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FINGERPRINTS MATCHING USING THE ENERGY AND LOW ORDER MOMENT OF HAAR WAVELET SUBBANDS

ZAINAB J. AHMED*
Department of Biology Science, College of Science, University of Baghdad, Baghdad, Iraq.
E-mail: zainabjahmed83@gmail.com

ABSTRACT

Fingerprint recognition is one among oldest procedures of identification. An important step in automatic fingerprint matching is to mechanically and dependably extract features. The quality of the input fingerprint image has a major impact on the performance of a feature extraction algorithm. The target of this paper is to present a fingerprint recognition technique that utilizes local features for fingerprint representation and matching. The adopted local features have determined: (i) the energy of Haar wavelet subbands, (ii) the normalized of Haar wavelet subbands. Experiments have been made on three completely different sets of features which are used when partitioning the fingerprint into overlapped blocks. Experiments are conducted on FVC2004 databases that have a four database; every database is eighty fingers and eight impressions per finger. The implemented recognition results of the proposed system show high recognition performance which is 100%.

Keywords: *Fingerprint Recognition, Identification System, Energy, Normalize, Haar Wavelet.*

1. INTRODUCTION

Biometrics refers to the utilization of distinctive anatomical (such as face, fingerprints, iris) and activity (such as speech) characteristics, referred to as biometric identifiers or characteristics. Biometrics recognition is becoming a necessary element of effective person identification solutions as a result of biometric identifiers cannot be misplaced or shared, and that they as such represent the individual bodily identity [1]. Fingerprint recognition gives reliable, an unbeatable and ideal identification of human beings. It is the easily available feature of biometrics [2]. A fingerprint is an individual pattern of valleys and ridges on the surface of a finger of an individual. A valley is the region between two adjacent ridges while a ridge is a single curved segment. Minutiae points are the local ridge discontinuities, which are utilized for deciding uniqueness of a fingerprint of an individual. Minutiae points are of two kinds: ridge endings and bifurcations [3].

Numerous algorithms have been proposed in the issue of the fingerprint matching, they are categorized as: (i) minutiae based, (ii) correlation based and (iii) ridge feature based approaches. The minutiae based algorithms appear minutiae points as a feature vector of constant length. These features include: (a) its orientation, (b) location, (c) type (e.g., ridge-bifurcation or ridge-ending), and (d) other local information. The matching of two minutiae sets is typically posed as a point pattern matching problem and the similarity between the two minutiae is proportional to the quantity of matching minutia pairs [4]. The noise and distortion through the gaining of the fingerprint and errors in the minutia extraction method and even though the minutiae pattern of every finger is very individual, they result in a number of unoriginal and missing minutiae. Different ridge features such as the ridge shape, orientation and the frequency of ridges and the texture information have been suggested for matching process since it's hard to dependably get the minutia points from a bad quality fingerprint image [5]. Though, the ridge feature algorithms have low recognition ability. In matching process using correlation based fingerprint to determine the degree of similarity between the query fingerprint images and template, they are spatially correlated [6]. The correlation should be calculated over all possible displacements and rotations when the displacement and rotation of the query with relation to the template aren't known. This calculation is so costly, additional the global correlation value between two impressions of the same fingers considerably decrease because the existence of non-linear distortion and noise [7].

Many researches have been presented in the literature. These studies produced different methods which vary in terms of recognition methods and efficiency. Fan et.al 2012 proposed a novel fingerprint recognition algorithm depend on the probabilistic graphical model. Firstly, minutiae in query fingerprint are viewed as random variables with the minutiae in template print as the realizations. Appropriating to the random variables, a 2-tree model is made via choosing two signal points from the query set. Secondly, a 2-tree model is turned into a Junction Tree (J.T.), and therefore the possibilities of the tree nodes are determined consistent with the essential characters of fingerprint. Then, the correspondence of the two sets of minutiae are got by implemented the J.T. algorithm. The process repeated by exchanging two sets to handle with many-to-one corresponding problem caused by the outliers. At last, utilizing the maximal posteriori probability generated by the J.T. algorithm and the number of common matching pairs, in order to the similarity of the two fingerprints is estimated. Some experiments were implemented on the databases of FVC2004 indicated proper system performance [8]. Arora and Sharma 2013 proposed an improvement for fingerprint image quality; it depends on an adaptive fingerprint enhancement method that is depending on contextual filtering. The term adaptive suggests that depending on the input fingerprint image, the parameters of the method are automatically adjusted. Once the fingerprint image is improved at the required level, the pores are extracted depending on the segmentation of fingerprint image by removing the fingerprint area above the threshold limit. The pores location and the inter distances are determined then saved in a database. Additionally, the minutiae are extracted and again their location and inter-distances are determined then saved in a database. The same procedure is repeated for and standard deviation and the query image are computed between the inter-distance of the query image database images. The fingerprint information based minutiae and on pores are combine together to get the matching score [9]. Kumar et.al 2016 developed a robust fingerprint matching system by extracting the round region of interest (ROI) of a radius of 50 pixels focused at the core point. Maximizing their orientation correlation aligns two fingerprints to be matched. For matching, the modified Euclidean distance computed between the extracted orientation features of the sample and query images is utilized. The tests implemented on two other proprietary databases of the AITDB and RFVC 2002 and performed over four benchmark fingerprint datasets of FVC2002. The results of the proposed method demonstrate the superiority over the well-known image-based approaches [10].

In this paper, the basic hypothesis have been adopted: (i) applying Haar wavelet transform on fingerprint image, (ii) dividing every sub-image into overlapping blocks to get more details of localization, (iii) extraction of features from each block by energy of Haar wavelet subband, (iv) extraction of features from each block by low order moment of Haar wavelet subband (v) investigate the recognition system accuracy using single features, and then combinations of features, (vi) the system is performed on low quality fingerprint database.

2. SYSTEM MODEL

Figure 1 presents the layout of proposed fingerprint recognition (identification) system contains five fundamental stages: (i) preprocessing, (ii) Haar wavelet transform, (iii) partitioning, (iv) features extraction, and (v) matching/Decision. The involved steps of these stages are clarified in the following stages:

2.1 Preprocessing: Preprocessing stage is important to organize the fingerprint image for more process. The primary objective of this stage is to localize the fingerprint ROI from the input image. In this work, a similar preprocessing stage to that mentioned in the article [11]. It comprises of four steps: Gray Image Preparation, Image Enhancement, Thresholding and Thinning. They are:

2.1.1 Gray image preparation: This step loads and decomposes the image data into three 2D-color arrays (i.e. Red, Green, and Blue). The color conversion from RGB color space to Gray array, the Gray image {G()} is the product of this step.

2.1.2 Fingerprint image enhancement: Image enhancement implies getting a clearer image. The basic steps required in the fingerprint enhancement process are similar to that mentioned in (11): **(A)** Inverting the color, **(B)** Noise elimination, **(C)** Brightness stretching, **(D)** Segmentation with the addition of a new step **(E)** Smoothing Spatial Filter. The Smoothing filters produce images with additional smooth appearance because they suppress any rapidly changing brightness values within the original image. Mean (or average) filter is one of the easiest linear filters. The mean filtering is basically to switch every pixel value in the image with the mean value of the pixel neighbors, together with itself. That led to removing pixel values that are unrepresentative to their surroundings. Weighted Mean filter is used to show that the pixels

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are multiplied within different coefficients, so the weight is giving additional importance to some pixels at the expense of other pixels. In this paper, the mean and weighted mean filters are utilized.

2.1.3 Image thresholding: Binarization is the method of turning a gray-scale image to a black and white image. To binarize our image, Otsu's method was used; it is an automatic threshold choice region based segmentation method (i.e., local thresholds). The binarization is based on the idea that the image to be binarized should consist of two classes of pixels or in other words its histogram is bi-modal (e.g. foreground and background), and then the optimum threshold has to be pre-assigned or calculated for separating these two classes [12].

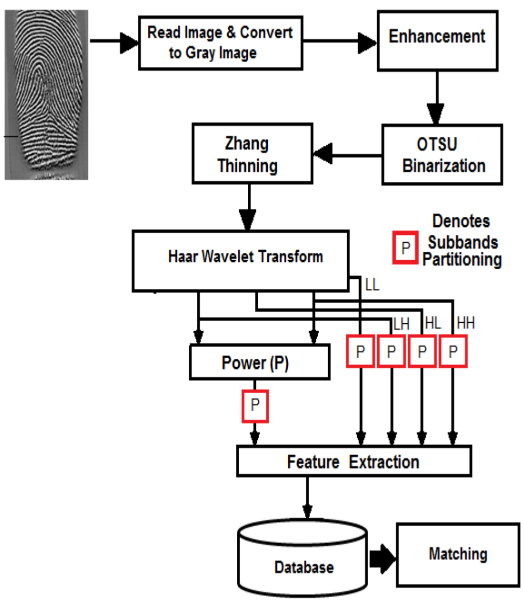

Figure (1): The System Model

2.1.4 Image thinning: Thinning is a morphological operation that is utilized to remove the selected pixels from the foreground in binary images. In this paper, the Zhang-Suen algorithm was used for morphology operation of thinning. This process is done pixel by pixel till the last for attaining the required thinning; the result of this morphology will look clearer and will be very useful in segmentation process [13].

2.2 Haar Wavelet Transform

Haar Wavelet transform is the simplest wavelet transform variant. It works with efficiency to discover the characteristics like contours and corners [14]. The Haar wavelet is chosen for many purposes: (1) it has low computational cost when comparing with the other types of transforms and (2) each wavelet (detail) sub-bands holds a particular type of edges (i.e., vertical, horizontal, or diagonal edges).

2.3 Partitioning the Wavelet Using Overlapping Scheme

In the proposed system the fingerprint image is divided into overlapping blocks, and then the local features of each block are determined; in order to: (i) discover the local features of the image (ii) give a primitive representation scheme and (iii) reduce the impact of grid shifting which can show up in the fingerprint samples. The block dimensions are determined by dividing the image into a number of blocks that have similar size, and the value of overlapping length is predefined as the ratio of block length. The impacts of both the number of blocks and overlapping ratio values were tested to find out their proper values, which should lead to appropriate recognition rate. It is necessary to note that since the width and height of the fingerprint image aren't equal; as result of blocks dimensions are different (i.e., their width and height are not equal).

2.4 Features Extraction

In the proposed fingerprint recognition system, a set of features is selected as discriminating features for recognition purpose. Thus, to extract this set of features from the fingerprint image the subsequent steps were applied:

(1): Decompose a given image with wavelet transform into four sub-images, as indicated in the figure 2, wherever LL symbolizes low frequency vectors (approximate), HL symbolizes high frequency vectors in horizontal direction, LH symbolizes high frequency vectors in vertical direction, and HH symbolizes diagonal high frequency vectors.

(2): For every decomposed image containing LL, LH, HL, HH and detail power.

(A): Divide each sub-band into overlapping blocks.

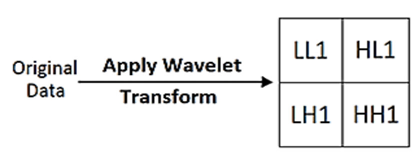

Figure (2): One Level Wavelet

(B): Compute the energy of each block belongs to wavelet subband (LL, LH, HL, HH, and P_E) using the subsequent equation:

$$Energy = \sum_{x=xs}^{xe-1}\sum_{y=ys}^{ye-1} wavelet^2(x,y) \quad (1)$$

Where (xs, ys) start point for each block, (xe, ye) endpoint for each block and wavelet (x, y) is the wavelet subbands.

The power (PE) is calculated with energy as showed in the equation:

P_E=Energy (LH) + Energy (HL) + Energy (HH) (2)

(C): The normalized of every wavelet subband (LL, LH, HL, HH, and PN) return to each image block is calculated as specified by the subsequent equation:

$$Norm = \sum_{x=xs}^{xe-1}\sum_{y=ys}^{ye-1} |wavelet(x,y)|^n \quad (3)$$

Where n=0.5 and 0.75.

The power (PN) is calculated with norm as showed in the equation:

P_N=Norm (LH) + Norm (HL) + Norm (HH) (4)

(3): Repeat Step (B), Step(C) and extract the set of features vectors from each block. Each extracted feature vector is saved in a database for recognition purpose.

2.5 Matching

The extracted features from fingerprint wavelet subbands are kept in a database, then for every class, the samples are divided into training and testing categories. In this stage, the closest neighbor classifier is adapted to classify each input image to its class. In this work, a collection of wavelet based features extracted from the subbands produced by one-level wavelet decomposition. The feature vectors are stored in intermediate database table. Subsequently, a statistical analysis was performed on these extracted features. In the proposed method the degree of similarity is assessed using the Normalized Mean Absolute Differences (NMAD) and Normalized Mean Square Differences (NMSD) metric; which are described as follows:

- Normalized Mean Absolute Differences

$$NMAD(p,f) = \sum \left|\frac{(F(p,i,f) - \bar{F}(p,f))}{\sigma(p,f)}\right| \quad (5)$$

- Normalized Mean Square Differences

$$NMSD(p,f) = \sum \left(\frac{(F(p,i,f) - \bar{F}(p,f))}{\sigma(p,f)}\right)^2 \quad (6)$$

Where, (p, i, f) are the person number, sample number, and feature number, respectively. $\bar{F}$ is the mean feature vector for each person and σ the corresponding standard deviation.

The proposed fingerprint recognition system is compared to the previously published work [11]; this work has the following differences:

- The smoothing spatial filter is applied in fingerprint image enhancement.
- The Otsu method is used in image thresholding.
- The Haar wavelet is applied first and then partitioning the wavelet fingerprint image into blocks.
- Extract of features from each block using the energy and low order moment of Haar wavelet.
- The power (P) is calculated with energy (PE) and norm (PN).
- The degree of similarity is determined using NMAD and NMSD.

The contribution of this work is the proposed system improved the recognition matching by using the features that extracted using energy and low order moment of Haar wavelet subbands.

3. TESTS RESULTS

The datasets (i.e.; DB1, DB2, DB3, and DB4) used for testing in this research is taken from FVC 2004 fingerprint database that are publicly available [15]. Each image is a gray scale that stored as bmp24 bit/pixel (bit depth). The datasets was taken from 40 persons, and for every person eight fingerprint samples were utilized.

The impact of energy wavelet features and low order moment in improving the recognition performance has been researched. The following results are observed:

- For the one-level Haar Wavelet decomposition, a subset consists of 5 features (LL; LH; HL; HH and detail power) are made, the test results showed that each database gave different recognition rate reach to is (100%).
- Additionally, for the combination of two Haar wavelet decomposition features, a subset comprising of 10 features (LL_LH; LL_HL; LL_HH; LL_P; LH_HL; LH_HH; LH_P; HL_HH; HL_P; and HH_P) has been made. The resulted recognition rate is 100%.
- At last, for the combination of three Haar wavelet decomposition features, a subset comprises

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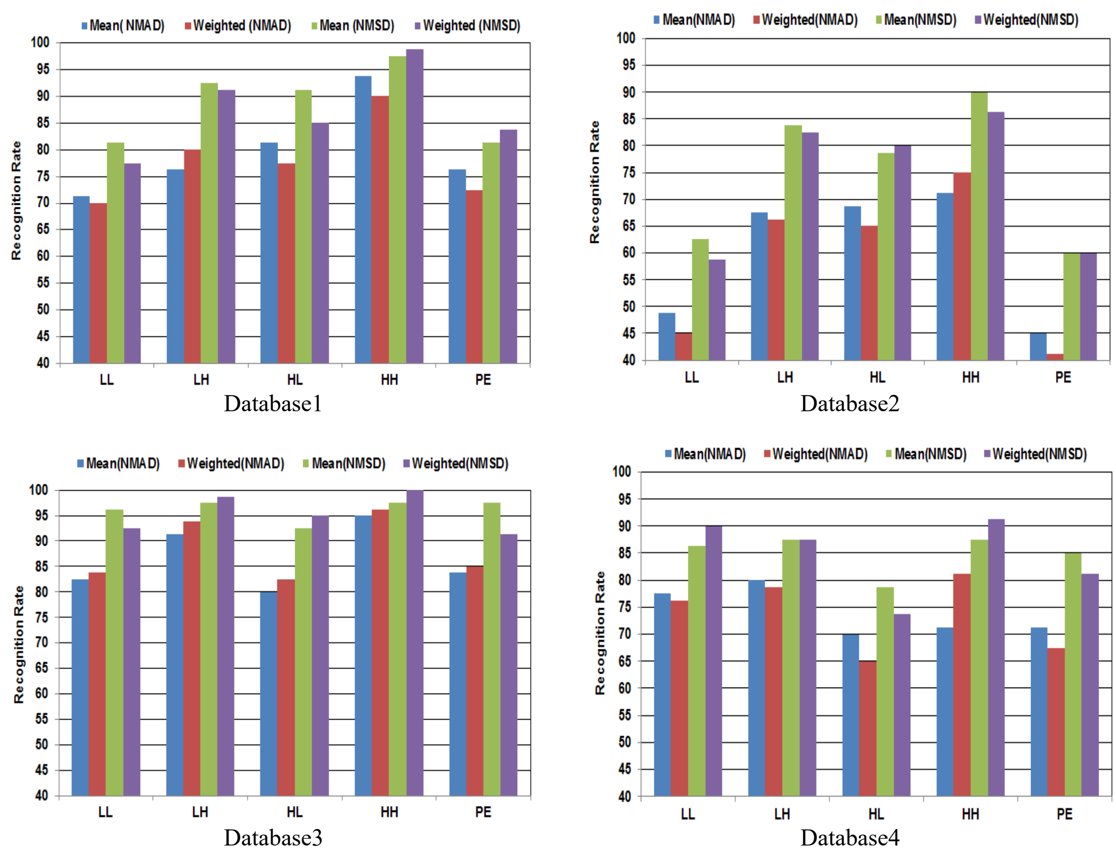
of 10 features (LL_LH_HL; LL_LH_HH;LL_HL_HH; LL_LH_P; LL_HL_P; LL_HH_P; LH_HL_HH; LH_HL_P; LH_HH_P; and HL_HH_P) are made. The resulted recognition rate is 100%.

Table 1 represents the band cases for each combination subband features with their symbol number. The results in Figures 3, figure 4 and figure 5 attained when the block size is taken (15×17), the overlapping ratio is set to (0.1). The recognition rate is calculated initial by utilizing the two distance measures (NMAD and NMSD) and two filters (i.e. mean and weighted mean filter).

Table (1): Band cases

Symbol number	Combination subband features
1	LL-LH
2	LL-HL
3	LL-HH
4	LL-P(P_E or P_N)
5	LH-HL
6	LH-HH
7	LH- P(P_E or P_N)
8	HL-HH
9	HL- P(P_E or P_N)
10	HH- P(P_E or P_N)
11	LL-LH-HL
12	LL-LH-HH
13	LL-HL-HH
14	LL-LH- P(P_E or P_N)
15	LL-HL- P(P_E or P_N)
16	LL-HH- P(P_E or P_N)
17	LH-HL-HH
18	LH-HL- P(P_E or P_N)
19	LH-HH- P(P_E or P_N)
20	HL-HH- P(P_E or P_N)



a. Energy wavelet feature

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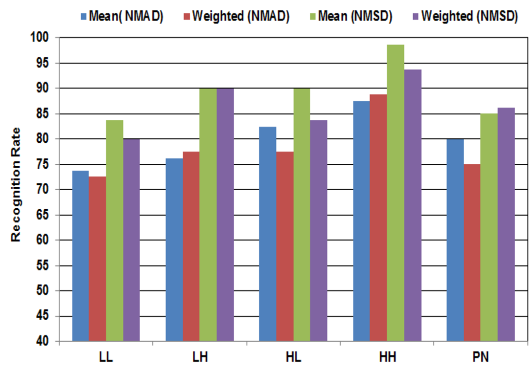

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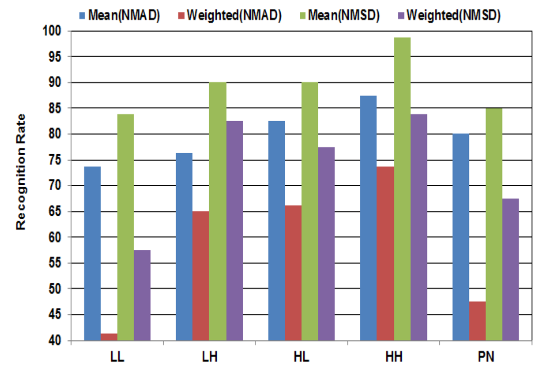
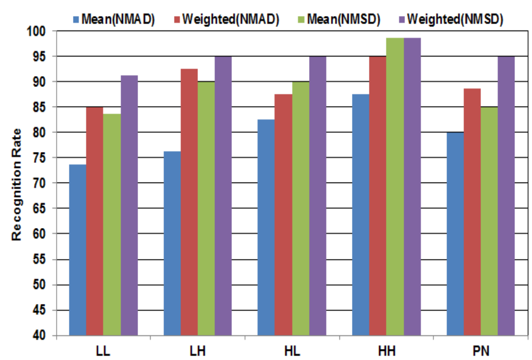


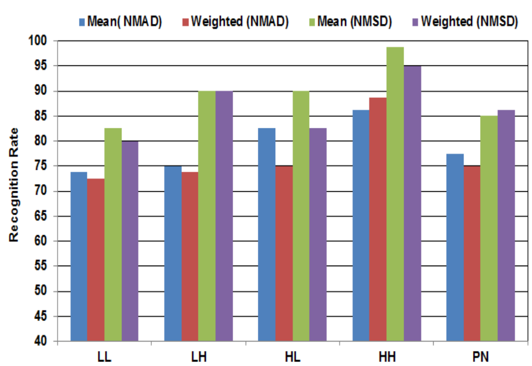
Database2



Database3

Database4

b. Low order moment(n=0.5)



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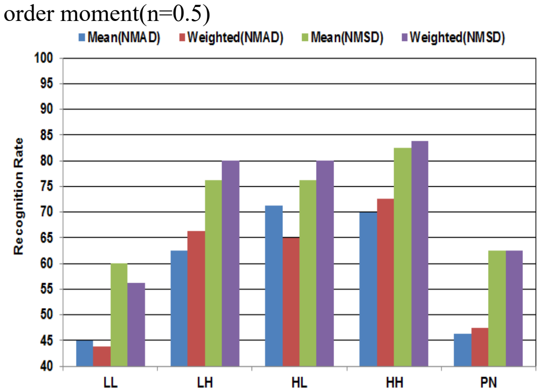

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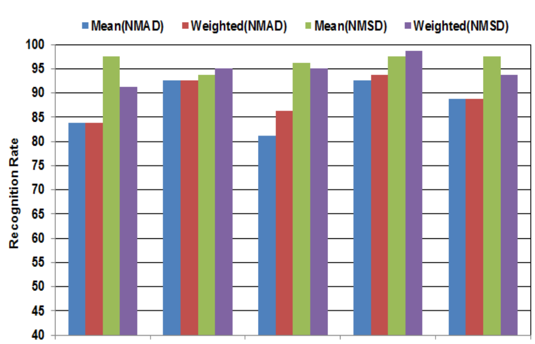

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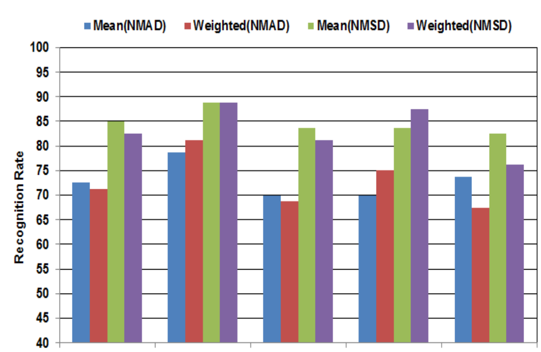

Database4

c. Low order moment(n=0.75)

Figure (3): The Recognition rate for one feature

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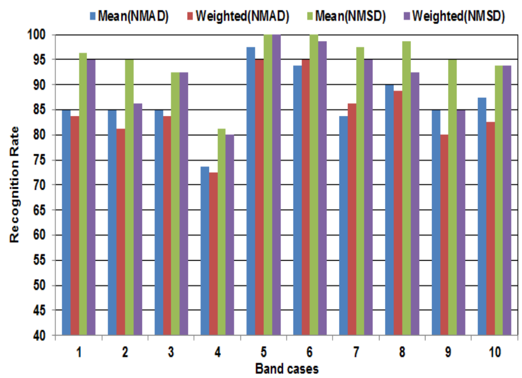

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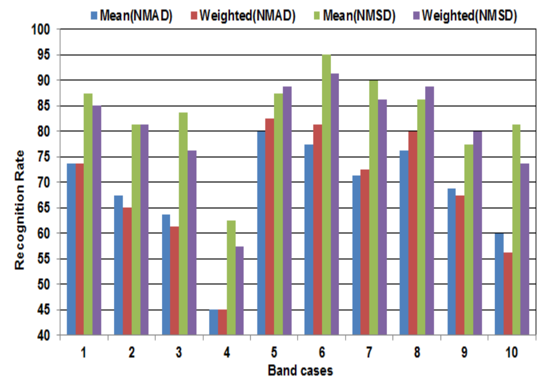

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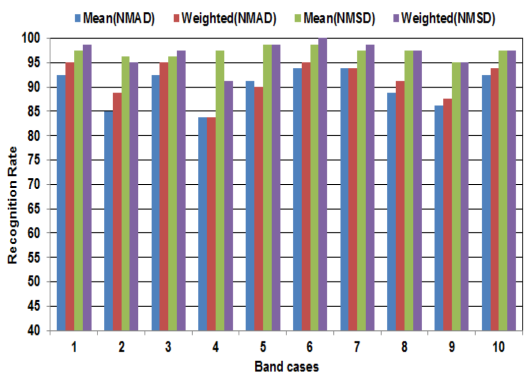

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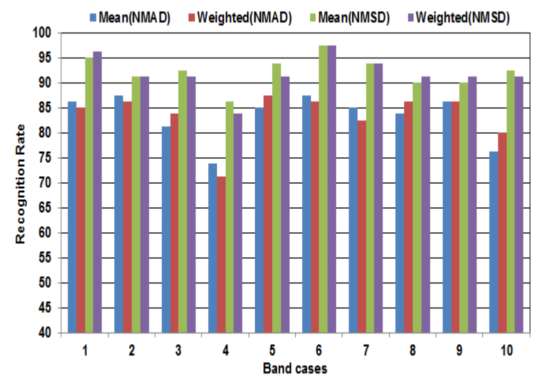

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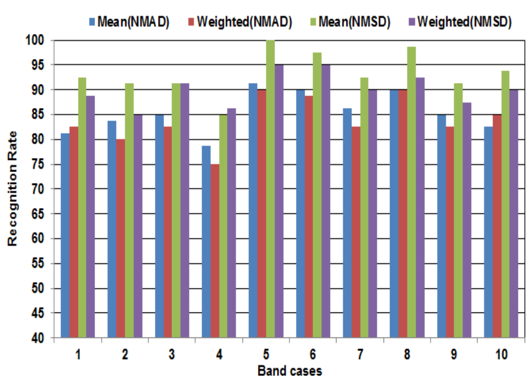

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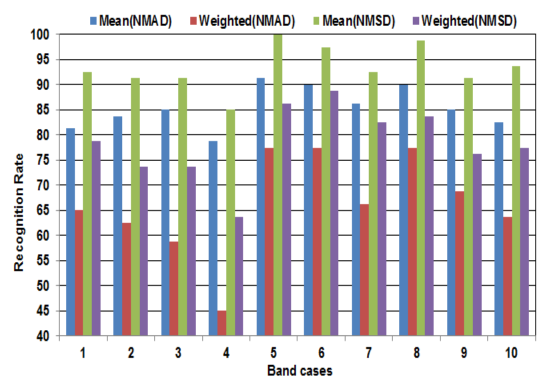

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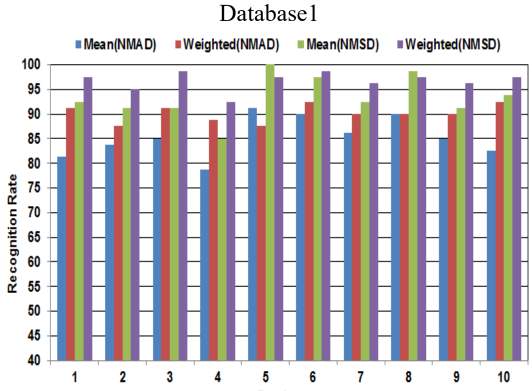

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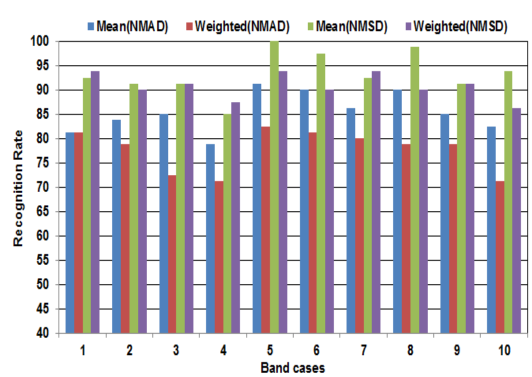

Database4

b. Low order moment(n=0.5)

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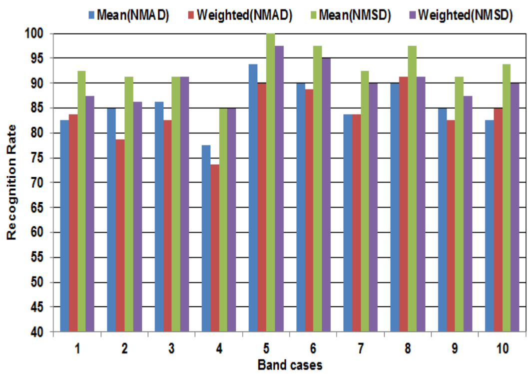

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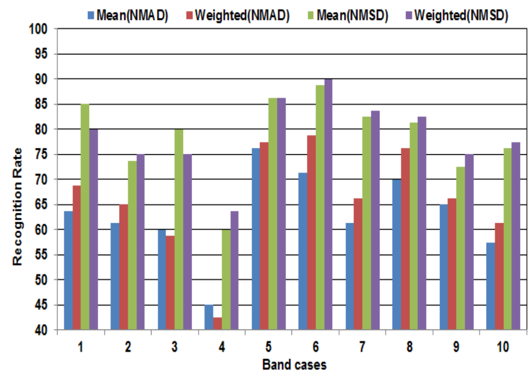

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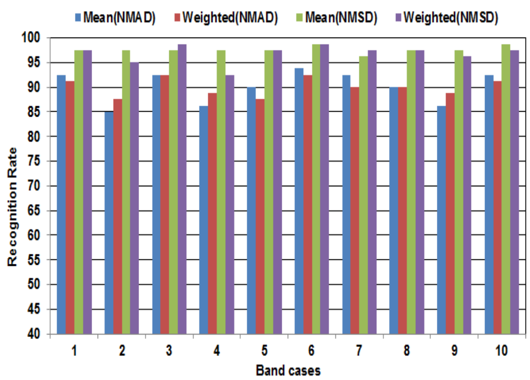

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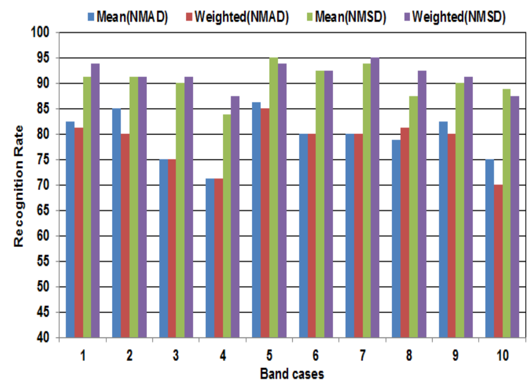
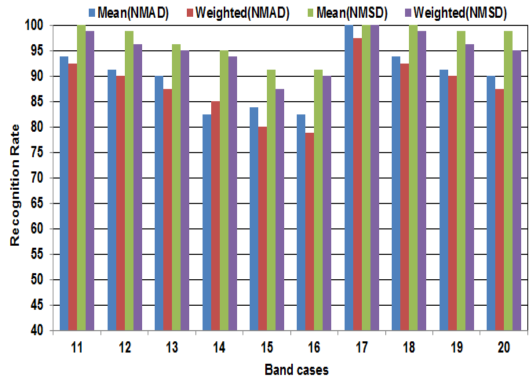


Database4

c. Low order moment(n=0.75)

Figure (4): The Recognition rate for combination of two features



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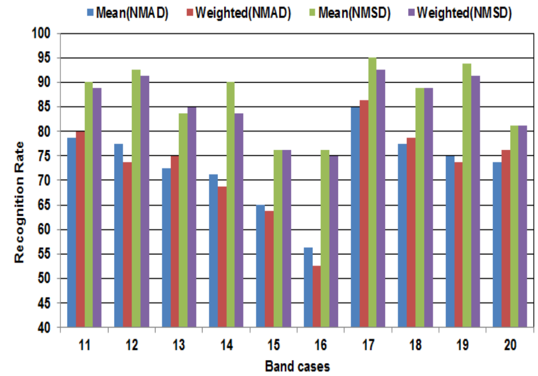

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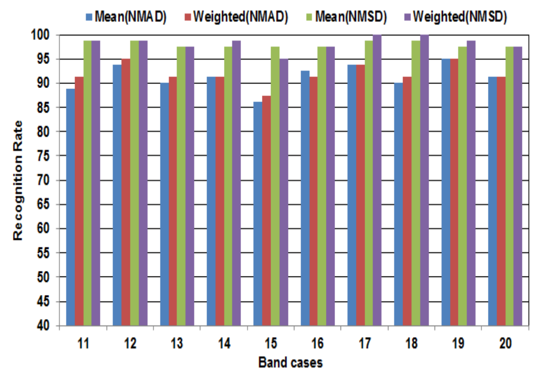

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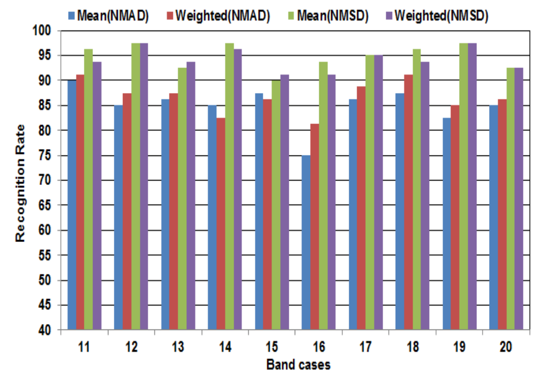

Database4

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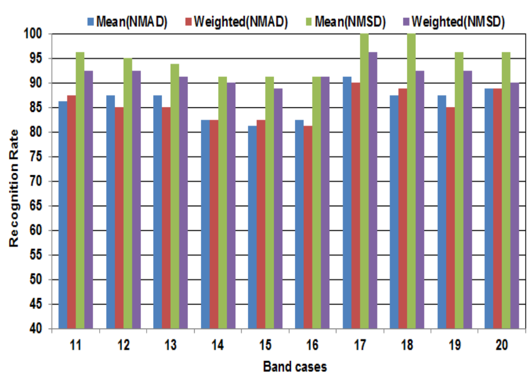

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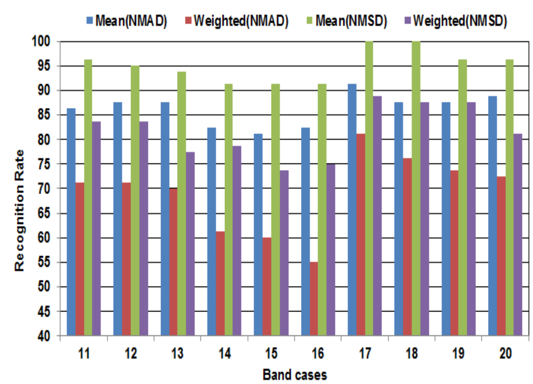

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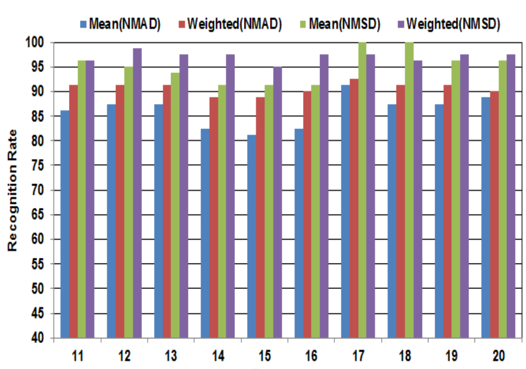

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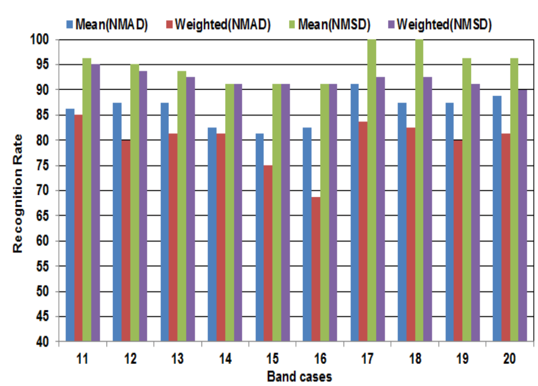

Database4

b. Low order moment(n=0.5)

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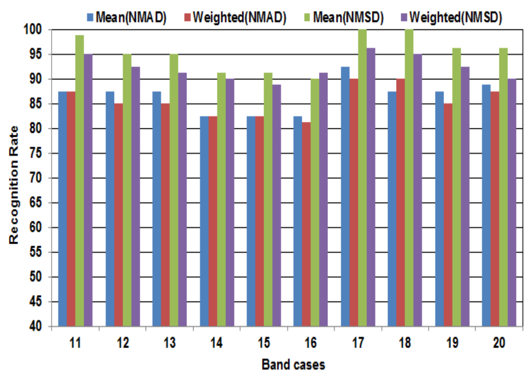

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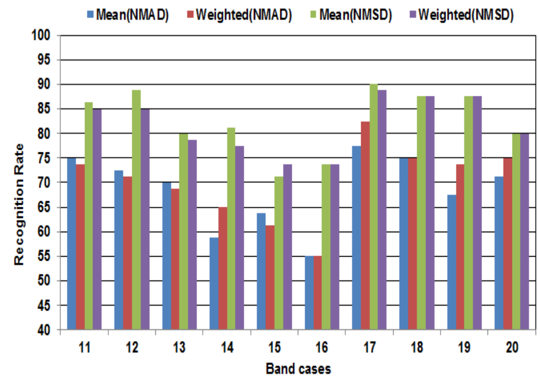

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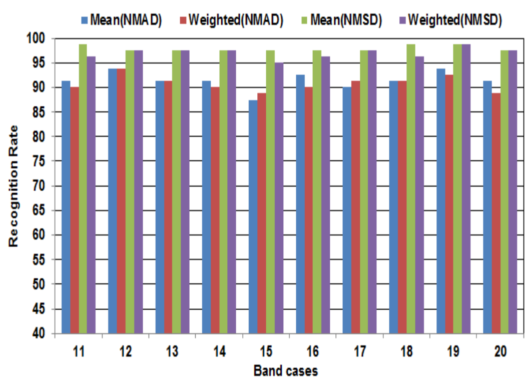

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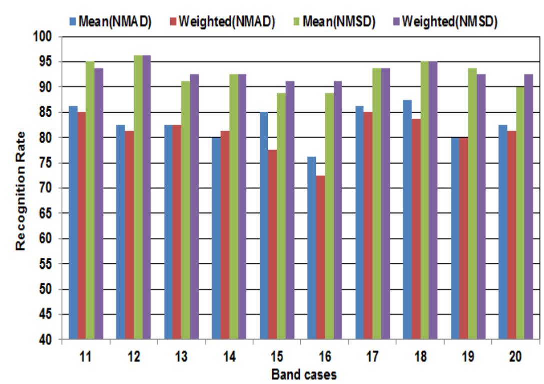
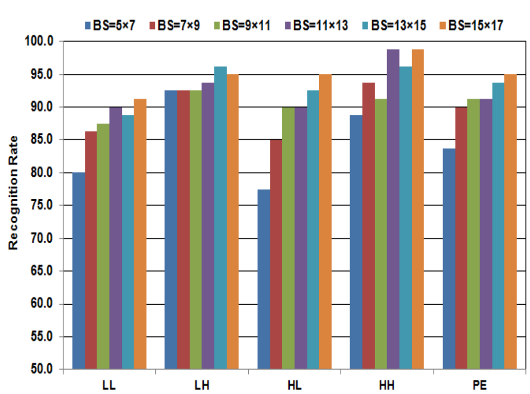


Database4

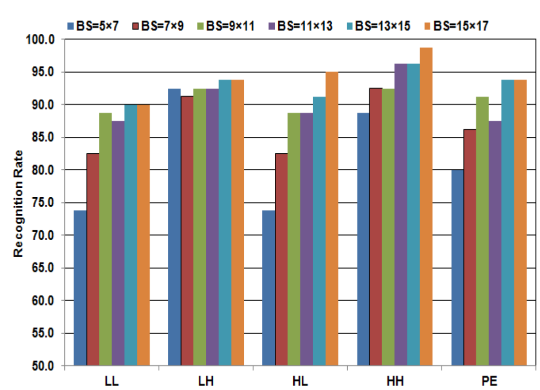
c. Low order moment(n=0.75)

Figure (5): The Recognition rate for combination of three features

Also, the overlapped partitioning had enhanced the recognition accuracy and overcome the partial loss in low quality fingerprint image and shifting in the localized fingerprint; as shown in figure 6.



Overlapping Ratio=0.1



Overlapping Ratio=0.2

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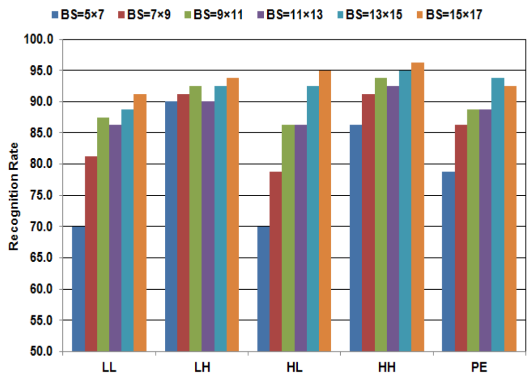
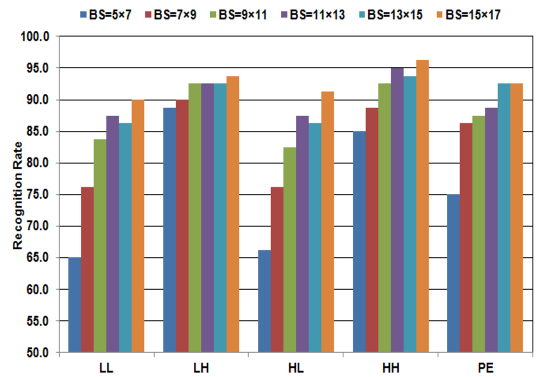


Overlapping Ratio=0.3



Overlapping Ratio=0.4

Figure (6): The recognition rates for different values of blocks using overlapping ratio in DB3 using NMSD

4. COMPARISONS WITH PREVIOUS STUDIES

Many methods for fingerprint matching have been developed in the past few years. In this section the results of our proposed fingerprint recognition scheme have been compared with some previously published methods that used the FVC 2004 fingerprint database and different recognition methods have been used.

Table 2 shows the recognition rate attained by our proposed scheme with those given in previous studies. The listed results demonstrate that our proposed scheme outperforms other methods.

Table (2): Comparing the recognition rate of our approach and previous studies

Reference	[16]	[11]	[17]	Proposed method
Recognition Rate	78.9%	94%	96.87%	100%

5. CONCLUSION

A fingerprint recognition (identification) system based on the Haar wavelet on a fingerprint was described. It containing preprocessing, partitioning, feature extraction, and matching is introduced, performed and examined. The extracted features for representing the fingerprint pattern from an unclear original image are the energy and low order moment. Before feature extraction stage the fingerprint image was well enhanced. The Haar wavelet decomposition features have given well recognition rate (100 %). The combination of two and three wavelet features to give these recognition rates has given sensible recognition rate (100%).

The experimental results showed that the adopted energy and moment gave different recognition rate, and the partitioning into overlapped blocks (instead of non-overlapped blocks) had made better the recognition accuracy because it is beneficial for compensating the small shifts.

For future work, the module can be extended to:

- Utilizing another collection of features for a matching method.
- Presenting the fingerprint verification to verify the authenticity of one person using his fingerprint and to prevent many people from utilizing the same identity.

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