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Fingerprint Recognition Using Haar Wavelet Transform and Local Ridge Attributes Only

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Abstract— Many of the existing human recognition applications are based on fingerprints. Most of fingerprint techniques use minutiae points for fingerprint representation and matching. Moreover, the techniques are mostly failed when partial fingerprint images are matched. This paper proposes a fingerprint recognition technique which uses local robust features for fingerprint representation and matching. The technique performs well in presence of partial fingerprints. The adopted local features include features extracted from the detail of Haar wavelet subheads. Experiments are performed using a database of 160 low quality fingerprint images collected from 40 subjects, (i.e., 4 images per subject). The test results indicated good system ability to signify low-quality fingerprint images even with existence of partial loss in fingerprint images. The technique has produced a recognition accuracy of 94.37% using one decomposition level and 96.87% using two decomposition levels of wavelet.

Keywords— Fingerprints, Automatic Fingerprint Recognition Systems, Fingerprint Recognition, Wavelet Transform, Haar Wavelet, minimum distance classifier, Region of Interest.

I. INTRODUCTION

Recognition of persons by means of biometric characteristics is an emerging technology in our society. Among the possible biometric traits like face, iris, speech, and hand geometry, fingerprint is the most widely used trait, because of its distinctiveness and persistence over time [1]. A fingerprint image is a pattern of ridges and valleys, with ridges as dark lines while valleys as light areas between the ridges. Ridges and valleys generally run parallel to each other, and their patterns can be analyzed on a global and local level [2]. Global analysis of the fingerprint image is done to extract singular regions like loop, delta, and whorl. Many matching algorithms use the center of the highest loop type singularity, known as the core, to pre-align fingerprint images for better results. These singularities help form the 5 major classes [3] of fingerprints. While the global level analysis allows for a general classification of fingerprints, analyzing the image at the local level provides a significant amount of detail. These details are obtained by observing the locations of ridge-discontinuities, known as minutiae points. The most common out of different types of minutia are terminations (a ridge ending abruptly) and bifurcations (a ridge forks). The other types of minutiae are somehow or other combinations of terminations and bifurcations [2]. Most of the existing AFRS use the determined minutia features for recognition [4].

The noise and distortion during the acquisition of the fingerprint and errors in the minutia extraction process mostly result in spurious and missing minutiae that easily degrade the performance of recognition rate. Another problem is that the rotation and displacement of the finger placed on the sensor, can lead to different images for the same fingerprint such that they have only a partial overlap area resulting in only a small number of corresponding minutiae points [5]. The problems with minutiae extraction can be more severe if the fingerprint is acquired using a compact solid-state sensor. They provide only a small contact area for the fingertip and, therefore, capture only a limited portion of the fingerprint pattern [6].

Since it is difficult to reliably obtain the minutia points from poor quality fingerprint images or from the small sensor images, it is highly necessary to exploit novel attributes (such as, local ridge attributes). Analyzing a fingerprint on the local level provides the necessary information to accurately distinguish one fingerprint from another.

Wavelets are flexible-window Fourier-transform and they are used to decompose the image signal into different levels of resolution to ease information interpretation. Wavelets offer high temporal localization for high frequencies while offering good frequency resolution for low frequencies. Therefore, wavelet analysis can be utilized to extract local features from images [Pok10]. In wavelet analysis, there is a mother wavelet and then, there are wavelet coefficients derived from this mother wavelet. These coefficients are independent and they create a set of features of the actual fingerprint image at different resolutions.

In this paper, we describe an approach for fingerprint recognition that works with the following steps: (1) Extraction of features from Fingerprint by Haar wavelet method with a combination of non minutia, local features of ridges, (2) Investigate the behavior of the recognition system accuracy using one decomposition of wavelet in comparison with using two decomposition of wavelet, (3) Divide each sub-image into overlapping blocks to get more details of localization. The system is applied on low quality fingerprint database. The system performance will investigated and the effectiveness of partial fingerprint features loss will be investigated.

In section II a brief review for some of related works in fingerprint recognition is given. In section III, an illustration for the fingerprint recognition model is presented. Experiment results are reported in Section IV. The effectiveness of system parameters is given in V and some conclusions are outline in VI.

II. Related Work

1. Pokhriyal and Lehri [2] discussed an approach for fingerprint verification, based on wavelets and pseudo Zernike moments (PZMs). They used different types of wavelets for study. The obtained verification rate using Haar wavelet was 94.72%.
2. Gawande et. al. [7] proposed a feature-level fusion framework for combining features of Iris and Fingerprint, as they contain most prominent features. They used Haar wavelet transform for extraction of fingerprint features. The recognition performance of Fingerprint and Iris systems were operated as uni-modal systems. The best attend result (i.e., 88%) is obtained for uni-modal Iris using block sum feature extraction. Fingerprint feature extraction by four decompositions of Haar wavelet exhibited lowest performance with 84% accuracy.
3. Sanjekar and Dhabe [8] developed fingerprint recognition method using Haar wavelet transform and achieved verification rate of 82.08 overall verification rate.

III. The proposed Fingerprint Recognition Model

The general structure of the proposed fingerprint Recognition system is shown in Fig. (1). A fingerprint biometric template based system is developed. It is consist of six major stages: (i) pre-processing, (ii) Haar wavelet transform, (iii) partition sub bands to blocks, (iv) feature extraction, (v) moment analysis, and (vi) matching.

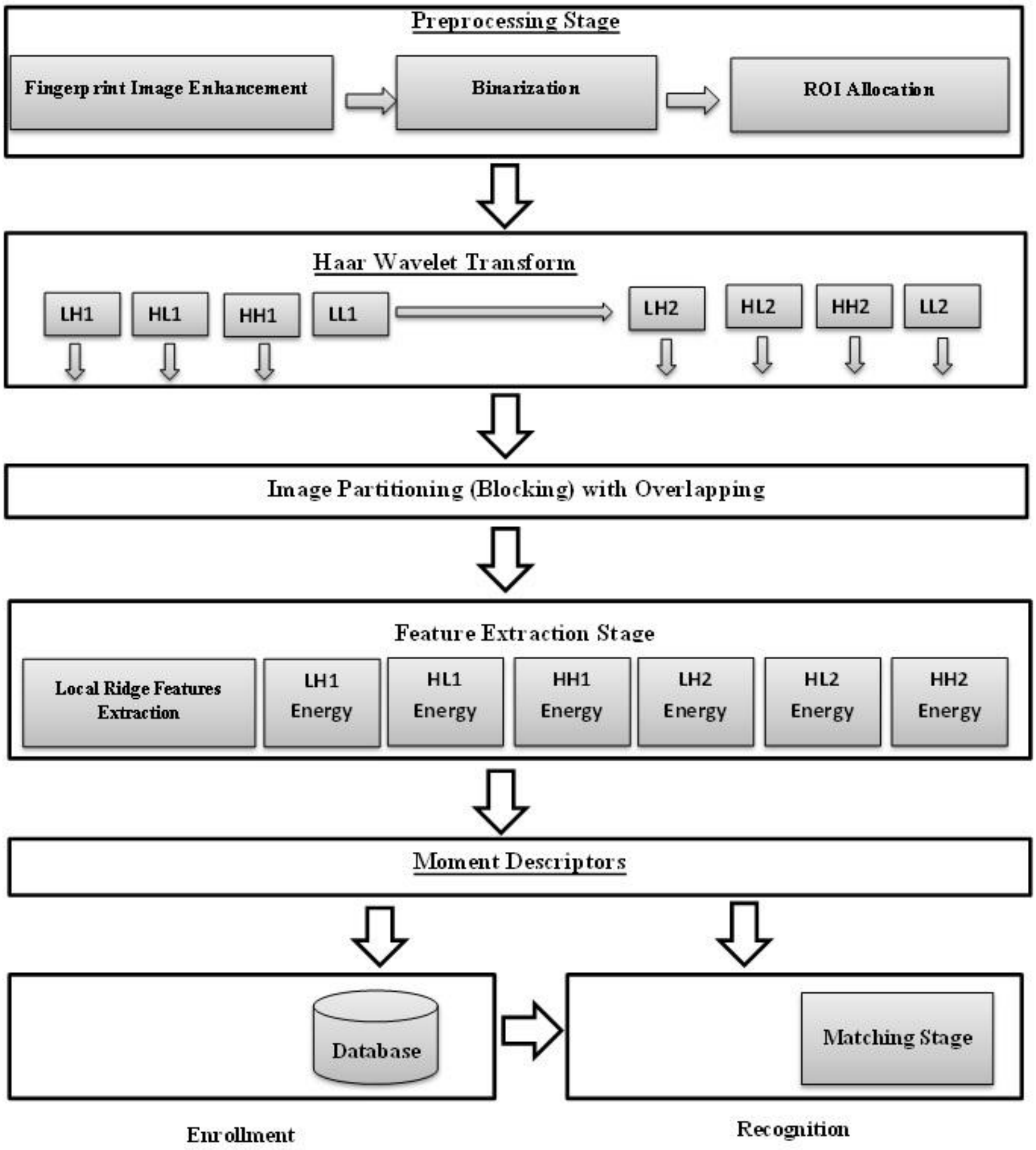

Fig. 1: Fingerprint Recognition System

A. Fingerprint Image Pre-processing Stage

The performance of extraction stage and matching stage depends heavily upon the quality of the input fingerprint image. Several reasons may degrade the quality of the fingerprint image such as the presence of scars, variations of the pressure between the finger and acquisition sensor, worn artifacts, and the environmental conditions during the acquisition process. Therefore, the pre-processing phase is considered as a necessary step in the established model. For fingerprint cognition tasks, pre-processing should cover three main tasks.

1) *Image Enhancement:* it is applied to improve the detection of important image details. The main steps involved in the image enhancement process are:
   - Convert to gray-scale image
   - Calculation the gray-scale statistics.
   - Pre_removel of false areas may formed in image background (globel thresholding).
   - Normalization.
   - Smoothing using Gaussian filter.
2) *Image Binarization:* an automatic binarization is applied on the gray level image; it is based on automatic determination of optimum threshold value (i.e., local thresholds); it should cause efficient separation of the region of interest ROI from their background.

3) *Extraction of Region of Interest:* The objective of this stage is to locate the fingerprint sprite region in the fingerprint image which depicting the ridges area and discard the regions of the image containing irrelevant information.

B. Haar Wavelet Transform

Wavelet transform (WT) represents image as a sum of wavelets on different resolution levels. The power of WT is that it offers high temporal localization for high frequencies while attempts good frequency resolution for low frequencies. Thus, WT is a good tool to extract local features of the image [2].

Wavelet transform is a mathematical tool based on many layer function decomposition. After applying wavelet transform, a signal can be described by many wavelet coefficients which represent the characteristics of signal. If the image has distinct features with some frequency and direction, the corresponding sub images have larger energies in wavelet transform. For this reason wavelet transform has been widely used in signal processing, pattern recognition and texture recognition. By applying wavelet transform, vital information of original image is transformed into compressed image without much loss of information. Haar wavelet transform technique, the most popular amongst wavelets, is applied for feature extraction from Fingerprint. The benefit of Haar transform is its ease of implementation and also it can work well on non-linear intensity image [7].

C. Blocking

In order to avoid the recognition failure caused by the appearance of partial loss of the fingerprint region, each decomposed sub-image is divided into overlapping blocks. The overlapping is adopted to suppress the shifting effect and the partial local distortion which may occur at any place of fingerprint. The value of overlapping length is taken as a ratio of block length. The block length is obtained by dividing the image length by the number of blocks. The effects of both the number of blocks and overlapping ratio values is tested to find their suitable values which lead to best cognition rate. We must notice that the width and height of the image may be not equal, so the block dimensions (i.e., width and height) may not equal. In order to handle this problem the shortest dimensions of the image is padded by adding empty rows or columns on both sides of the image. After partitioning, the features are extracted from each block.

D. Feature Extraction

In this work, features are extracted from the energy distribution in the Haar wavelet transform and a combination of local ridges properties. Wavelet Transform breaks an image down into four sub-sampled images and then analyses each component with resolution matches its scale. In this stage, two possible wavelet levels are considered adopted: the first one includes extracting a feature vector using first-level Wavelet decomposition, and the second includes extracting a feature vector using two-level Wavelet decomposition. A set of wavelet features and local ridge features that represent the input fingerprint image have been extracted by applying the following steps:

Step 1: Decompose a given image with 2-D wavelet transform into four sub-images, as indicated in Figure (2) , where LL represents low frequency vectors (approximate), HL represents high frequency vectors in horizontal direction, LH represents high frequency vectors in vertical direction, HH represents diagonal high frequency vectors. After first decomposition, LL quarter (i.e., the approximate sub band) is submitted for next decomposition, as indicate in Figure (3).

LL1	LH1
HL1	HH1

Fig. 2: One-level Wavelet Decomposition

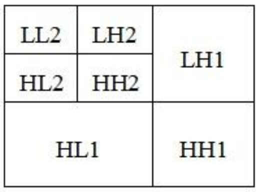

Fig. 3: Two-level Wavelet Decomposition.

Step 2: For each decomposed image including LH1, HL1, and HH1 generated in the first pass and LL2, HL2, and HH2 which are generated during the second transform pass:

Step 2.1: Divide each sub-image into overlapping blocks.

Step 2.2: Compute the energy of each block belong to wavelet sub band using the following equation:

$$E = \sum_{x=xs}^{x2-1} \sum_{y=ys}^{y2-1} \text{wavelet}(i,j)^2 \quad (1)$$

Where (Xs, Ys) are the range of coordinates of the tested image, wavelet (i, j) is the wavelet sub bands.

Step 3: For the decomposed image including LL1 in the first wavelet pass and LL2 after the second.

Step 3.1: Repeat Step 2.1

Step 3.2: Extract the set of local ridge features listed in Table (I) from each block.

TABLE (I): LOCAL RIDGE FEATURES

Feature Name	Description
No_points	The number of pixels that have value equal to one (i.e., ridge value),
Maxv	The maximum number of vertical crossings to the existing ridges.
Minv	The minimum number of vertical crossings to the existing ridges.
Mid_v	The mid number of vertical crossings to the existing ridges
Maxh	The maximum number of horizontal crossings to the existing ridges.
Minh	The minimum number of horizontal crossings to the existing ridges.
Mid_h	The mid number of horizontal crossings to the existing ridges
Hits_y	The number of horizontal ridge cut lines at the central vertical line
Hits_x	The number of vertical ridge cut lines at the central horizontal line
Hits_diag	The number of ridge cut lines at the diagonal line
Hits_2diag	The number of horizontal ridge cut lines at the second diagonal line

E. Feature Analysis and Evaluation

Each feature array extracted from the fingerprint image is fed as an input vector to the analysis stage in order to provide a feature vector invariant for scale, shifting, and rotation. In our proposed system, the seven invariant moments, which have been proposed by Hu [9], are adopted.

F. Training Rule and Features Analysis

A training set of fingerprint samples is used to train the classifier and to address the feature list. Then this set is used to assess the recognition accuracy of the system (after the training phase).In this work, a set of invariant moments (i.e., 119 moment descriptors) have been used to represent the feature vector given by 11 local ridge features, and 6 wavelet features from two-level decomposition. The feature vectors are stored in intermediate data base table. Then, a statistical analysis was performed on these extracted features. The statistical analysis involves the determination of the mean and standard deviation of each feature and for each class as the following:

$$M(p,f) = \sum_{i=1}^{s_T} Fe(p,i,f)/s_T$$

(2)

$$\sigma(p,f) = \sqrt{\sum_{i=1}^{s_T} Fe(P,i,f) - M(p,i,f)}$$

(3)

Where p and fare the person number and feature number, respectively, and s_T is the total number of samples taken for p-person.

The second stage in enrollment phase is feature analysis. The aim of this stage is to evaluate the discrimination power of each feature, and then to build the decision rule which should use the best set of features leads to highest possible recognition. For feature analysis, the ability of each feature alone to perform successful discrimination is determined. For defining the best discriminating features, the minimum distance classification method measure based on single feature is applied, and its true-positive matching ratio (i.e., efficiency) is determined.

The best forty features which led to highest matching ratio are chosen. Then, the minimum distance classifier (MDC) based on two features from the forty features is applied and the best couple of features which gave best matching efficiency is chosen, then the minimum distance rule is re-calculated using the combination of three, and next four features, and so forth till reaching the highest recognition rate. It is found that the use of 19 features led to matching efficiency (96.87%).

Also, a set of invariant moments (i.e., 98 moment descriptors) have been used to represent the feature vector given by 11local ridge features, and 3 wavelet features from one-level decomposition is chosen. Then, it is found that the use of 20 features led to matching efficiency (94.37%).

G. Matching

The absolute difference (D) for each feature is computed between corresponding values taken from the test fingerprint value and the template mean vector for each person divided by the corresponding standard deviation. By combining the square difference of the selected best 19 features (aDi), the recognition of the finger with the best similar finger in database is done by selecting the smallest value of aDi.

$$D(p,f) = \sum_{i=1} \left(\frac{Fe(p,i,f) - M(p,f)}{\sigma(p,f)}\right)^2$$

(4)

$$aDi(p) = \sum_{f=1}^{19} D(f)$$

(5)

Where p, f are the person number and the feature number, respectively.

IV. EXPERIMENT RESULT

The effect of local ridge and wavelet features, which introduced in this research, in improving the recognition performance has been investigated using fingerprint samples taken from FVC 2004 DB3_A [10]. The foll-owing results are observed.

For the one-level Wavelet decomposition and local ridge features combination, a subset consists of 20 features have been selected from the overall set of features (i.e. 98 features). This selection is due to incremental comprehensive tests which were conducted on the training set of samples to find out the best set of features that can be used to yield best matching rates. The final highest recognition rate is (94.37%) after 13 rounds and the total number of features is 20 features. During the repeated additions some of the features have been selected many times. The result is shown in table (II).

TABLE (II): The LOCAL RIDGE FEATURES SET ADDED at EACH TRAINING ROUND

Round	Selected Features	n_C	R
1	50, 84	39	24.37%
2	78, 22	72	45%
3	92, 36	97	60.62%
4	87, 79	111	69.37%
5	29, 94	122	76.25%
6	84, 40	133	83.12%
7	89, 0	137	85.62%
8	95, 30	143	89.37%
9	42, 30	145	90.62%
10	84, 33	147	91.87%
11	97, 40	148	92.5%
12	78, 3	149	93.12%
13	92, 85	151	94.37%

TABLE (III): The NAME and the NUMBER of REPETITION of EACH FEATURE SELECTED THROUGH 12 ROUNDS

No.	Feature No.	Repeat Times	Type of Feature	Feature Name	No.	Feature No.	Repeat Times	Type of Feature	Feature No.
1	84	3	Wavelet	HH	11	40	2	Local Ridge	Maxh
2	50	1	Local Ridge	Hit_x	12	0	1	Local Ridge	No_points
3	78	2	Wavelet	HH	13	89	1	Wavelet	HL
4	22	1	Local Ridge	Mid_h	14	95	1	Wavelet	LH
5	92	2	Wavelet	LH	15	30	2	Local Ridge	Maxh
6	36	1	Local Ridge	Maxh	16	42	1	Local Ridge	Mid_h
7	87	1	Wavelet	HL	17	33	1	Local Ridge	Minh
8	79	1	Wavelet	HH	18	97	1	Wavelet	LH
9	29	1	Local Ridge	Minh	19	3	1	Local Ridge	No points
10	94	1	Wavelet	LH	20	85	1	Wavelet	HL

Also, for the combination of second-level wavelet decomposition features, and local ridge features, a subset consists of 19 features have been selected from the overall set of features (i.e. 119 features). The resulted recognition rate is 96.87%. This result is shown in table (IV). During the repeated additions some of the features were also repeated many times. The result is shown in table (V).

TABLE (IV): The FEATURES SET ADDED DURING EACH ROUND DURING TRAINING SET

Round	Selected Features	n_C	R
1	105, 84	40	25%
2	92, 112	82	51.25%
3	78, 40	117	73.12%
4	107, 94	128	80%
5	89, 99	135	84.37%
6	78, 28	139	86.87%
7	91, 72	143	89.37%
8	84, 42	144	90%
9	114, 79	149	93.12%
10	92, 85	150	93.57%
11	84, 112	151	94.37%
12	87, 78	152	95%
13	89, 110	153	95.62%
14	92, 40	155	96.87%

TABLE (V): The NAME and the NUMBER of REPETITION of EACH FEATURE DELECTED THROUGH 11 ROUNDS

No	Feature No.	Repeat times	Type of Feature	Feature Name
1	105	1	Wavelet	HL2
2	84	3	Wavelet	HL
3	92	3	Wavelet	LH
4	112	2	Wavelet	LH2
5	78	3	Wavelet	HH
6	40	2	Local Ridge	Maxh
7	107	1	Wavelet	HL2
8	94	1	Wavelet	LH
9	89	2	Wavelet	HL
10	99	1	Wavelet	HH2
11	28	1	Local Ridge	Minh
12	91	1	Wavelet	LH
13	72	1	Local Ridge	Hits_2diag
14	42	1	Local Ridge	Mid_h
15	114	1	Wavelet	LH2
16	79	1	Wavelet	HH
17	85	1	Wavelet	HL
18	87	1	Wavelet	HL
19	110	1	Wavelet	HL2

V. THE EFFECTIVENESS OF SYSTEM PARAMETERS

The involved parameters of our system include the following: (1) the number of blocks and (2) the overlapping ratio. The test results showed that their values have significant effects on the performance of the proposed system. The performance is examination first by using the combination of local ridge and first-level Haar wavelet decomposition features. The recognition rate is calculated with using normalized Euclidean distance measures. The result show in Table (VI) belong to different values for the number of blocks, different values of overlapping ratio, and the highest recognition rate (94.37%) is achieved when the number of blocks is taken(4) and the overlapping ratio is set(0.7). Also, the performance is examined by using a combination of local ridge and second-level Haar wavelet decomposition features. The result are show in Table (VII) where the highest achieved recognition rate is (96.87%) when the number of blocks is taken (4) and the overlapping ratio is set (0.7) too.

TABLE (VI): The FINAL RECOGNITION RATES for DIFFERENT VALUES of BLOCKS and DIFFERENT VALUES of OVERLAPPING RATIO USING the COMBINATION OF LOCAL RIDGE and FIRST-LEVEL WAVELET DECOMPOSITION FEATURES

No. of Blocks	3	4	5
Overlapping Ratio	Recognition Rate		
0.5	84.37%	85%	82.57%
0.6	86.25%	93.12%	87.5%
0.7	89.37%	94.37%	86.87%
0.8	83.12%	88.12%	86.87%

TABLE (VII): The FINAL RECOGNITION RATES for DIFFERENT VALUES of BLOCKS and DIFFERENT VALUES of OVERLAPPING RATIO USING the COMBINATION OF LOCAL RIDGE and SECOND-LEVEL WAVELET DECOMPOSITION FEATURES

No. of Blocks	3	4	5
Overlapping Ratio	Recognition Rate		
0.6	90.62%	91.87%	88.75%
0.7	91.25%	96.87%	91.87%

0.8	90%	95.62%	93.12%
0.9	89.37%	93.75%	91.87%

VI. CONCLUSIONS AND FUTURE WORK

In this research, a fingerprint recognition model including preprocessing, Haar wavelet transform, partitioning, feature extraction, and matching. At the feature extraction stage, new local ridge set of features in combination with first or second-level haar wavelet decomposition features can use and tested. The experimental result shows that although the first-level haar wavelet decomposition features have given good recognition rate (94.37%), the more decomposition features can increase the recognition rates up to (96.87%). In addition, the combination of other local ridge features can also work in combination with wavelet features to give these recognition rates. The experimental results show that the partitioning into blocking with overlap has improved the recognition accuracy and helps to overcome on the partial loss in low-quality fingerprint image. The recognition rate is high affected by variation of block length and overlapping ratio.

For future work, our module can be extended in different direction such as: using another enhancement method that may provide us with higher enhancement, divide the fingerprint image using another mechanical or using more levels of decompositions; this may increase the recognition rate to 100% without the need for the combination with the other features (local ridge features), using another matching method instead of minimum distance such as neural method which may increase the power of our system, and finally using a dedicated hardware to speed up the processing time.

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