FINGERPRINT RECOGNITION USING WAVELET FEATURES

Marius Tico, Eero Immonen, Pauli Rämö, Pauli Kuosmanen, and Jukka Saarinen

Digital Media Institute,
Tampere University of Technology
P.O.BOX 553, FIN-33101, Tampere, FINLAND
E-mail: tico@cs.tut.fi

ABSTRACT

A new method of fingerprint recognition based on features extracted from the wavelet transform of the discrete image is introduced. The wavelet features are extracted directly from the gray-scale fingerprint image with no pre-processing (i.e. image enhancement, directional filtering, ridge segmentation, ridge thinning and minutiae extraction). The proposed method has been tested on a small fingerprint database using the k-nearest neighbor (k-NN) classifier. The very high recognition rates achieved show that the proposed method may constitutes an efficient solution for a small-scale fingerprint recognition system.

1. INTRODUCTION

The use of fingerprints for personal identification has a very long history. Archaeological evidences reveal that fingerprints have been used as a form of identification since 7000 BC [1]. The formation of the fingerprints depends on the initial conditions of the embryonic development, and their ridge pattern is unchanged throughout the entire life (immutability). In addition, since the first scientific studies of fingerprints in the mid-1800 till today no two fingerprints from different fingers have been found to have the same ridge pattern (uniqueness). Both the immutability and the uniqueness properties have determined the use of fingerprint matching as one of the most reliable techniques of people identification [2]. A fingerprint image exhibits a quasiperiodic structure of ridges (darker regions) and valleys (lighter regions). The local characteristics of this structure (i.e. ridge endings and ridge bifurcations) called minutiae form a unique pattern for each fingerprint.

Various approaches of automatic fingerprint matching have been proposed in the literature. They include minutiae-based approaches, and image-based approaches as the most prominent classes of fingerprint matching methods. Minutia-based approaches are the most popular ones being included in almost all contemporary fingerprint identification and verification systems. Although rather different from one other the minutiae-based approaches require extensive preprocessing operations in order to reliably extract the minutia features. The preprocessing operations include image enhancement, orientation flow estimation, ridge segmentation, ridge thinning, minutiae detection [3-7]. In addition, a minutiae purification stage is also required in order to reduce the number of false minutiae erroneously detected in noisy fingerprint images [8, 9]. The minutiae form a pattern of points, and hence fingerprint matching may be seen as a point pattern matching problem. Several minutiae attributes (e.g., position, type, orientation, ridge count) are used in order to simplify the general point pattern matching problem which is essentially intractable [4-7]. Image-based approaches do not use the minutiae features for fingerprint matching. They are usually applied directly onto the gray-scale fingerprint image without pre-processing, and hence they may achieve higher computational efficiency than minutiae-based methods. In addition, the image-based approaches may be the only choice to match fingerprints which have too low image quality to allow a reliable minutiae extraction. The main disadvantage of image-based approaches consist in their limited ability to track with variations in position, scale and orientation angle. Usually the variation in position between the two fingerprints is cancelled by choosing a reference point in each fingerprint. Such reference point may be the core point which can be detected using for example methods like those proposed in [10-12]. Image-based approaches include methods based on optical correlation [13, 14] and transform based features [15].

In this paper we propose an image-based method of fingerprint recognition. The fingerprint patterns are matched based on wavelet domain features which are directly extracted from the gray-scale fingerprint image without preprocessing.

The paper is organized as follows. This introduction serves as the first section. The following section presents the proposed method of wavelet features extraction. Experimental results including k-NN classification experiments are shown in Section 3, and finally a brief conclusions section will summarized the paper.

0-7803-6685-9/01/$10.00©2001 IEEE

2. WAVELET FEATURE EXTRACTION

Wavelet transforms have important characteristics which make them valuable tools for many tasks in signal processing. The two-dimensional (2D) wavelet decomposition on J octaves of a discrete image $a_0[n, m]$ represents the image in terms of $3J + 1$ subimages

$$\left[a_J, \{d_j^1, d_j^2, d_j^3\}_{j=\overline{1,J}}\right], \tag{1}$$

where a_J is a low resolution approximation of the original image, and d_j^k are the wavelet subimages containing the image details at different scales (2^j) and orientations (k). Wavelet coefficients of large amplitude in d_j^1, d_j^2, and d_j^3 correspond respectively to vertical high frequencies (horizontal edges), horizontal high frequencies (vertical edges), and high frequencies in both directions [16].

It is well known [16], that in most of the natural images the amplitude of wavelet coefficients increases when the scale 2^j increases. Nevertheless, the above property is not valid for oscillatory patterns. High frequency oscillations create coefficients at large scales that are typically smaller than at the fine scale which matches the spatial frequency of the oscillation. Such oscillatory patterns are encountered in fingerprint images. The energy of certain middle scales subimages d_j^k may exceed the energy of higher scales subbands. Therefore the energy distribution over different scales (2^j) and orientations (k) is a quite informative criterion for fingerprint pattern classification. The energy of different subbands give information regarding both the ridge spatial frequency as well as the ridge orientation. We propose a compact representation of these information based on the standard deviation of each wavelet subimage. A wavelet decomposition on J octaves of the the discrete image is used to compute a feature vector of length $3J$

$$[\{\sigma_j^1\ \sigma_j^2\ \sigma_j^3\}_{j=\overline{1,J}}], \tag{2}$$

where σ_j^k stands for the standard deviation of the wavelet coefficients in the subimage d_j^k.

The feature vector computed as in (2) has important discriminatory properties for fingerprint images as shown in Figures 1, and 2. The images shown in these figures have been decomposed on $J = 4$ octaves and a feature vector of length 12 have been extracted. To facilitate the visual inspection the feature vectors are represented in gray-levels emphasizing also the scale level (j) and the orientation (k) of each feature component. One may note high similarities between feature vectors extracted from images representing the same finger, as shown in Figure 1. On the other hand, important differences may be noted between feature vectors extracted from images which represent different fingers, as shown in Figure 2.

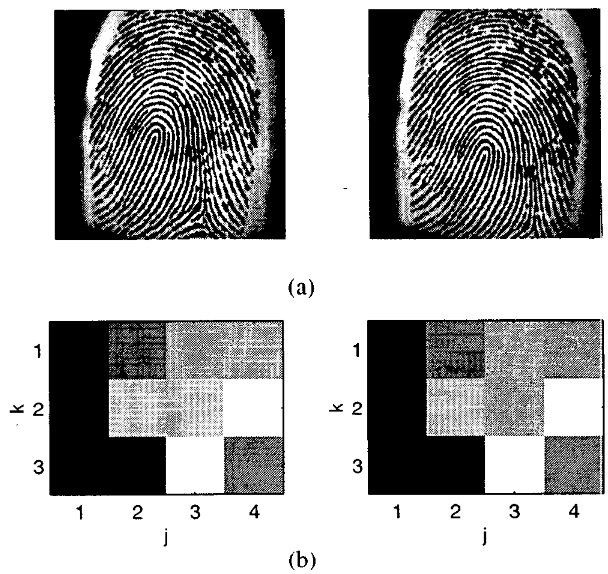

Figure 1: Fingerprint images acquired from the same finger (a), and their corresponding feature vectors (b).

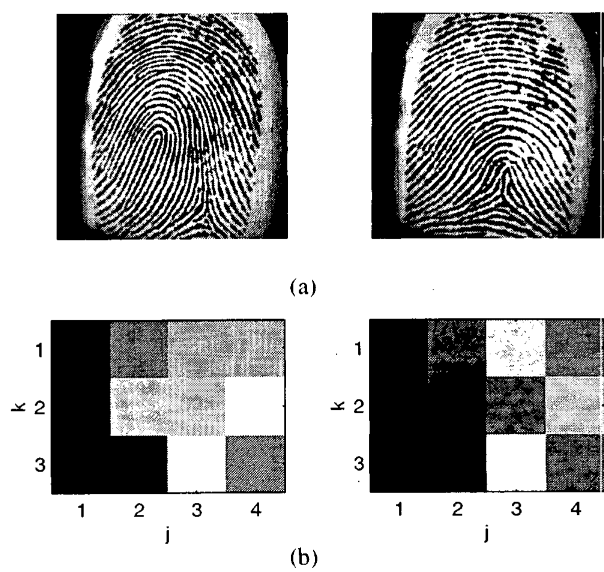

Figure 2: Fingerprint images acquired from different fingers (a), and their corresponding feature vectors (b).

The above wavelet features extracted from the entire image do not preserve information concerning the spatial location of different details. A better strategy is to use wavelet features extracted from small non-overlapping blocks of size $W \times W$ pixels, located inside the fingerprint pattern (region of interest). Once the two fingerprint images are registered based on their core points, they may be compared by individually match each pair of corresponding blocks.

Our method of feature extraction is applied as follows:

1. Detect the reference point (core point) in the fingerprint image.

2. Crop from the fingerprint image a $N \times M$ rectangular region centered in the reference point and located inside the fingerprint pattern. In the following we will use the name *central subimage* for this rectangular region.

3. Divide the central subimage into non-overlapping blocks of size $W \times W$.

4. Compute the wavelet decomposition on J octaves of each $W \times W$ block and calculate its $3J$ wavelet features (2).

5. Construct a global feature vector which includes the wavelet features extracted from all $W \times W$ blocks of the central subimage.

3. EXPERIMENTAL RESULTS

A database of 104 fingerprint images of size 256×256 including 8 images per finger from 13 individuals have been used for experiments. The images have been selected from the database [17] based on the position of the fingerprint pattern inside the image, being prefered those images where the core point is located close to the center of the image.

The following parameters have been used in the experiments: $N = M = 64$, $W = 32$, and $J = 4$. The core points have been pointed out manually in each fingerprint in order to avoid errors caused by a core point detection algorithm. We have chosen $N = M = 64$ such that the central subimage to be entirely located inside the fingerprint pattern in all images. Finally a global feature vector of length 48 is extracted from each fingerprint using the approach described in the previous section.

The recognition performances achieved by using the proposed wavelet features have been evaluated using a k-NN classifier, with no rejection option. A number of k images from each individual (for a total of $13k$ images) have been used as the training set, whereas the remaining $8-k$ images from each individual (for a total of $13 \times (8-k)$ images) have been used for testing.

Table 1: Comparative results of k-NN recognition rate.

Filter	1-NN [%]	2-NN [%]	3-NN [%]	4-NN [%]
Our method				
Haar	90.1	94.9	100	100
Daubechies 2	93.4	97.4	96.9	98.1
Daubechies 3	95.6	100	100	100
Daubechies 4	95.6	98.7	100	100
Daubechies 5	96.7	97.4	96.9	100
Daubechies 6	98.9	97.4	100	100
Daubechies 7	95.6	96.2	96.9	98.1
Daubechies 8	96.7	100	100	100
Daubechies 9	95.6	100	100	100
Daubechies 10	96.7	97.4	98.5	100
Symmlet 4	95.6	100	100	100
Symmlet 5	97.8	100	100	100
Symmlet 6	97.8	100	100	100
Symmlet 7	95.6	98.7	100	100
Symmlet 8	93.4	100	100	100
Symmlet 9	100	100	100	100
Symmlet 10	96.7	97.4	98.5	100
The method proposed in [15]				
Gabor	90.1	98.7	100	100

We have tested our method using different wavelet basis. The best results have been obtained using Daubechies and Symmlet orthonormal wavelet filters [16], as shown in Table 1. The name of each basis shown in this table is followed by the number of vanishing moments of the corresponding wavelet filter used. It is worth noting the excellent results achieved when using Symmlet orthonormal wavelet filters with 9, 5, 6, 4 and 8 vanishing moments, as well as Daubechies wavelet filters with 8, 9, and 3 vanishing moments.

We have compared our method with the method proposed by Lee and Wang in [15]. They have used Gabor filter-based features for fingerprint recognition. In our implementation the 64×64 central subimage is divided into 64 non-overlapping blocks of 8×8 pixels, and magnitude Gabor features on 4 orientations are extracted from each block. In this way a feature vector of length $4 * 64 = 256$ which contains magnitude Gabor features is created from each fingerprint image. The only difference with respect to the original method is the size of the central subimage chosen in each fingerprint. We found out that a larger central subimage than 64×64 would include also extraneous details located outside the fingerprint pattern and therefore would decrease the performance of Lee and Wang's method.

The k-NN recognition rates achieved with the method proposed in [15] are shown for comparison in the last line of Table 1. They are slightly inferior to the performances achieved in some wavelet basis using the method proposed here. In addition, we use a smaller feature vector (of length 48) than the feature vector (of length 256) required in this case by the method of Lee and Wang.

4. CONCLUSIONS

A new method of fingerprint recognition using wavelet based features have been proposed. The features are extracted directly from the gray scale fingerprint image without preprocessing, and hence the proposed method achieves lower computational complexity than conventional methods based on minutiae features. The method has been successfully compared against one of the methods recently proposed in the literature. The high recognition rates achieved by our method as well as its low computational complexity reveal that the method can be used to efficiently solved a security problem involving a small number of fingerprint images.

5. REFERENCES

[1] A.K. Jain, R. Bolle, and S. Pankanti, Eds., *Biometrics - Personal Identification in Networked Society*, Kluwer Academic Publishers, 1999.

[2] H.C.Lee, R.E.Gaenssleh, Eds., *Advances in Fingerprint Technology*, Elsevier, New-York, 1991.

[3] Nalini K. Ratha, Shaoyun Chen, Anil K.Jain, "Adaptive Flow Orientation-Based Feature Extraction in Fingerprint Images", *Pattern Recognition*, vol.28, no.11, pp.1657-1672, 1995.

[4] Nalini K. Ratha, Kalle Karu, Shaoyun Chen, Anil K.Jain, "A Real-Time Matching System for Large Fingerprint Databases", *IEEE Trans. on Pattern Recognition and Machine Intelligence*, vol.18, no.8, pp.799-813, 1996.

[5] Anil Jain, Lin Hong, Ruud Bolle, "On-Line Fingerprint Verification", *IEEE Trans. on Pattern Recognition and Machine Intelligence*, vol.19, no.4, pp.302-313, 1997.

[6] Anil K. Jain, Lin Hong, Sharath Pankanti, Ruud Bolle, "An Identity - Authentication System Using Fingerprints", *Proceedings of the IEEE*, vol.85, no.9, pp.1364-1388, 1997.

[7] A.Wahab, S.H.Chin, E.C.Tan, "Novel Approach to Automated Fingerprint Recognition", *IEE Proc.-Vis. Image Signal Processing*, vol.145, no.3, pp.160-166, 1998.

[8] D.C. Douglas Hung, "Enhancement and Feature Purification of Fingerprint Images", *Pattern Recognition*, vol.26, no.11, pp.1661-1671, 1993.

[9] M.Tico, P.Kuosmanen, "An Algorithm for Fingerprint Image Postprocessing", accepted to *The 34-th Asilomar Conference on Signal, Systems, and Computers*, Pacific Grove, California, Oct.29-Nov.1, 2000.

[10] Kalle Karu, Anil K.Jain, "Fingerprint Classification", *Pattern Recognition*, vol.29, no.3, pp.389-404, 1996.

[11] A.K. Jain, S. Prabhakar, and L. Hong, "A Multichannel Approach to Fingerprint Classification", *IEEE Trans. on Pattern Recognition and Machine Intelligence*, vol. 21, no. 4, pp. 348-359, 1999.

[12] M. Tico, P. Kuosmanen, "A Multiresolution Method for Singular Points Detection in Fingerprint Images", *Proc. of IEEE International Symposium of Circuits and Systems (ISCAS'99)*, vol. IV, pp. 183-186, 1999.

[13] F.T. Gamble, L.M. Frye, and D.R. Grieser, "Real-time Fingerprint Verification System", *Applied Optics*, vol. 31, no. 5, pp. 652-655, 1992.

[14] C.L. Wilson, C.I. Watson, and E.G. Paek, "Effect of resolution and image quality on combined optical and neural network fingerprint matching", *Pattern Recognition*, vol. 33, no. 2, pp. 317-331, 2000.

[15] C.J. Lee, S.D. Wang, "Fingerprint feature extraction using Gabor filters", *Electronics Letters*, vol. 35, no. 4, pp. 288-290, 1999.

[16] S. Mallat, *A Wavelet Tour of Signal Processing*, Academic Press, 1998.

[17] Biometric Systems Lab., University of Bologna, Cesena-Italy, (www.csr.unibo.it/research/biolab/).