Fingerprint Recognition Technique using Wavelet Transform

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Abstract

This paper is concerned with the study and design of a fingerprint recognition system based on *wavelet transformation*. Fingerprints of 25- persons were taken as test data. These fingerprints were scaled, rotated and translated accordingly and compared with the original images. The system proved to be successful in the presence of these effects, where the obtained recognition accuracy is about 82%. To improve the recognition rate of the system, statistical features were extracted from spatial domain and combined with the wavelet features. The selected statistical features are well known for their capability to recognize images in general. The recognition accuracy, after the combination, was highly improved. It gives about 100% for the conditions covered in the tests. In the case of recognizing multiple instances for the same person, the results show that wavelet descriptors (compared with moment descriptors) are an efficient representation that can provide reliable recognition in problems with large input variability.

***Keywords**: Wavelet Transformation, Fingerprint Recognition, Image Processing, and Feature Extraction.*

1. Introduction

Fingerprints have been used as a mean for identifying individuals for a long time since fingerprints are unique and stay unchanged through out an individual lifetime [1]. Early attempts of fingerprint recognition highly depend on human visual recognition ability, or depend on the analysis based on a mathematical model that describes the fingerprint curves. Recently, automatic recognition system is needed to speed up the recognition process [1]. The goal of all automation in fingerprinting is to produce a low-cost system that is reliable, fast and accurate [2].

Fingerprint image analysis for automatic identification technology has been developed to the point where it can be used in a number of major applications such as: banking, entry and access control systems, crime investigation, …etc [1].

Wavelets have been used in image analysis where multiresolution decomposition of images and representation of an image at given resolutions are necessary [3]. Due to the capabilities of wavelet transform (at which images are transformed to time-frequency domain of localized frequency bands), the pictorial information of an image (features) could be extracted into very compact wavelet features while conserving the most significant global and local visual characteristics of the image [4].

This paper is organized as follows: Section 2 provides the wavelet transform of fingerprints image. Next, the proposed modeling system is described. Section 4; report the obtained recognition results when testing the system with 25-fingerprint samples. Finally, the significant results of this study were summarized and discussed.

2. Wavelet Transform of Fingerprints Image

Wavelet Transform represents a windowing technique with variable-sized regions. It cut up data into different frequency components, and then analyzes each component with a resolution matched to its scale. Instead of fixing the time and the frequency resolutions, both of them can be varied in time-frequency plane in order to obtain a multiresolution analysis [5, 6].

The wavelet transform allows the decomposition of a one- or two-dimensional signal into a time-frequency joint representation. The signal to be analyzed is correlated with a bank of functions, called *wavelets*. Each of these wavelets $\{\psi_{j,k}(t)\}$ is derived from an original *mother wavelet* $\psi(t)$ by means of dilation and shifting operations [7];

$$\psi_{j,k}(t) = 2^{j/2}\,\psi(2^{j}t - k) \qquad (1)$$

where j and k are integers. Due to the orthonormal property, the wavelet coefficients of a signal $x(t)$ can be easily computed via

$$a_{j,k} = \int_{-\infty}^{\infty} x(t)\,\psi_{j,k}(t)\,dt \qquad (2)$$

and the synthesis formula

$$x(t) = \sum_{k}\sum_{j} a_{j,k}\,\psi_{j,k}(t) \qquad (3)$$

can be used to recover $x(t)$ from its wavelet coefficients.

To construct the mother wavelet $\psi(t)$, we may first determine a *scaling function* $\varphi(t)$, which satisfies the two-scale difference equation [1, 8]

$$\varphi(t) = \sum_{n} \mathrm{h}(n)\,\sqrt{2}\,\varphi(2t - n) \qquad (4)$$

where n is integer. Then, the wavelet kernel $\psi(t)$ is related to the scaling function via

$$\psi(t) = \sum_{n} \mathrm{g}(n)\,\sqrt{2}\,\varphi(2t - n) \qquad (5)$$

where $g(n) = (-1)^n h(1-n)$ (6)

The coefficients $h(n)$ in (4) have to meet several conditions for the set of basis wavelet functions in (1) to be unique, orthonormal, and have certain degree of regularity [1, 8].

The wavelet transform has been found very useful for the time-scale representation and has been widely used in signal processing and computer vision [9]. The most interesting dissimilarity from other kinds of transforms is that individual wavelet functions are *localized* in space. This localization feature makes many functions and operators using wavelets "sparse" when transformed into the wavelet domain and results in a number of useful applications such as data compression and detecting features in images [5].

The generation of wavelets and the calculation of the Discrete Wavelet Transform (DWT) are well matched to the digital computer. There are no derivatives or integrals, just multiplication and additions–operations. The DWT analyzes the signal at different frequency bands with different resolutions by decomposing the signal into coarse approximation and detail information. DWT employs two sets of functions, called *scaling functions* and *wavelet functions*, which are associated with lowpass and highpass filters, respectively. The decomposition of the signal into different frequency bands is simply obtained by successive highpass and lowpass filtering of the time domain signal. The original signal *x(n)* is first passed through a half-band highpass filter $g(n)$ and a lowpass filter $h(n)$ [10]. A time-scale representation of a digital signal is obtained using digital filtering techniques. At the heart of the DWT is pair of filters h and g, lowpass and highpass, respectively. The block diagram of one-level DWT is shown in Figure (1). The one-dimensional signal, x, is convolved with highpass filter to analyze the high frequencies, and it is convolved with lowpass filter to analyze the low frequencies, and each result is down-sampled by two, yielding the transformed signals x_g and x_h. A DWT is obtained by further decomposing the low-pass output signal x_h by means of a second identical pair of analysis filters. This process may be repeated, and the number of such stages defines the *level* of the transform [10, 11, 12].

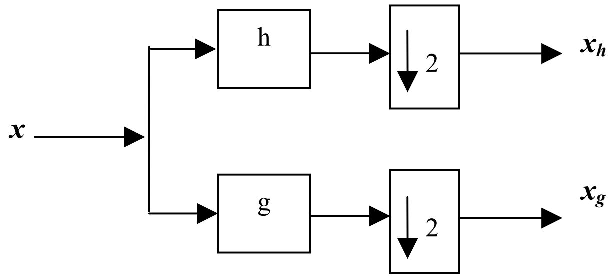

Figure (1) Building Block for the one-level DWT

The procedure starts with passing this signal (sequence) through a half band digital lowpass filter with impulse response $h(n)$. Filtering a signal corresponds to the mathematical operation of convolution of the signal with the impulse response of the filter. The convolution operation in discrete time is defined as follows [10]:

$$x(n) * h(n) = \sum_{k=-\infty}^{\infty} x(k) \cdot h(n-k) \qquad (7)$$

where * denotes convolution operation.

An efficient way to implement this scheme using filters was developed in 1988 by Mallat. The Mallat algorithm is in fact a classical scheme known in the signal processing community as a *two-channel subband coder.* This very practical filtering algorithm yields a *fast wavelet transform* [10].

3. System Model

The block diagram for the proposed system model is shown in Figure (2):

In this system, the input image (fingerprint image) is prepared to extract features by a preprocess steps (shifting, rotation, and/or gray scale modification), feature extraction (from wavelet domain, and/or moment calculation) is performed, finally a selection from this combined features-sets vector is performed at which only features that are useful in fingerprint recognition application are chosen (feature analysis). The City block distance is used to measure the difference between the features vector of the query fingerprint with the features vector of the potential target fingerprint in the database. The next subsections will cover the details of each stage.

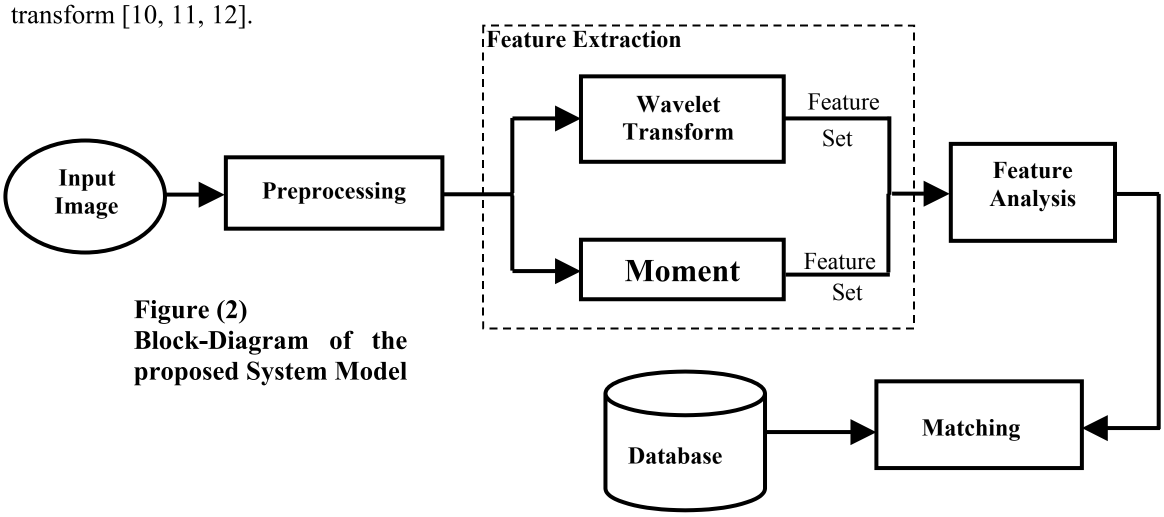

Figure (2) Block-Diagram of the proposed System Model

3.1 Input Image

The input image used for testing and measuring the performance of this work is the right-thumb fingerprint of persons. The principle of getting the fingerprint image and transforming it to the new format requires the following two steps [1]:

a) The fingerprint thumb is covered with ink by using an inked stamp and then copied to a clean, clear and light paper (the finger should be pressed carefully on the paper or else many spots may appear on the scanned image).

b) The conversion of the input image from the physical mode into digital mode is performed by a page scanner and saved in BMP format at 300dpi resolution of 256 gray-levels.

3.2 Preprocessing of the Fingerprint Images

Generally, images come along in different sizes and aspect ratios. Therefore, standardization of fingerprint image size is needed. The original images are first resized in a preprocessing step to white square thumbnails of dimension 256×256 with 256 gray levels. After getting a unified size for all the fingerprints, a number of processes can be applied [1]:

a) Rotation: Rotate the original image at a random angle about its center.

b) Shifting: Shift the original image randomly in the square window of size 256×256 pixels (where the entire fingerprint should be inside the square window).

c) Rotation with Shift: Shift the rotated image randomly in the square window of size 256×256 pixels.

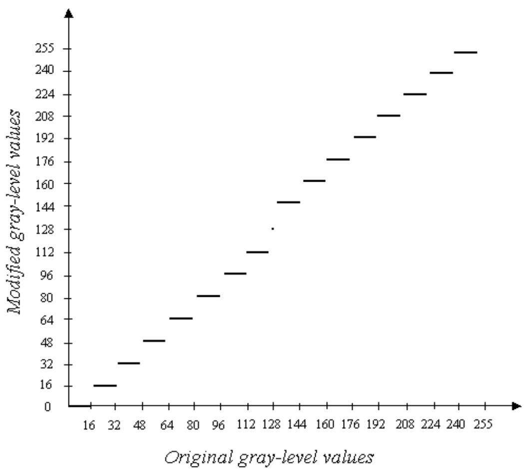

Figure (3) Quantization of Gray-level values

d) Gray-scale modification (Scalar Quantization): It belongs to the category of point operations and function by changing the pixel's (gray-level) values by a mapping equation. The mapping equation is typically linear and maps the original gray-level values to quantized levels. Typically this is useful in applications including *contrast enhancement* and *feature improvement*. Overall, the enhancement methods are application dependent and are often developed empirically. What works for one application may not be suitable for another application [13]. Figure (3) indicates the graphical representation of the proposed gray scale modifications.

3.3 Database of Fingerprint-Images

In order to evaluate the recognition performance of the proposed system, a simple database of fingerprint images called "DB25" was built by collecting right-thumb fingerprints from 25-persons (single instance for each one). The tested databases can be broken into two main categories:

a) Fingerprints without gray scale modification: Three databases were constructed by saving fingerprints without gray scale modification. These databases are:

i. A database for testing the process of rotation named "DB_R": For each fingerprint image that belongs to the original database "DB25", a rotation process is performed to produce different fingerprint copies at angles of 10^0, 20^0, 30^0, …, and 90^0, as shown in Figure (4) .

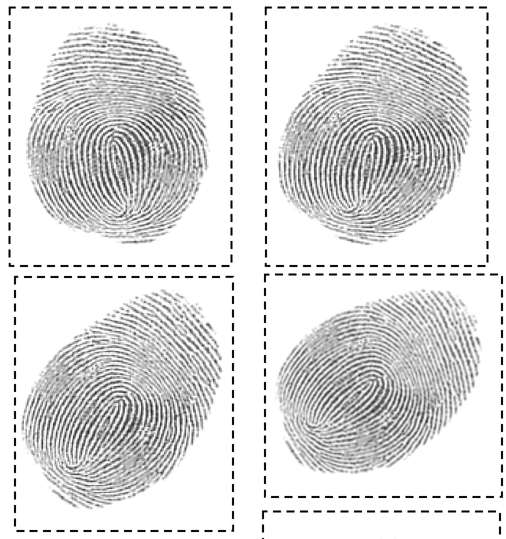


Figure (4)

Rotation of a fingerprint sample at different angles

ii-A database for testing the process of shifting named "DB_S": Consider the same fingerprint sample in Figure (4) to perform the process of shifting on it in a random way as shown in Figure (5).

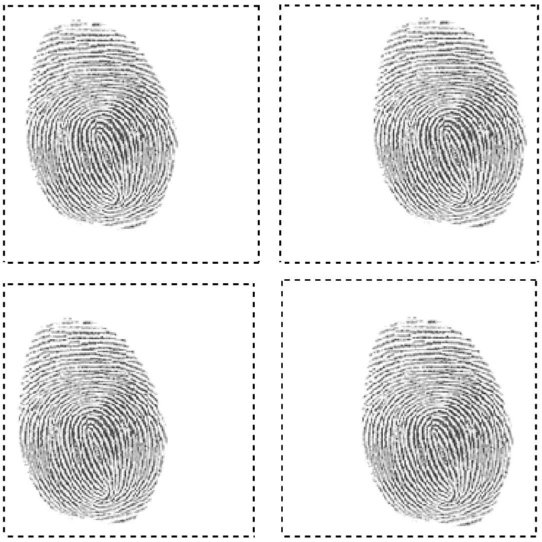

Figure (5) Shifting fingerprint sample randomly

iii- A database for testing the process of rotation with shift at the same time, named "DB_RS": Consider the same fingerprint sample in the previous databases to perform the process of shifting on "DB_R", as shown in Figure (6).

Figure (6) Random Shift the fingerprint sample on "DB_R"

***b) Fingerprints with gray scale modification*:** Practically, the application of the scalar quantization process on the testing databases "DB_R", "DB_S", and "DB_RS" generates new test set of databases "DB_Rmap", "DB_Smap", and "DB_RSmap", respectively. Also "DB25_map" is generated as the result of performing this process on the original database "DB25". The application of the mapping process on a sample fingerprint improves the contrast of fingerprint edges as indicated in Figure (7).

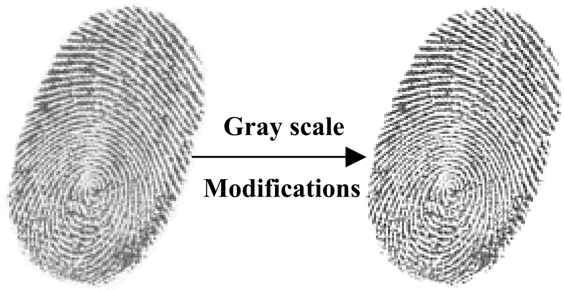

Figure (7) Gray-Scale modification of a fingerprint sample

3.4 Features Extraction

For each fingerprint image, two sets of features were computed as follows, either from the spectral properties of the wavelet transform, or from the spatial properties of the direct image.

<u>a. Moment Features Set:</u> The first fourth moments (ϕ_1, ϕ_2, ϕ_3 and ϕ_4) are calculated directly from the query fingerprint (i.e. from spatial domain). These features represent statistical properties of the input image [1, 14].

$$\phi_1 = \eta_{20} + \eta_{02} \quad (8)$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11} \quad (9)$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (10)$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (11)$$

The normalized central moments, denoted by η_{pq} are defined as:

$$\eta_{pq} = \mu_{pq} / \mu^{\gamma}_{00} \quad (12)$$

where

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q I(x,y) \quad (13)$$

$$\gamma = \frac{p+q}{2} + 1 \text{ , for p, q = 0, 1, 2, . . .} \quad (14)$$

$$\bar{x} = \frac{m10}{m00} \quad , \quad \bar{y} = \frac{m01}{m00} \quad (15)$$

and

$$m_{pq} = \sum_x \sum_y x^p y^q I(x,y) \text{ ,} \quad \text{for p,q = 0, 1, 2,} \quad (16)$$

<u>b. Wavelet Features Set:</u> After converting the query fingerprint image from the spatial domain (the lowest level of pixel data) to its corresponding wavelet domain (the higher level-representation of wavelet coefficients) (see [1], a two-dimensional wavelet transform is obtained by repeated application of the one-dimensional discrete wavelet transform algorithm), a set of wavelet features were calculated by using Algorithm (1), in which features can be extracted by recursively decomposing the wavelet transform representation in the low frequency channels.

<u>Algorithm (1):</u> Pyramidal Wavelet Transform Decomposition [1]

<u>Step1:</u> Decompose a given image with 2-D wavelet transform into 4 subimages, the image is divided into four subbands after wavelet transform: horizontal, vertical, diagonal subimages and low resolution subimage, which can be viewed as the parent and children nodes in a tree, as shown in Figure (8).

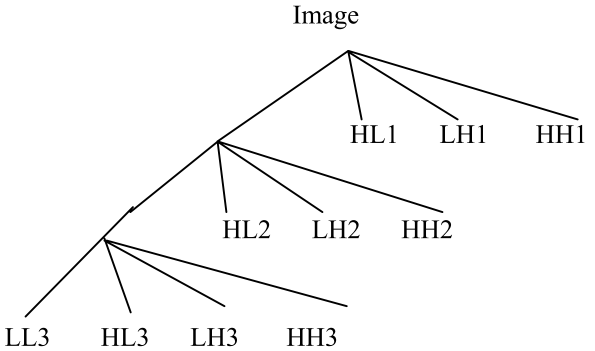

Figure (8) Quadtree representation of three-level wavelet decomposition image

<u>Step2:</u> Calculate the value of ***e*** for each decomposed image (children node). That is, if the decomposed image is ***x(m,n)***, with $1 \leq m \leq M'$ and $1 \leq n \leq N'$, the value of ***e*** is [8]:

$$e = \frac{1}{M'N'} \sum_{m=1}^{M'} \sum_{n=1}^{N'} | x(m,n) | \qquad (17)$$

Practically, the size of the smallest subimages should be used as a stopping condition for the iterative decomposition process. If the decomposed channel has a very narrow size, the location and the value of ***e*** for the feature may vary widely from image to image so that the feature may not be reliable. According to extensive experimental tests carried out in [1], the size of the smallest subimages should not be less than 16×16. Consequently, if the input image size is 256 × 256 (or 64 × 64), a 4-level (or 2-level) pyramidal wavelet transform is appropriate [8].

3.5 Feature Analysis

In a pattern recognition problem, one is usually faced with the task of selecting which of many available features should actually be measured and presented as parameters to the discrimination function. The aim is to select, among all the available features, those whose combination in a discrimination function will lead to an optimal classification [15]. Exactly what we do with the features will be application dependent.

a) **The Sorting of Features:** The extraction of features from a fingerprint sample image “P” belongs to the original database in different angles 0^0, 90^0, 180^0, and 270^0 is shown in Table (1) by using D2 wavelet coefficients.

The results in Table (1) clearly indicate that the features of the same fingerprint with anti-phases are identical (0^0 with 180^0 and 90^0 with 270^0). By comparing between features of phase 0^0 to that of 90^0 at each level, it was found that the horizontal details in phase 0^0 become vertical details in phase 90^0 and vise versa. Therefore, *a sort process is required between LH and HL details*.

b) **Selecting Features From Features Vector:** From the previous table, it is clear that any fingerprint which has right angle or in opposite angle from its origin, gives equivalent features vector in the case of sorting LH and HL details. So the variation in features vectors for a rotated fingerprint between phases 0^0 through 90^0 is investigated further as shown in Table (2).

Table (2) shows the features for phase rotations of 0^0, 10^0, 20^0 … 90^0. If the HH columns are considered for phases 0^0 and 90^0, they give the same results. But for phase rotations of 10^0, 20^0 … 80^0, the HH columns are affected by the rotation process. Generally, the system of fingerprints recognition must not be affected by the direction of the input print, so HH features are not considered as a member in features vector.

If one considers the image of fingerprint in general, then much of its information is concentrated in the sharp edges that constitute the fingerprint’s pattern. Looking at these edges, they are predominantly oriented horizontally and vertically. This explains why the best tree algorithm has “chosen” not to decompose the diagonal details [6].

Table (1) Features values for a fingerprint sample with 3-level wavelet decomposition, angles 0^0,90^0,180^0,270^0.

	LH1	**HL1**	**HH1**	**LH2**	**HL2**	**HH2**	**LH3**	**HL3**	**HH3**	**LL3**
P0^0	1.2472	1.5160	1.6969	0.6687	1.0818	1.7023	0.7193	0.5672	0.6902	2.8604
P180^0	1.2472	1.5160	1.6969	0.6687	1.0818	1.7023	0.7193	0.5672	0.6902	2.8604
P90^0	1.5160	1.2472	1.6969	1.0818	0.6687	1.7023	0.5672	0.7193	0.6902	2.8604
P270^0	1.5160	1.2472	1.6969	1.0818	0.6687	1.7023	0.5672	0.7193	0.6902	2.8604

Table (2) Features value of 3-level wavelet decomposition for a fingerprint sample at angles 0^0, 10^0, …, 90^0.

	LH1	HL1	HH1	LH2	HL2	HH2	LH3	HL3	HH3	LL3
P0⁰	1.2472	1.5160	1.6969	0.6687	1.0818	1.7023	0.7193	0.5672	0.6902	2.8604
P10⁰	1.2869	1.5143	1.7467	0.7437	0.9621	1.8200	0.7420	0.6206	0.7341	2.8699
P20⁰	1.3352	1.4521	1.7669	0.8362	0.9476	1.7118	0.7498	0.5955	0.7651	2.8547
P30⁰	1.4084	1.3564	1.6910	0.8849	0.9004	1.7554	0.7626	0.7041	0.8192	2.9686
P40⁰	1.4113	1.3391	1.5066	0.9862	0.8206	1.6470	0.7111	0.6971	0.8677	2.9532
P50⁰	1.4183	1.2413	1.5129	1.0078	0.8181	1.5330	0.7169	0.6825	0.8445	2.9772
P60⁰	1.4440	1.1981	1.4792	1.0049	0.7812	1.4975	0.7428	0.6842	0.8081	3.0230
P70⁰	1.4810	1.1828	1.5565	1.0978	0.7387	1.5752	0.6969	0.7185	0.7858	3.0288
P80⁰	1.5115	1.1680	1.6232	1.0664	0.7205	1.5817	0.6227	0.6749	0.7884	2.9953
P90⁰	1.5160	1.2472	1.6969	1.0818	0.6687	1.7023	0.5672	0.7193	0.6902	2.8604

3.6 Matching

A query fingerprint is compared with potential target fingerprints in the database by determining the distance between their corresponding features vectors. Due to the compact size of the fingerprint features vector, the complexity of the distance computation is reduced to a small fixed number of coefficients [4]. The primary methods for discrimination process are either to measure the difference or similarity between the two vectors [13]. The difference between the two features vectors was considered in this work. Different distance measures may be used; one common used is *City block distance* (D_C).

City block distance is also called ***absolute value metric***, which is a common metric for measuring the distance between two vectors. Given the two vectors A and B, where A = [a_1 a_2 a_3 …a_n] and B = [b_1 b_2 b_3 …b_n], then the City Block distance is given by [13]:

$$D_C = \sum_{i=1}^{n} \left| a_i - b_i \right| \qquad (18)$$

4. Experimental Results and Discussion

In this section, a number of experiments were performed to study the system behavior with different criteria concerning: wavelet level selection, wavelet features selection, single instance fingerprint recognition, and multiple instances fingerprint recognition. The recognition rate (accuracy) of the system can be defined as the ratio of correct identified fingerprints to the total number of fingerprints in the database (which corresponds to a nearest neighbor decision rule).

$$\text{Recognition Rate} = \frac{\text{Correct FP identification}}{\text{Total number of FP in the DB}} * 100$$

• <u>*Experiment 1*</u>: **The Selection of Wavelet Level:** A well-known wavelet function (Daubechies) is considered for the work [11]. For wavelet recognition there is a need to determine the appropriate level for wavelet decomposition, which is shown in Table (3). The test properties are summarized as follows:

<u>Properties:</u>

► The tested database: "DB_RS"

► Most relevant fingerprint information has been removed by iteratively low pass filtering; the ***e***-value of HH is also considered as a member in features vector.

► For each level there is a sort process between LH and HL features.

Table (3) Fingerprint recognition rates for the wavelet features extracted from level 1,2,3,4 and 5.

	Level1	Level2	Level3	Level4	Level5
D2	60	64	65.33	68	64
D4	57.33	62.66	68.88	68.44	64.44
D6	57.33	61.77	66.66	64	49.77
D8	56	63.11	70.22	72.88	70.66
D10	57.33	65.33	72.44	76	72
D12	61.33	63.55	70.66	72.88	69.33
D14	60.44	63.11	68.88	63.55	36.88
D16	60	64.44	69.33	70.66	52.88
D18	57.77	61.33	71.11	75.11	63.55
D20	59.55	65.33	71.11	73.77	69.77

In Table (3), the letter D stands for Daubechies wavelet coefficients retrieved from external file (for more information see [1]). From the results of the table, one can deduce that four decomposition levels are most appropriate for feature vector construction and therefore the size of the smallest subimages should not be less than 16×16.

• <u>*Experiment 2*</u>: **The Elimination of HH Bands**: After determining the appropriate wavelet decomposition level, there is a need to give the reason of eliminating HH features from features vector, as shown in Table (4). The test properties are summarized below:

<u>Properties:</u>

► The tested database: "DB_RS"

► Most relevant fingerprint information has been removed by iteratively low pass filtering; the e-value of HH was eliminated from features vector.

► For each level there is a sort process between LH and HL features.

Table (4) Fingerprint recognition rates using level 1, 2, 3 and 4 after eliminating HH bands.

	Level1	Level2	Level3	Level4
D2	61.77	65.33	67.11	67.11
D4	59.55	66.22	69.33	71.55
D6	60	63.55	67.11	64
D8	58.22	64.88	71.55	76
D10	56.88	68	75.55	78.66
D12	58.22	64.44	70.66	74.66
D14	57.33	65.33	67.11	60.88
D16	59.11	65.77	71.55	70.66
D18	58.66	64.88	74.66	78.66
D20	59.11	64.44	72.44	76.44

From Table (4), it is clearly seen that the elimination of the HH features from features vector generate positive influence in the overall table results compared with the results of Table (3).

- *Experiment 3*: **Single Copy from the Same Thumbprint:** The computation of recognition rates using *wavelet transformation, and statistical features* for the testing databases ("DB_R", "DB_S", "DB_RS", "DB_Rmap", "DB_Smap" and "DB_RSmap", which consist of single thumbprint copy per person) will reflect the ability of the system to recognize fingerprints with large input variability from its origin (fingerprints that are rotated, shifted and rotated with shifting operation). The following tests show the effects of each features-set on the system behavior:

  a) **The Use of Wavelet Features:** Wavelet features were selected from wavelet domain in which most relevant fingerprint information has been removed by iteratively low pass filtering; the e-value of HH features was eliminated from features vector. At each level there is a sort process between LH and HL features, as shown in Table (5).

Table (5) Fingerprint recognition rates for wavelet features according to different databases

	DB_R	DB-S	DB_RS	DB Rmap	DB Smap	DB RSmap
D2	72	96	67.11	76	98	70.22
D4	68.44	100	71.55	72	100	72.88
D6	65.33	99	64	66.22	99	67.11
D8	73.77	99	76	75.11	99	76.88
D10	76.44	99	78.66	78.66	99	**82.22**
D12	71.11	100	74.66	75.11	100	76.44
D14	65.77	100	60.88	68.88	99	65.33
D16	71.11	100	70.66	74.22	100	72.88
D18	78.22	99	78.66	78.66	99	80
D20	76.88	99	76.44	78.66	99	80

From the results of Table (5), it is clearly shown the improvement of the recognition-accuracy after applying the proposed quantization process on the testing databases ("DB_R", "DB_S" and "DB_RS").

b) **The Use of Moment Features:** The first fourth moment features ($\phi1$, $\phi2$, $\phi3$ and $\phi4$) were extracted from Equations (8) to (11). The test properties are summarized below:

Properties:

► The tested databases: "DB_R", "DB_S", "DB_RS", "DB_Rmap", "DB_Smap" and "DB_RSmap".

► Moment features were extracted from the negative of the image.

Table (6) Fingerprint recognition rates for moment features according to different databases

	DB_R	DB_S	DB RS	DB Rmap	DB Smap	DB RSmap
Moment Accuracy	100	100	100	100	100	100

From Table (6), it is clearly seen that the extraction of moment features from the tested databases gives optimum recognition results.

c) **Combined Moment and Wavelet Features:** In order to improve wavelet recognition accuracy (Acc.), as shown in Table (7), wavelet features (9-features) were combined with moment features (4-features) into a single features vector. The test properties are summarized as follows:

Properties:

► The tested database: "DB_RSmap".

► Most relevant fingerprint information has been collected from wavelet domain by iteratively low pass filtering with added moment features from spatial domain (M = Moment).

Compared with wavelet recognition accuracy, Table (7) illustrates higher improvement in the overall recognition rates, when the features vector becomes a combination between wavelet and moment features. This combination is preferred because it gives better accuracy than using wavelet features alone.

Due to the results of experiment-3, it is clearly seen that D10 wavelet coefficients often gives better results when compared to other Daubechies wavelet coefficients. So it will be used in the next tests for fingerprints of different scale size and for more than one thumbprint instance per person.

d) **Different Scale Size by the use of Wavelet Features:** Another test is needed for the sake of recognizing different scale size of fingerprint images. For example, the fingerprint of "P" that belongs to the database is resized to half its height and width named here "P-half". The test properties are summarized below:

Properties:

► The tested database: "DB_RSmap"

► D10 is used as wavelet coefficients.

After performing the previous test, the "P-half" fingerprint is recognized to its origin "P" when computing the City block distance for level 2, 3 and 4, as indicated by Table (8). The features of the first level are neglected because the size of the smallest subimages should not be less than 16×16 if the input image size is 256×256 (or 128×128), a 4-level (or 3-level) pyramidal wavelet transform is appropriate.

- *Experiment 4*: **Multiple Copies from the Same Thumbprint:** As an example of more than one fingerprint instance for the same person, four fingerprints of X and Y (where X and Y belongs to the original database) are considered, as shown in Figure (9):

Table (7) Fingerprint recognition rates for the combined features of Wavelet and moments (Di+M| i=2,4 …20)

	D2+M	D4+M	D6+M	D8+M	D10+M	D12+M	D14+M	D16+M	D18+M	D20+M
Acc.	100	99.55	99.11	99.55	100	99.55	99.11	99.11	100	100

Table (8) Four-level wavelet features of "P" and its half size "P-half" with omitting level 1.

	LH1	HL1	LH2	HL2	LH3	HL3	LH4	HL4	LL4
P	1.7361	1.2180	1.16868	0.76481	0.81145	0.63680	1.24989	0.81009	3.36481
P-half	––	––	1.12317	0.74297	0.74486	0.64482	1.24879	0.80887	3.34663

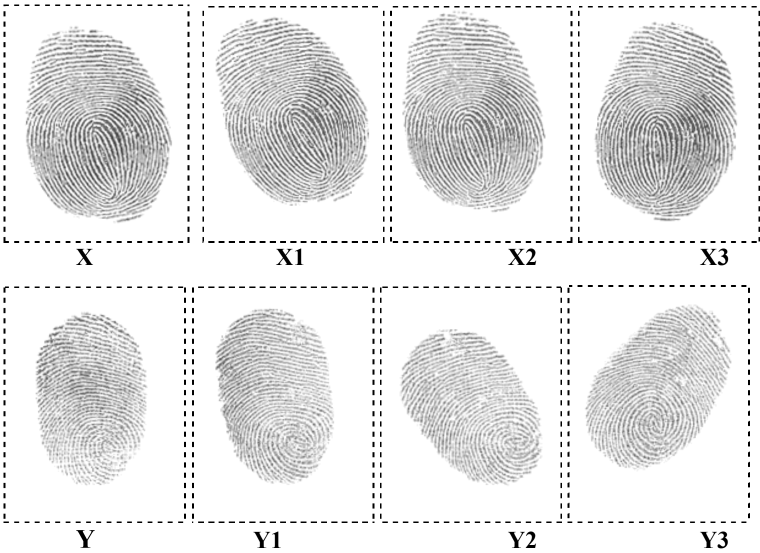

Figure (9) Demonstrate four different instances for X and Y.

To test the ability of the system for recognizing more than one instance for the same person, Table (9) is considered for this purpose. The test properties are summarized below:

Properties:

► The tested database: "DB25_map".

► The left side of each column represents the match order of the query fingerprint to its origin in the database (i.e., when there is a match the order is 1 and when its City block distance measure is the second nearest from its origin the order is 2 and so on).

From Table (9), it is clearly shown that wavelet features gives better recognition accuracy than moment features when they used to compare different fingerprint instances for the same person, as shown in the first and second columns respectively. The combination between wavelet and moment features improves the system recognition accuracy, as shown in the third column.

Table(9) Distance measure values with its corresponding order for multiple fingerprint instances of "X" & "Y".

	D10		Moment		D10 + Moment	
X1	**1st**	1.02756	**3rd**	2.06863	**1st**	3.09618
X2	**2nd**	1.06108	**2nd**	1.97964	**1st**	3.04072
X3	**1st**	0.53181	**2nd**	0.89853	**1st**	1.43035
Y1	**1st**	0.61229	**2nd**	2.43759	**1st**	3.04989
Y2	**2nd**	0.88446	**3rd**	1.62403	**1st**	2.50850
Y3	**1st**	0.40133	**2nd**	0.94902	**1st**	1.35036

5. Conclusion

This work has presented an attempt to design a fingerprint recognition system, which is invariant to the input fingerprint in the case of rotation, translation and scale size. Further improvements in the ability of the system can be achieved by combining spectral and statistical features together in a single vector. Based on the results of computer simulation tests, a number of conclusions can be drawn, these are:

1. The experimental results show that the four wavelet decomposition levels provides the most appropriate features set for fingerprint discrimination process.
2. The sorting process of HL and LH wavelet features in each level is considered a very important operation, which in turn increase the performance of the recognition process. This is due to the fact that HL features represent the horizontal details of the transformed image, while LH features represents the vertical details of the transformed image. So when image is rotated, the horizontal and vertical details could roughly swap positions according to the rotation phase.
3. The elimination of HH features from wavelet features vector improves the recognition accuracy. This is due to the fact that HH features contain information about the diagonal details, which highly affects the accuracy of rotated fingerprint recognition process.
4. The extraction of moment features takes more computational time than the extraction of wavelet features. On the other hand, it gives best recognition results for the case of single instance per person.
5. Using wavelet features (by applying D10) gives better recognition accuracy than using moment features for the case where different fingerprint images for the same person are used.
6. Combining the wavelet features with the moment features gives the highest recognition accuracy in the case of multiple instances per person.
7. According to the obtained results, the proposed image scalar quantization needs to be performed before extracting the wavelet and statistical features, since it improves the recognition accuracy.

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