pixel represents a value that approximates the orientation of ridges in the fingerprint. This directional image will be used as an input image for the matching process mixture. If we let θ be the estimated orientation, then by using only the horizontal and vertical details obtained from wavelet transform decomposition, then we calculate θ using equation 5. The functions $h_x(r,c)$ and $h_y(r,c)$ refer to the horizontal and vertical details of the second stage wavelet transform respectively, while the variables r and c denote the position in terms of row and column of a pixel respectively.

$$\theta_{(r,c)} = \tan^{-1} \frac{h_y(r,c)}{h_x(r,c)} \qquad (5)$$

We then quantized the values of θ into eight grey level values representing eight directions. After the quantization process, the resulting image is smoothed to remove any high fluctuation of the directional change, as this is not normally found in the fingerprint. Averaging and rounding the value back to the nearest quantization levels mentioned above do this. The filter used for this operation was 7x7.

To ensure that the pattern is compatible with its original image, the directional image is superimposed with the original image. The comparison is shown in Figure 6 where the white lines are the boundary of the orientation change. The comparison is made to all the five types of the fingerprint to make sure that the directional image can represent every type of the fingerprint.
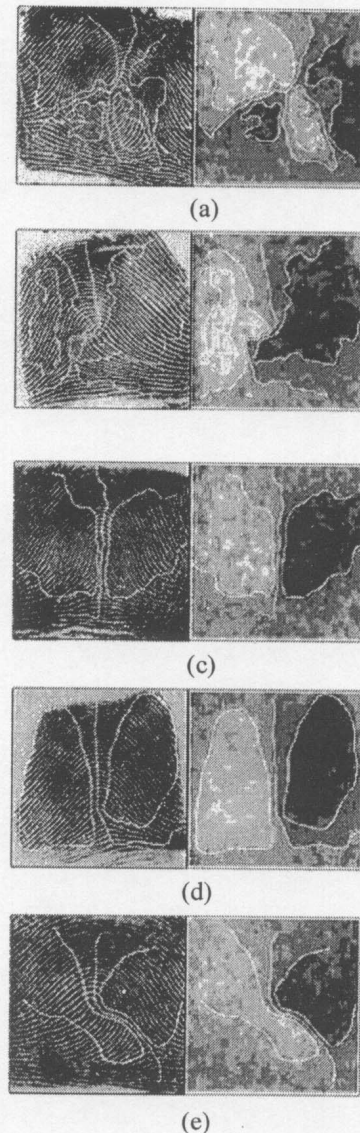

(a)

(b)

(c)

(d)

(e)

Figure 6 Comparing orientation pattern in directional image with its original image: (a) whorl, (b) right loop, (c) tented arch, (d) arch, (f) left loop

4. Matching

For the matching of the fingerprint, we used simple error measurement technique. However, in order to reduce the amount of computation involved we further wavelet transformed the directional image using the original Haar wavelet transform. Only the approximation component of the wavelet transform will be used. This is because the approximation component will not alter the pattern of the directional image like the other component of the wavelet transform. Note that the second level directional image used as the input to the matching module has a size of 128x128.

The error criteria we used is the standard minimum mean square (MSE) error technique, which is given in Equation 6. In Equation 6, A_{input} denotes the approximation of the test directional image while A_{dbase} denotes the approximation of the directional image stored in the database. Parameters M and N are the size of the directional image approximation. From the equation, the stored A_{dbase} that gives the smallest mse will be taken as the matched fingerprint with the input A_{input}.

$$mse = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left[A_{input}(x,y) - A_{dbase}(x,y) \right]^2 \quad (6)$$

5. Experimental Results

To test the matching algorithm, 150 samples collected from 30 persons (5 samples per person) were used. The tests were conducted on three different wavelet stages and the results are shown in Figure 7. These wavelet stages are referring to the process in Section 4, which is to reduce the size of the approximation image. We also measured the time taken to match the fingerprint, which is shown in Table 1. Considering the trade-off between accuracy and computation time derived from these two results we concluded that the 2nd level wavelet transform of the directional image is the best choice.
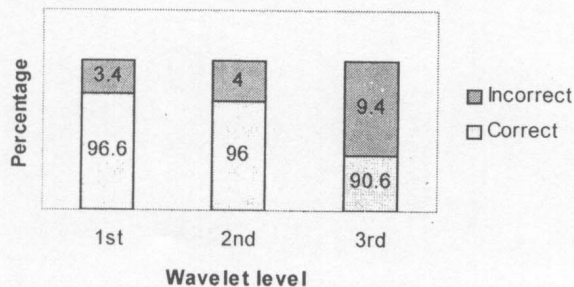

Figure 7 Matching accuracy

Table 1 Processing time for matching process

Wavelet Transform Stage	Processing Time (s)
1st	0.48
2nd	0.22
3rd	0.11

The accuracy obtained is likely the same with a few previous works. In 1997, Woo Kyu Lee and Jae Ho Chung used Symlet wavelet [4]. They achieved 97% of accuracy. In 1997, A.K. Jain and his group introduced a multicahannel approach that involved technique that is almost similar to the wavelet transforms [2]. They achieved 98% of accuracy.

Conclusion

We have presented in this paper a technique that can be used for matching a fingerprint based on the directional image. This directional image was constructed from the mid-range frequencies of the expanded second level Haar wavelet. To match the fingerprint we compared this directional image with the directional image pre-stored in a database using the mean square error criteria. In order to reduce the computational load we further reduce the size of the directional image by again using the Haar wavelet transform. From our experiments we found that further decomposing the directional image into a 2nd level approximation component is a good trade off between accuracy and speed. With this setup we have achieved 96% accuracy for fingerprint matching.

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