Fingerprint Recognition with Improved Wavelet Domain Features

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Abstract

A fingerprint recognition algorithm based on the wavelet domain features of a fingerprint image is proposed in this paper. Critical wavelet coefficients are selected to form a feature vector of the fingerprint. As compared with a recently reported algorithm of similar approach, the proposed algorithm is superior in terms of both recognition rate and computational complexity.

I. Introduction

Fingerprint recognition is the most widely used method in biometrics identification. Accordingly, various algorithms were proposed in the literature. Basically, they can be classified into two approaches. The first one is minutiae-based approach and the second one is image-based approach. Minutiae-based approaches require extensive pre-processing operations such as ridge thinning and minutiae detection in order to reliably extract the minutiae features [1]. Image-based approaches do not require the extensive pre-processing. It treats the whole image as an input to extract the features. However, the ability to track variations in position, scale, and rotation angle is limited.

Recently, Tico, Kuosmanen and Saarinen proposed an effective image-based algorithm for fingerprint recognition [3]. The fingerprint patterns are matched based on wavelet domain features, which are directly extracted from the gray-scale fingerprint image without pre-processing.

In this algorithm, the two-dimensional (2D) wavelet decomposition on J octaves is performed on a discrete gray-scale fingerprint image I to produce $3J+1$ subimages, say,

$$[a_J, \{d_j^1, d_j^2, d_j^3\}_{j=1,\ldots,J}] \qquad (1)$$

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 in d_j^1, d_j^2 and d_j^3 correspond, respectively, to vertical high frequency components (horizontal edges), horizontal high frequency components (vertical edges), and high frequency components in both directions [2].

A wavelet domain feature vector of $3J$ elements is then formed with the ordered normalised L2-norms of the wavelet subimage d_j^k and is given as

$$[\{e_j^1\ e_j^2\ e_j^3\}_{j=1,\ldots,J}] \qquad (2)$$

where

$$e_j^k = \frac{\left\|d_j^k\right\|_2}{\sum_{i=1}^{J}\sum_{l=1}^{3}\left\|d_i^l\right\|_2} \qquad (3)$$

for all $j=1,\ldots,J,$ and $k=1,2,3.$

This vector exhibits valuable discriminatory properties for fingerprint patterns. In recognition, the similarity between two feature vectors was measured based on the intersection operator proposed in [4].

Based on some simulation results we have had, we found that some wavelet coefficients are insignificant and do not contribute too much to the recognition accuracy. Some of them may even spoil the matter by disturbing the stability of the feature vectors extracted from different fingerprints of an identical finger. In this paper, we select appropriate wavelet coefficients to form the feature vector such that we can improve the recognition rate and reduce the computational effort simultaneously. The modified version is actually a generalized version of [3]

II. Proposed Algorithm

Without losing generality, let us consider the case that a database of $O \times P$ fingerprint images are constructed for future recognition by collecting P fingerprints from each of O individuals. Here we assume that all images of the same individual come from a single finger. This database can be used as a training set. Prior to recognition, the wavelet coefficients of the images of the database are evaluated to select appropriate coefficients for generating a feature vector. This is a one-off exercise and need not be carried out again unless new fingerprints are added to the database.

In practical situations, even fingerprints captured from the same finger deviate a bit from each other. Some wavelet coefficients are sensitive to this deviation and they should not be included in the feature vector. For each individual, these coefficients can be identified by evaluating their variances in the P fingerprint images

$$(\sigma^k_{j,(o,c)})^2 = \frac{1}{P}\sum_{p=1}^{P}(I^k_{j,(o,p,c)} - m^k_{j,(o,c)})^2 \qquad (4)$$

where

$$m^k_{j,(o,c)} = \frac{1}{P}\sum_{p=1}^{P} I^k_{j,(o,p,c)}$$

is the mean of the corresponding coefficients of the o^{th} individual and $I^k_{j,(o,p,c)}$ is the c^{th} coefficient of the wavelet subimage d^k_j of the p^{th} fingerprint image of the o^{th} individual.

Coefficients of index (k,j,c) will be abandoned if their associated $(\sigma^k_{j,(o,c)})^2$ are larger than a predefined threshold T_l. This test is done for each individual. In formulation, we define a wavelet subimage mask $ML^k_{j,(o)}$ and its c^{th} element is defined as

$$ML^k_{j,(o,c)} = \begin{cases} 1 & if\ (\sigma^k_{j,(o,c)})^2 \le T_l \\ 0 & else \end{cases} \qquad (5)$$

Only those coefficients that can survive after all tests can proceed to another test as follows.

Obviously, the more coefficients are involved in the computation of the feature vector, the more computational effort is required. We found that some insignificant wavelet coefficients are not critical to the recognition rate and can be abandoned without penalty. The significance of the coefficient indexed by (k,j,c) can be estimated by its variance

$$(\sigma^k_{j,(c)})^2 = \frac{1}{OP}\sum_{o=1}^{O}\sum_{p=1}^{P}(I^k_{j,(o,p,c)} - m^k_{j,(c)})^2 \qquad (6)$$

where

$$m^k_{j,(c)} = \frac{1}{OP}\sum_{o=1}^{O}\sum_{p=1}^{P} I^k_{j,(o,p,c)}$$

is the mean of the corresponding coefficients of all fingerprint images. Only coefficients whose $(\sigma^k_{j,(c)})^2$ are larger than a predefined threshold T_g are retained. Accordingly, we define a wavelet subimage mask MG^k_j whose c^{th} element is defined as

$$MG^k_{j,(c)} = \begin{cases} 1 & if\ (\sigma^k_{j,(c)})^2 > T_g \\ 0 & else \end{cases} \qquad (7)$$

An overall wavelet subimage mask for all tests on (k,j), say W^k_j, can be defined as

$$W^k_{j,(c)} = MG^k_{j,(c)} \cdot \prod_{o=1}^{O} ML^k_{j,(o,c)} \qquad (8)$$

where $W^k_{j,(c)}$ is the c^{th} element of W^k_j. Each element of W^k_j is either 0 or 1, which corresponds to the weight for an abandoned or a retained coefficient.

After all, the elements of the feature vector of a fingerprint image is determined by

$$e^k_j = \frac{\left\|d^k_j\right\|^2_{W^k_j}}{\sum_{i=1}^{J}\sum_{l=1}^{3}\left\|d^l_i\right\|^2_{W^l_i}} \qquad (9)$$

for $j = 1,\dots,J$ and $k = 1,2,3$, where $\|\bullet\|^2_{W^k_j}$ denotes the weighted L2-norm and W^k_j is the overall wavelet subimage mask for wavelet subimage (k,j).

One can see that the algorithm proposed in [3] is actually a special case of our proposed algorithm. In particular, it happens when all coefficients are retained. The reduction of the coefficients in our approach reduces the realization effort of fingerprint recognition in two ways. First, it reduces the effort for computing the L2-norms when extracting feature vectors. Second, useless wavelet coefficients need not be evaluated.

III. Simulation and Comparative study

Simulation was carried out with a database obtained from [5]. This database contains 168 fingerprints collected from 21 individuals. Each individual has 8 fingerprint images of size 256×256 each. For each individual, k of 8 fingerprints were randomly selected to form a training set and the remaining images were used for testing. J is set to be 6 in the simulation as in [3]. The matching criterion used to test two feature vectors is based on the intersection operator [4] and is defined as

$$H(Q,D)=\frac{\sum_{i=1}^{3J}\min(Q_i,D_i)}{\sum_{i=1}^{3J}D_i} \tag{10}$$

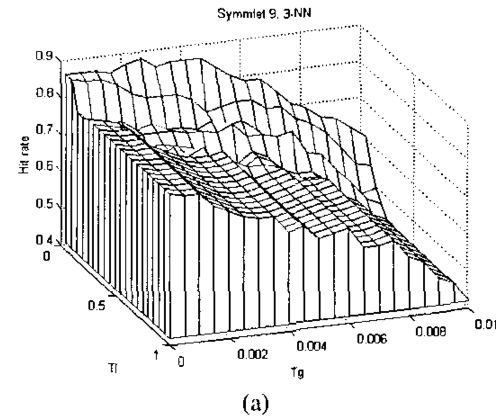
where Q_i is the i^{th} element of the query feature vector Q and D_i is the i^{th} element of a particular feature vector D in the database.

The performance was evaluated using a k-NN classifier, with no rejection option. No pre-processing such as core point detection, thinning, orientation estimation and extraction of region of interest was performed in the simulation.

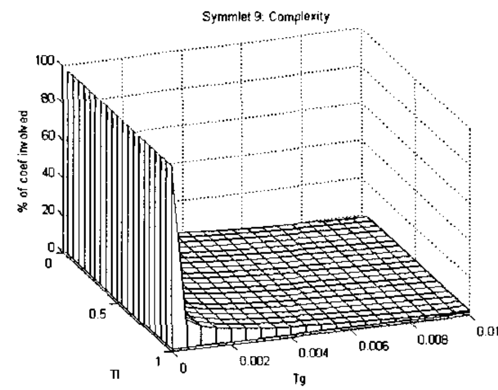
Figure 1 shows how T_l and T_g affects the recognition rate when k equals to 3 and a Symmlet filter with 9 vanishing moments (Symmlet 9) is used. Here, T_l and T_g are, respectively, normalised with respect to the maximum values of $\{(\sigma_{j,(o,c)}^k)^2 \mid \forall\ o, j, k, c\}$ and $\{(\sigma_{j,(c)}^k)^2 \mid \forall\ j, k, c\}$. It shows that there is no need to include all wavelet coefficients and some of them may even spoil the matter. Similar results were obtained for other filters and values of k. Figure 2 shows the case when k equals to 4 and a Daubechies filter with 6 vanishing moments (Daubechies 6) is used. Note that Tico's approach [3] corresponds to the case when T_l=1 and T_g=0.

Tables 1 and 2 show the comparison of recognition rate and the percentage of coefficients involved in Tico's [3] and the proposed algorithm. The results were obtained when normalised T_l and T_g were set to be, respectively, 0.05 and 0.0005.

Simulation results show that this setting was good for all evaluated filters though it was not optimal for individual filters. The result shows that the proposed algorithm can provide a better recognition rate and save more than 80% of the computational effort as compared with [3].

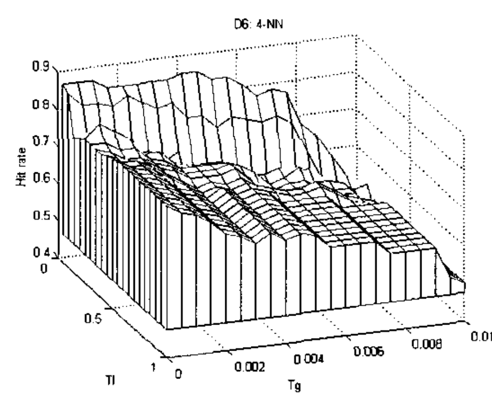


(a)

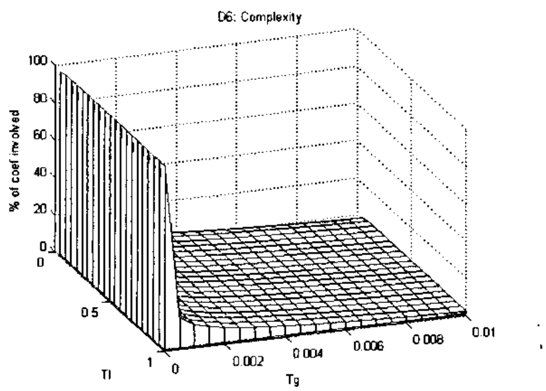


(b)

Figure 1. (a) Recognition rates and (b) complexity of the proposed algorithm at different settings of T_l and T_g for Symmlet 9: 3-NN



(a)



(b)

Figure 2. (a) Recognition rates and (b) complexity of the proposed algorithm at different settings of T_l and T_g for Daubechies 6: 4-NN

Filter	Recognition Rate (%)					
	2-NN		3-NN		4-NN	
	[3]	Ours	[3]	Ours	[3]	Ours
Daubechies 5	74.60	85.71	75.24	82.86	84.52	88.10
Daubechies 6	69.05	84.13	73.33	80.95	80.95	88.10
Daubechies 10	65.08	74.60	68.75	79.05	73.81	77.38
Symmlet 6	84.13	86.51	88.57	87.62	88.10	91.67
Symmlet 9	80.16	86.51	80.95	87.62	85.71	92.86
Symmlet 10	81.75	84.13	82.86	84.76	83.33	85.71
Average	75.79	83.60	78.25	83.81	82.74	87.30

Table 1. Comparison of the recognition rate of Tico's [3] and the proposed algorithm

Filter	% of coefficients involved as compare with [3]		
	Ours		
	2-NN	3-NN	4-NN
Daubechies 5	15.39	15.10	14.92
Daubechies 6	17.12	15.80	16.21
Daubechies 10	17.88	17.38	17.34
Symmlet 6	16.11	16.19	15.69
Symmlet 9	15.96	16.05	15.82
Symmlet 10	15.75	15.81	15.27
Average	16.37	16.05	15.87

Table 2. Comparison of the coefficients involved of Tico's [3] and the proposed algorithm

IV. Conclusions

In this paper, an improved fingerprint recognition algorithm based on [3] is proposed. Insignificant or destructive wavelet coefficients are not selected to form the wavelet domain feature vector. Simulation results show that this modification improves the recognition rate at a significant reduction of computational effort.

Acknowledgement

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