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Fingerprints Recognition Using the Local Energy Distribution over Haar Wavelet Subbands

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Abstract: ***Fingerprints are commonly utilized as a key technique and for personal recognition and in identification systems for personal security affairs. The most widely used fingerprint systems utilizing the distribution of minutiae points for fingerprint matching and representation. These techniques become unsuccessful when partial fingerprint images are capture, or the finger ridges suffer from lot of cuts or injuries or skin sickness. This paper suggests a fingerprint recognition technique which utilizes the local features for fingerprint representation and matching. The adopted local features have determined using Haar wavelet subbands. The system was tested experimentally using FVC2004 databases, which consists of four datasets; each set holds 80 fingers with 8 samples per finger. The attained test results showed encouraging system capability to recognize low quality fingerprint images although with presence of partial loss in fingerprint images.***

Keywords: Fingerprint, Identification System, Minutiae, Fingerprint Recognition, Energy, Haar Wavelet.

1. Introduction

Biometrics is the capability to recognize a person using distinguishing traits (like, face, retina, fingerprints, hand geometry, voice, and iris from the eye). Fingerprint recognition is widely implemented as biometric trait in comparison with other traits types [1]. Fingerprint is a pattern of furrows ridges and minutiae, which are extracted using inked impact on sensors or a paper [2]. Fingerprints is still commonly accepted as one form of authentication for criminal investigation, personal identification, and access control for restricted web based private applications because of its distinction [3].

All people have unparalleled fingerprints. Generally, fingerprint matching systems depending on one of four kinds of fingerprint representation schemes: minutiae, gray scale image, skeleton image, and phase image. Minutiae indicate to particular points in a fingerprint, they used to specify fingerprint's attributes that are the most important marks for fingerprint recognition task [4]. The distinction of a fingerprint is exclusively located by the local ridge feature and their relationships. The two most notable local ridge features are: (1) ridge ending and, (2) ridge bifurcation. A ridge ending is specified as the point where a ridge ends suddenly. A ridge bifurcation is specified as the point where ridge diverges or forks into branch ridges. Together with these features are called minutiae [5]. The fingerprint matching approaches are:

1. Minutiae-based matching: The major agreeable fingers scan technology depends on minutiae. Minutiae based techniques represent the fingerprint by its local features; such as bifurcation and termination. The distribution of minutiae points varies from subject's fingerprint to other; so the fingerprints can be distinguished by minutiae [6].
2. Feature-based matching: These approaches compare fingerprints using the features extracted from ridges pattern. This approach is the backbone of the current fingerprint recognition products [7].
3. Correlation-based matching: In this approach the two fingerprint images are superimposed and the correlation between identical pixels is calculated for various alignments [8].

Several studies have been developed to handle the problem of fingerprint matching. Feng et al. 2006 presented a novel fingerprint matching algorithm, which builds both minutiae correspondences and the ridge correspondences between two fingerprints. The initial results displayed that ridge matching approach implements similarly with the minutia-based one. Abdullah 2012 put the preformation of Artificial Neural Networks to prepare an active matching algorithm for fingerprint authentication. The algorithm presented preferable match for the specified fingerprint parameters. Mela et.al 2014 proposed a fingerprint recognition technique which utilizes robust local features for fingerprint matching and representation. The test results showed well system capacity to recognize low-quality fingerprint images even with presence of partial loss in fingerprint images.

The aim of this study is to investigate the introduced recognition system accuracy that utilizing the local energy distribution of Haar wavelet transform. The system workflow implies the following steps: (1) Partition each fingerprint image into overlapped blocks to get more details of localization; (2) Extract a set of features from each block of Haar wavelet method; (3) Investigate the behavior of the recognition system accuracy using single feature, pairs of features, and combinations of three features; (4) The system establish the fingerprint feature database. The rest of this paper is organized as follows: section 2 clarifies the layout of the proposed fingerprint recognition system model, its workflow and descriptions for the steps of the proposed system. The test results are listed and discussed in section 3, lastly the derived conclusions are given in section 4.

2. System Model

The general structure of the proposed fingerprint identification system is appeared in Figure (1). It comprises of five primary stages: preprocessing, Partitioning the image with overlapping, Haar wavelet transform, Features extraction and Matching (enrollment). The neediness of fingerprint image quality makes the preprocessing stage a necessary stage. The steps of extraction stage and matching stage depend on the discriminating features extracted from the input fingerprint image. The preprocessing stage comprises of four steps:

1) Read fingerprint image and convert to gray image.
2) Enhancement.
3) Binarization (thresholding).
4) Thinning.

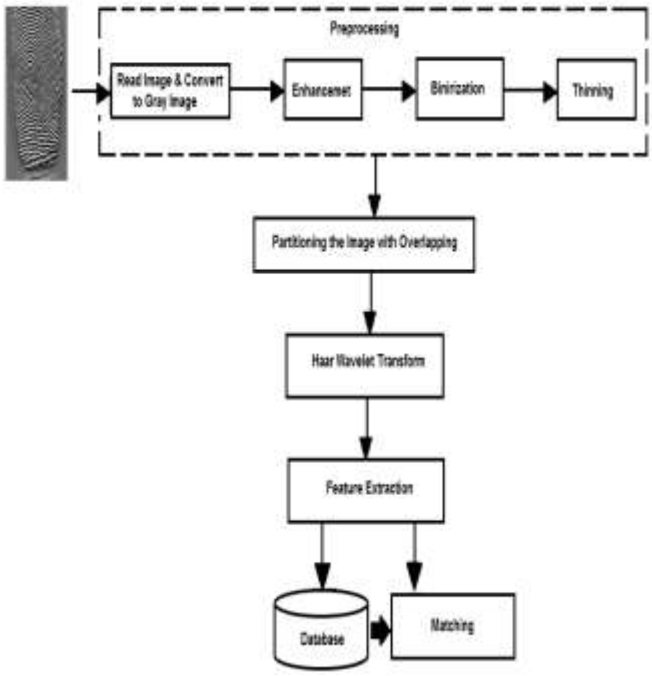

Figure 1: The proposed System Model

The input to the system is a bitmap (BMP) image file; the image data is loaded and then it passed into the enhancement step to produce a processed image that is more appropriate for recognition task. The enhanced gray image variant is changed to a binary image by applying the binarization step. Then, the binary image subjected to thinning process utilizing one of the Skelton methods. Subsequently, a collection of fingerprint attributes are calculated, and lastly, the fingerprint feature vector are extracted by computing the energy of the overlapping partitions of each Haar wavelet subband (i.e., LL, LH, HL and HH). The computed feature vector is utilized to define the template feature vectors. At matching stage, the calculated template feature vectors are utilized to match them with the determined feature vector for unknown tested fingerprint for recognition process.

2.1 Preprocessing Stage

It is a substantial point in any biometric system because certain image processing steps are needed to suppress some visual information whose existence is not proper to perform some specific analysis task. The goal of preprocessing is enhancing some image substantial features for future processing or handling the image data that suffer from unwanted distortion.

I. Load Fingerprint Image: BMP image file is the fingerprint image that used as input to establish identification. In case the color resolution of input image is 24 bit/pixel; then, the image data (i.e., Red, Green and Blue components) is loaded, and its Gray scale image variant is calculated. The Gray image, G(), is the product of this step.

II. Fingerprint Image Enhancement*:* It is used to get better visual clearness of the important image details. Image enhancement includes the manipulation or improvement off image data. Manipulation means the result is more suitable for subsequent use, while image improvements may mean the image become more acceptable for analysis or viewing. The essential steps involved in fingerprint enhancement process are: **A)** Color Inversion, **B)** Removing noise, **C)** Contrast Enhancements, and **D)** Segmentation:

A. Color Inversion: It is the first step in region of interest allocation. This step is essential to allocate only the minutia data existing in the limited region and to avoid the spurious minutiae that are incorrectly uncovered in the surrounding bad background areas. Figure (2) illustrates the outcomes color inversion. The local gray-scale information is determined utilizing a moving window with size of (n×n). At each window position instance, the mean is calculated, then the following thresholding criterion is performed:

$$G'(x,y) = \begin{cases} Mean - G(x,y) & if\ G(x,y) < Mean \\ 0 & otherwise \end{cases} \qquad (1)$$

Where G () is original gray fingerprint image, G'() is the image after color inversion.

Before **After**

Figure 2: The effect of color inversion

B. Removing noise: Noise removal step eliminates the undesirable noise (i.e., the little points appear in the fingerprint image area). Global thresholding is utilized to eliminate the undesirable noise. At first, compute the mean value for the image, afterwards for each non zero pixel the following condition criterion is performed:

$$G''(x,y) = \begin{cases} 0 & if\ G'(x,y) - Mean < Tnoise \\ G(x,y) & otherwise \end{cases} \qquad (2)$$

Where G"() is the output image after removing noise, T_{noise} threshold is utilized to eliminate the appeared noise in the background region.

C.Contrast Enhancements: In order to stretch the bright regions, a simple nonlinear gamma correction function is applied to enhance the visual appearance of the image details by raising the image pixels intensity to power called gamma (γ). The significance of this step is to get a clear image of the fingerprint so as to abstain merging the fingerprint area with its surrounding background. The general form for gamma correction (G_{stre}) for image pixels intensity (G_s) is [12]:

$$G_{stre} = 255 \times \left(\frac{G_S(x,y)}{255}\right)^{\gamma} \qquad (3)$$

Linear contrast stretching technique tries to improve the contrast of an image by linearly stretching the pixel values of a high-contrast image or low-contrast image by extending the dynamic range over the entire image spectrum. The applied mapping function for this enhancement type is described by equation (4); it linearly maps the highest gray level (Max) and lowest gray level (Min) to lie at specific extent from the mean of the image. The other gray levels are mapped linearly to be between Min and Max limits [13]:

$$G_S(x,y) = \begin{cases} 255 & \text{if } G''^{(x,y)} \geq Max \\ 128 & \text{if } G''^{(x,y)} \leq Min \\ 127\left(\frac{G''(x,y) - Min}{Max - Min}\right) + 128 & \text{if } G''(x,y) > Min \text{ And } G''(x,y) < Max \end{cases} \qquad (4)$$

The values of *Min* & *Max* are calculated utilizing the following equations:

$$Min = \mu - \alpha\sigma \qquad (5a)$$
$$Max = \mu + \alpha\sigma \qquad (5b)$$

Where, μ and σ are the mean and standard deviation values of the image, respectively. The parameter α is utilized to control the strength of implemented linear extent.

Each of the conventional (non-adaptive) contrast enhancements methods (i.e., gamma correction and linear stretching) was utilized to enhance the images as depicted in figure (3).

before **After**

Figure 3: The effect of Contrast Enhancements

D.Segmentation (Clipping): The goal of this step is to determine the actual region in the fingerprint image that describes the finger area and ignore the regions of the image consisting non pertinent information. The segmentation of Region of Interest (ROI) is the foremost wanted stage so as to avoid the inclusion of false features extracted from regions lay the outside the fingerprint object due to the existence false details (outliers) in the image.

III. Image Binarization (Thresholding): Thresholding technique is one of the most important popular methods utilized in image segmentation processes, because thresholding is a straightforward process, and can be effectively implemented; it is only assigning the gray image pixel that has a value greater than '0', which means '255' a value of '1'.

IV. Image Thinning: It is simpler to discover special points (e.g., minutiae) from thin image; which are helpful in pattern matching process. This step intends to decrease the width by erasing the dark point's pattern and changes the pattern into thin lines drawing recognized as a "skeleton". This thinning process is implemented by applying Zhang-Suen algorithm (ZS algorithm) [14]. It is a fast and basic parallel algorithm for thinning binarized digital patterns. The algorithm requires just the basic computing operations, and it is intended to be implemented on the binary regions. It separates the skeleton of an image by eliminating all the contour points of the image except those points that return to the skeleton. Figure (4) shows the impact of thinning on fingerprint.

Before **After**

Figure 4: The effect of Zhang-Suen thinning algorithm

2.2 Partitioning the Image into Overlapped Blocks

In order to discover the local features of an image and prepare a primitive representation scheme, and to avoid the recognition failure caused by the appearance of partial loss of the fingerprint region; the fingerprint image is partitioned into overlapped blocks. The value of overlapping ratio length is taken as a ratio of block length. The block length is determined by dividing the image length by the predefined number of blocks. The impacts of both overlapping ratio and the number of blocks values is investigated using trial and error mechanism such that they should lead to best recognition rate.

It is necessary to note that the width and height of the image could not be equal, therefore the block dimensions (i.e., width and height) might not equal. So as to handle this drawback the shortest dimensions of the image is padded by adding empty rows (or columns) on both sides of the image. Then, after partitioning step, Haar wavelet transform is calculated for every block. Figure (5) illustrates however the fingerprint image is partitioned into overlapped blocks.

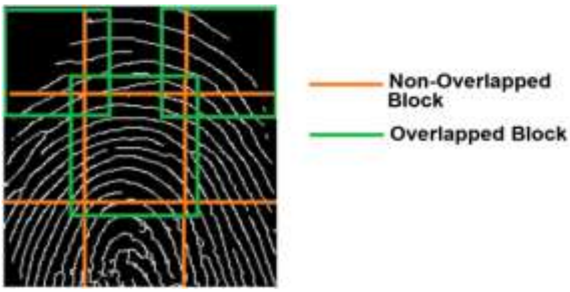

Figure 5: Image partitioning into overlapped blocks

2.3 Haar Wavelet Transform

Wavelets are functions that fulfill the particular mathematical needs and are utilized in representing data or different functions. The fundamental concept behind wavelet transform is to hierarchically decompose the input image signal into a series of successively lower resolution reference signals and their associated detail signals. At every level, the reference signal and also the detail signal include the information required to reconstruct the reference signal at the following higher resolution level [15].

In discrete form, Haar wavelets are associated with a mathematical operation known as the Haar transform. The Haar transform serves as a prototype for other different wavelet transforms. The tempting options of Haar wavelet, for example: (i) considering the fact that Haar functions are the least complex wavelets, (ii) and has quick implementation, (iii) finally, it has the capacity to investigate the local feature by deciding wherever the low frequency and high frequency areas are. Every one of the components () make it reasonable for current signal processing applications [16].

2.4 The Features Extraction Stage

Feature extraction mechanisms are stratified in so as get the useful discriminating features to classify and recognize images. The objective of feature extraction technique is to lessen the numbers of attributes of patterns and at the same time to retain the maximum amount, as could be expected, of their discriminatory information. The feature extraction step creates a feature vector comprises of considerable characteristics which are reflective to the distinctive attributes of fingerprint grid.

In this work, features are extracted from the energy distribution in the Haar wavelet domain. Wavelet Transform decomposes the input image into four sub-sampled images, and then analyses every element with resolution matches its scale. During this stage, a feature vector is extracted utilizing first-level Wavelet decomposition. A set of wavelet features that represent the input fingerprint image is extracted by applying the following steps:

Step 1: Decompose a given image with 1-D wavelet transform into four subbands (i.e.; LL, LH, HL, and HH); wherever LL represents low frequency vectors (approximate), LH represents high frequency vectors in vertical direction, HL represents high frequency vectors in horizontal direction, and HH represents diagonal high frequency vectors.

Step 2: The energy of every wavelet subband (LL, LH, HL, and HH) belong to each image block is computed to determine the feature vector, as indicated by the subsequent equation:

$$Energy = \sum_{x=x_s}^{x_e} \sum_{y=y_s}^{y_e} wavelet(x,y) \quad (6)$$

Where (x_s, y_s) are the coordinates of the start point for each block, (x_e, y_e) the coordinates of end point for each block and (x, y) the coordinated of considered wavelet sub bands.

Step 3: Repeat Step 1, Step2 to extract the set of local features vectors from every block.

Then, each extracted feature vector is saved in a database for recognition reason.

2.5 Matching Stage

Feature matching is the most important part of any biometric system. The matching result should be high for fingerprints samples belong to same finger and low for those belong to completely different fingers. To implement matching, the calculated discriminating features vectors are utilized to yield the template mean feature vector for every person for identification. The determined template mean feature vector ($\bar{F}$) of every person, and the relating standard deviation vector (σ) are saved in a database, as an output of the feature extraction stage. The extracted feature vectors are matched with the templates saved in the Database (DB) to form a choice. In matching stage the mean and standard deviation template vectors for all persons are loaded from the database; then their comparability degree are registered with the feature vector extracted from the tested fingerprint. The mean and standard deviation vectors are computed by utilizing the following equations:

$$\bar{F}(p,f) = \frac{1}{S}\sum_{i=1}^{S} F(p,i,f) \quad (7)$$

$$\sigma(p,f) = \sqrt{\frac{1}{S}\sum_{i=1}^{S}\left(F(p,i,f) - \bar{F}(p,f)\right)^2} \quad (8)$$

Where, *(p, i, f)* are the person number, sample number, and feature number, respectively. *F* is the feature vector and *S* is the total number of samples.

The difference (*Di*) is computed between the features vector of the template stored within the DB and of the tested image. In the proposed method the degree of similarity is set using Mean Absolute Distance (MAD) and Mean Square

Differences (MSD) metric; which are defined as follows [17]:

(1) Mean Absolute Differences

$$Di = MAD(p,f) = \sum |F(p,i,f) - \bar{F}(p,f)| \quad (9)$$

(2) Mean Square Differences

$$Di = MSD(p,f) = \sum (F(p,i,f) - \bar{F}(p,f))^2 \quad (10)$$

The tested fingerprint will appointed an identification number of the person whose template feature vector led to smallest total (tDif):

$$tDi(p) = \sum_{f=1} D(f) \quad (11)$$

Tests Results

Four databases (i.e.; DB1, DB2, DB3, and DB4) were used for performing an assessment for the performance of the proposed strategy. The database was taken from FVC 2004 [18]. They usually utilized for testing the performance of developed fingerprint recognition; each set is comprised of various samples which belong to forty persons; and for every person a subset consists of eight fingerprint samples are used. The fingerprint images are BMP 24 bit/pixel (bit depth), and each database has the subsequently properties as shown in table (1).

Table 1: Databases properties

Database	*Image Size*	*Resolution*
DB1	640×480 pixels	96 dpi
DB2	328×364 pixels	
DB3	300×480 pixels	
DB4	288 ×384 pixels	

The impact of energy wavelet features, which are presented in this research, for improving the recognition performance has been investigated. For one-level Haar Wavelet decomposition, a subset consists of 4 features (LL; LH; HL; and HH) are made. The subsequent results are observed; the final highest recognition rate is (94%). The results are shown in table (2). Additionally, for the combination of two Haar wavelet decomposition features, a subset comprised of 6 features (LL-LH; LL-HL; LL-HH; LH-HL; LH-HH; and HL-HH) was made. The resulted recognition rate is 91%; as shown in table (3). At last, for the combination of three Haar wavelet decomposition features, a subset comprises of 6 features (LL-LH-HL; LL-LH-HH; LL-HL-HH; and LH-HL-HH) are made. The attained resulted recognition rate was 94%; as shown in table (4). The results in tables (2), (3) and (4) were attained when the block size was taken (13×15) and (15×17) and the overlapping ratio was set to (0.5).

Table 2: The Recognition rate for one feature

a. Mean Absolute Differences

	DataBase1 BS= 13×15	DataBase1 BS= 15×17	DataBase2 BS= 13×15	DataBase2 BS= 15×17
LL	72.5	73.75	58.75	62.5
LH	82.5	83.75	68.75	68.75
HL	70	75	53.75	62.5
HH	73.75	81.25	67.5	66.25

	DataBase3 BS= 13×15	DataBase3 BS= 15×17	DataBase4 BS= 13×15	DataBase4 BS= 15×17
LL	68.8	72.5	70	72.5
LH	80.0	81.3	80.5	81.25
HL	75.0	80.0	74.75	80.25
HH	87.5	94.0	88.75	91.25

b. Mean Square Differences

	DataBase1 BS= 13×15	DataBase1 BS= 15×17	DataBase2 BS= 13×15	DataBase2 BS= 15×17
LL	70	70	58.75	60
LH	85	85	68.75	67.5
HL	71.25	75	60	63.75
HH	78.75	83.75	71.25	73.75

	DataBase3 BS= 13×15	DataBase3 BS= 15×17	DataBase4 BS= 13×15	DataBase4 BS= 15×17
LL	70.0	71.3	73.75	76.25
LH	77.5	78.8	76.25	78.25
HL	75.0	76.3	77.25	77
HH	88.8	94.0	85	92.5

Table 3: The Recognition rate for combination of two features

a. Mean Absolute Differences

	DataBase1 BS= 13×15	DataBase1 BS= 15×17	DataBase2 BS= 13×15	DataBase2 BS= 15×17
LL-LH	82.5	82.5	62.5	65
LL-HL	77.5	77.5	61.3	62.5
LL-HH	71.3	75	61.3	62.5
LH-HL	80	91.3	73.8	75
LH-HH	80	91.3	72.5	76.3
HL-HH	77.5	78.8	65	62.5

	DataBase3 BS= 13×15	DataBase3 BS= 15×17	DataBase4 BS= 13×15	DataBase4 BS= 15×17
LL-LH	78.8	82.5	88.8	88.8
LL-HL	76.3	76.3	88.8	88.8
LL-HH	75	76.3	85	86.3
LH-HL	83.8	83.8	77.5	81.3
LH-HH	87.5	89.8	88.8	85
HL-HH	80	82.5	88.8	90.5

b. Mean Square Differences

	DataBase1 BS= 13×15	DataBase1 BS= 15×17	DataBase2 BS= 13×15	DataBase2 BS= 15×17
LL-LH	80	81.3	60	61.3
LL-HL	72.5	77.5	62.5	63.8
LL-HH	71.3	71.3	60	60
LH-HL	86.3	87.5	77.5	77.5
LH-HH	87.5	87.5	72.5	73.8
HL-HH	76.3	81.3	65	66.3

	DataBase3 BS= 13×15	DataBase3 BS= 15×17	DataBase4 BS= 13×15	DataBase4 BS= 15×17
LL-LH	78.8	78.8	87.5	88.8
LL-HL	76.3	78.8	90	91.3

LL-HH	70	71.3	LL-HH	83.8	86.3
LH-HL	83.8	88	LH-HL	86.3	88.8
LH-HH	86.3	86.3	LH-HH	81.3	82.5
HL-HH	76.3	78.8	HL-HH	81.3	86.3

Table 4: The Recognition rate for combination of three features

a. Mean Absolute Differences

DataBase1			DataBase2		
	BS= 13×15	BS= 15×17		BS= 13×15	BS= 15×17
LL-LH-HL	83.8	83.8	LL-LH-HL	66.3	68.8
LL- LH-HH	81.3	83.8	LL-LH-HH	65	65
LL-HL-HH	75	78.8	LL-HL-HH	62.5	65
LH-HL-HH	90	91.3	LH-HL-HH	71.3	78.8

DataBase3			DataBase4		
	BS= 13×15	BS= 15×17		BS= 13×15	BS= 15×17
LL-LH-HL	81.3	83.8	LL-LH-HL	87.5	90
LL-LH-HH	81.3	86.3	LL-LH-HH	87.5	88.8
LL-HL-HH	77.5	80	LL-HL-HH	87.5	88.8
LH-HL-HH	87.5	94	LH-HL-HH	83.8	86.3

b. Mean Square Differences

DataBase1			DataBase2		
	BS= 13×15	BS= 15×17		BS= 13×15	BS= 15×17
LL-LH-HL	80	82.5	LL-LH-HL	66.3	67.5
LL-LH-HH	80	82.5	LL-LH-HH	60	61.3
LL-HL-HH	71.3	76.3	LL-HL-HH	62.5	63.8
LH-HL-HH	86.3	87.5	LH-HL-HH	73.8	77.5

DataBase3			DataBase4		
	BS= 13×15	BS= 15×17		BS= 13×15	BS= 15×17
LL-LH-HL	83.8	83.8	LL-LH-HL	91.3	91.3
LL-LH-HH	78.8	78.8	LL-LH-HH	87.5	87.5
LL-HL-HH	76.3	78.8	LL-HL-HH	90	91.3
LH-HL-HH	85	91	LH-HL-HH	87.5	90

The system parameters set implies: (1) the number of blocks, (2) the overlapping ratio, (3) T_{noise} threshold for noise removing, (4) gamma (γ), and (5) alpha (α). The recognition rate is calculated with utilizing the two distance measures (MAD and MSD). The results are listed in Table (5); where there are completely different values to the number of blocks (5×7; 7×9; 9×11; 11×13; 13×15; and 15×17) and the overlapping ratio is taken to be within the range [0.1, 0.5]. The results listed in table demonstrate that the increase in block size causes increase in recognition rate. The tests results indicated that the effect of overlap ratio is insignificant; for this reason these values were set fixed as 0.5 because this value led to little more recognition rate.

Table 5: The recognition rates for different values of blocks using overlapping ratio in DB3

a. Mean Absolute Differences

Overlapping Ratio=0.1						
	BS=5×7	BS=7×9	BS=9×11	BS=11 ×13	BS=13× 15	BS=15×1 7
LL	61.3	66.3	65.0	70.0	70.0	68.8
LH	73.8	78.8	80.0	82.5	80.0	87.5
HL	66.3	72.5	75.0	76.3	76.3	81.3
HH	62.5	71.3	76.3	78.8	82.5	83.8
Overlapping Ratio=0.2						
	BS=5×7	BS=7×9	BS=9×11	BS=11 ×13	BS=13 ×15	BS=15×1 7
LL	55.0	58.8	68.8	68.8	72.5	73.8
LH	71.3	76.3	81.3	80.0	82.5	82.5
HL	61.3	70.0	73.8	78.8	77.5	81.3
HH	77.5	83.8	86.3	86.3	88.8	88.8
Overlapping Ratio=0.3						
	BS=5×7	BS=7×9	BS=9×11	BS=11 ×13	BS=13 ×15	BS=15×1 7
LL	52.5	55.0	61.3	68.8	71.3	76.3
LH	70.0	77.5	78.8	81.3	82.5	82.5
HL	62.5	63.8	71.3	76.3	78.8	80.0
HH	73.8	80.0	83.8	86.3	88.8	87.5
Overlapping Ratio=0.4						
	BS=5×7	BS=7×9	BS=9×11	BS=11 ×13	BS=13 ×15	BS=15×1 7
LL	51.3	55.0	62.5	66.3	66.3	72.5
LH	71.3	73.8	77.5	81.3	82.5	80.0
HL	58.8	62.5	70.0	73.8	76.3	80.0
HH	67.5	76.3	85.0	83.8	86.3	90.0
Overlapping Ratio=0.5						
	BS=5×7	BS=7×9	BS=9×11	BS=11 ×13	BS=13 ×15	BS=15×1 7
LL	48.8	52.5	61.3	65.0	68.8	72.5
LH	73.8	75.0	76.3	75.0	80.0	81.3
HL	53.8	63.8	65.0	73.8	75.0	80.0
HH	70.0	81.3	83.8	85.0	87.5	94.0

b. Mean Square Differences

Overlapping Ratio=0.1						
	BS=5×7	BS=7×9	BS=9×1 1	BS=11× 13	BS=13× 15	BS=15× 17
LL	63.8	66.3	70.0	75.0	75.0	76.3
LH	81.3	81.3	81.3	81.3	80.0	81.3
HL	70.0	70.0	77.5	77.5	75.0	77.5
HH	80.0	86.3	88.8	90.0	91.3	90.0
Overlapping Ratio=0.2						
	BS=5×7	BS=7×9	BS=9×1 1	BS=11× 13	BS=13× 15	BS=15× 17
LL	60.0	60.0	68.8	70.0	70.0	75.0
LH	77.5	78.8	81.3	80.0	78.8	82.5
HL	65.0	70.0	72.5	76.3	75.0	75.0
HH	78.8	85.0	90.0	86.3	91.3	90.0
Overlapping Ratio=0.3						
	BS=5×7	BS=7×9	BS=9×1 1	BS=11× 13	BS=13× 15	BS=15× 17
LL	55.0	57.5	65.0	67.5	70.0	75.0
LH	72.5	77.5	82.5	80.0	80.0	82.5
HL	61.3	67.5	70.0	75.0	75.0	75.0
HH	76.3	83.8	88.8	88.8	91.3	86.3
Overlapping Ratio=0.4						
	BS=5×7	BS=7×9	BS=9×1 1	BS=11× 13	BS=13× 15	BS=15× 17
LL	55.0	55.0	61.3	66.3	67.5	71.3
LH	75.0	77.5	80.0	80.0	82.5	82.5
HL	58.8	66.3	70.0	72.5	73.8	77.5
HH	72.5	78.8	85.0	83.8	88.8	91.3
Overlapping Ratio=0.5						
	BS=5×7	BS=7×9	BS=9×1 1	BS=11× 13	BS=13× 15	BS=15× 17
LL	48.8	55.0	60.0	66.3	70.0	71.3

LH	73.8	77.5	78.8	77.5	77.5	78.8
HL	56.3	68.8	66.3	72.5	75.0	76.3
HH	76.3	77.5	83.8	88.8	88.8	94.0

The window size (n×n) has little effect so it is taken (8×8). The results demonstrated that T_{noise} impact is insignificant; consequently its value is set fixed at (2) because this value led to slightly higher of recognition ratio. Figure (6) demonstrates the results of applying gamma correction (γ) with gamma values [0.5, 1, 1.5, 2]; and the results of applying contrast stretching (α) with alpha values [0.5, 1, 1.5, 2] on the original image. The results demonstrate that the decrease of gamma (γ) causes increase in brightness region; this indicates that linear stretching mapping is better than gamma mapping choice. With respect to the impact of alpha (α) is insignificant, for this reason this value is set to 0.5.

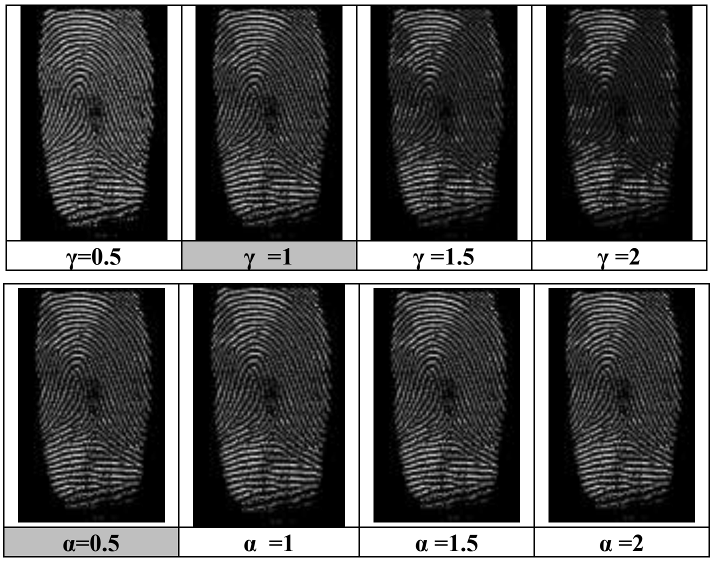

Figure 6: The effect of γ and α in contrast enhancement

4. Conclusion

From the results of the proposed algorithm, the following remarks were stimulated:

- The test results showed that the proposed method is promising and can be further developed to be much precise. The Haar wavelet decomposition features have given good recognition rate (94%).
- The combination of two wavelet features to give these recognition rates had given sensible recognition rate (91%) and the combination of three wavelet features had improved the attained recognition rates (94%).
- The tests' results indicated that the partitioning into blocks with overlap has helped to overcome the partial loss in low-quality fingerprint image and enhanced the recognition accuracy.
- The recognition rate is highly influenced by variation of block length and has limited impact by the overlapping ratio.

As future work, the module can be extended in various directions for example:

- Using more sophisticated enhancement method which may lead to higher enhancement.
- Partition the fingerprint image utilizing another hierarchal partitioning method (like, Quadtree or K-d).
- Using another matching method (for example: normalized Euclidean distance measure which may increase the power of the system.

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