FINGERPRINT IDENTIFICATION BY USING WAVELET TRANSFORM AND STATISTICAL TEXTURE MEASURES

THAER SULTAN

MAY 2015

FINGERPRINT IDENTIFICATION BY USING WAVELET TRANSFORM AND STATISTICAL TEXTURE MEASURES

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES OF
ÇANKAYA UNIVERSITY

BY
THAER SULTAN DARWEESH

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE
IN
THE DEPARTMENT OF
COMPUTER ENGINEERING

MAY 2015

Title of the Thesis: **Fingerprint Identification by Using Wavelet Transform and Features Extraction.**

Submitted by **Thaer SULTAN**

Approval of the Graduate School of Natural and Applied Sciences, Çankaya University.

Prof. Dr. Taner ALTUNOK
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

Prof.Dr. Müslim BOZYİĞİT
Head of Department

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

Assist. Prof. Dr. Reza HASSANPOUR
Supervisor

Examination Date: 25.05.2015

Examining Committee Members

Assist. Prof. Dr. Reza HASSANPOUR	(Çankaya Univ.)	
Assoc. Prof. Dr. Hakan MARAŞ	(Çankaya Univ.)	
Assoc. Prof. Dr. Fahd JARAD	(THK Univ.)	

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ABSTRACT

FINGERPRINT IDENTIFICATION BY USING WAVELET TRANSFORM AND STATISTICAL TEXTURE MEASURES

SULTAN, Thaer
M.Sc., Department of Computer Engineering
Supervisor: Assist. Prof. Dr. Reza ZARE HASSANPOUR
MAY 2015, 46 pages

In this thesis a method has been proposed which is based on the features of fingerprints patterns. Same technique has been used for fingerprint identification. In proposed method fingerprint identification have been processed by using MATLAB, and we used the standard UPEK Fingerprint database. In this thesis we used wavelet transformation based on Daubechies wavelets for image compression. Here the first level of wavelet transformation is considered and then from the result of wavelet transform we took the gray level co-occurrence matrix GLCM. Results have proved the ability of the proposed method. Feature extraction is performed using Co-occurrence matrix without losing too much information. We have extracted the features of the fingerprints classification of image then the comparative simulation results measuring identified image is done by employing Euclidian distance method. Many variants scenario of these algorithms have also been implemented wherever it was appropriate.

Keywords: Fingerprint, Identification, Wavelet, Co-occurrence, Euclidian Distance.

ÖZ

DALGACIK DÖNÜMÜ VE İSTATİSTİKSEL ÖLÇÜMLER KULLANARAK PARMAK İZİ TANIMI

SULTAN, Thaer
Yüksek Lisans, Bilgisayar Mühendisliği Anabilim Dalı
Tez Yöneticisi: Yrd. Doç. Dr. Reza ZARE HASSANPOUR
Mayıs 2015, 46 sayfa

Bu tezde, parmak izi desen özelliklerine göre bir yöntem sunulmuştur. Aynı teknik parmak izi tanımlaması için kullanılır olmuştur. Önerilen parmak izi tanıma yöntemi, standart UPEK Parmak İzi veritabanı kullanılan MATLAB yazılım sistemi kullanılarak yapılmıştır. Bu tezde görüntü sıkıştırma için Daubechies Wavelet dönüşümü kullanılmıştır. Wavelet dönüşümü ilk seviye olarak yapılmıştır ve daha sonra Wavelet sonucu bir gri seviyeli eş-oluşum matrisi (GLCM) kullanarak öznitelikler hesaplanmıştır. Sonuçlar önerilen yöntemin yeteneğini kanıtlamıştır. Özellik çıkarımı çok fazla bilgi kaybetmeden eş-oluşum matrisi kullanılarak yapılmıştır. Görüntünün parmak izi sınıflandırma özellikleri bulunduktan sonra karşılaştırmalı simülasyon sonuçları Öklid mesafesi yöntemi kullanılarak yapılmıştır. Uygun olduğu yerde bu algoritmaların birçok varyasyonları da uygulanmıştır.

Anahtar Kelimeler: Parmak İzi, Kimlik, Dalgacık, Eş-oluşum, Öklid Mesafesi.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to Assist. Prof. Dr. Reza HASSANPOUR for his supervision, special guidance, suggestions, and encouragement through the development of this thesis.

It is a pleasure to express my special thanks to my family for their valuable support.

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LIST OF ABBREVIATIONS

DNA	Deoxyribonucleic Acid
DWT	Discrete Wavelet Transform
DCT	Discrete Cosine Transform
CIF	Combined Invariant Feature
FD	Fractal Dimension
SVD	Singular Value Decomposition
1D	One Dimension
2D	Two Dimension
FVC	Fingerprint Verification Competition
DB1	Database One
NIST	National Institute of Standards and Technology
MRA	Multi–Resolution Analysis
FAR	False Acceptance Rate
FRR	False Reject Rate
DLDA	Direct Linear Discriminant Analysis
MEGFE	Minutiae Extraction Gabor Filter Enhancement
NRC	National Registration Cards
ROI	Region Of Interest
GLCM	Gray Level Co-occurance Matrix

CHAPTER 1

BIOMETRIC SYSTEMS

1.1 Overview

In this chapter a review of human identification systems is presented. The various biometric techniques are described. The physiological and behavioural characteristics of humans which can be used as a biometric identifier to identify a person are presented too.

1.2 Biometric Systems

Biometric systems are mechanisms to verify personal specific physiological characteristics unique to the human body which are stored in the system shareware. The biometrics of the human body in more ways personal check is easy to use and the most reliable and secure, cannot be theft or stolen, because it is fixed and it is not change. The verification system consists of a set of basic components: a device (system) to save the image scanning (digital / Videos) the person's vital, the treatment system and comparison, and the application interface to show the result of the operation to confirm or deny personal. The most important physiological properties that characterize the human body are fingerprint. Here an identification using a number of physiological properties of human fingers is used [3].

Biometric system is a device that is committed to identify a particular person using biological characteristics of the individual. This feature as Figure 1 can be grouped into two main categories:

1. Physiological traits: show all static data from a person such as, fingerprints, iris pattern, and shape of the hand or the face image.

2. Behavioural traits: it refers to the actions taken by the person concerned, and then talks about his writings, audio track, and method of pounding the keyboard.

In general, the physiological properties do not vary with the pass of time or for the most part are subject to small changes while affected by the behavioural characteristics of the psychological state of the individual. For this reason, identity verification systems based on behavioural characteristics need frequent updates. The main task of a biological system is to identify the individual.

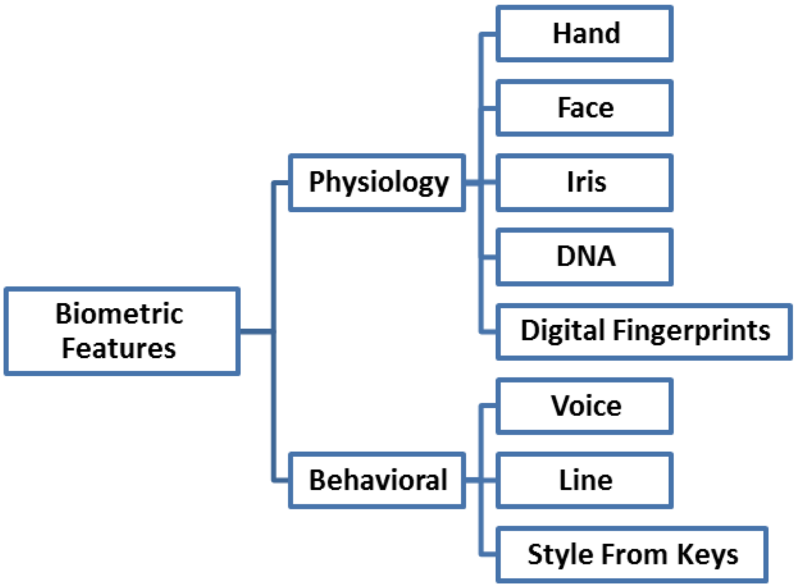


Figure 1 Biometric Feature

The recognition system can carry two different tasks:

1. Identifying verification: is to declare whether a person is really the person who claims to be Fig. 2. a.

2. Recognition of identities: It concerns with determining whether a person matches with an existing instance in an archive. It is not necessary to declare the identity Fig. 2 .b.

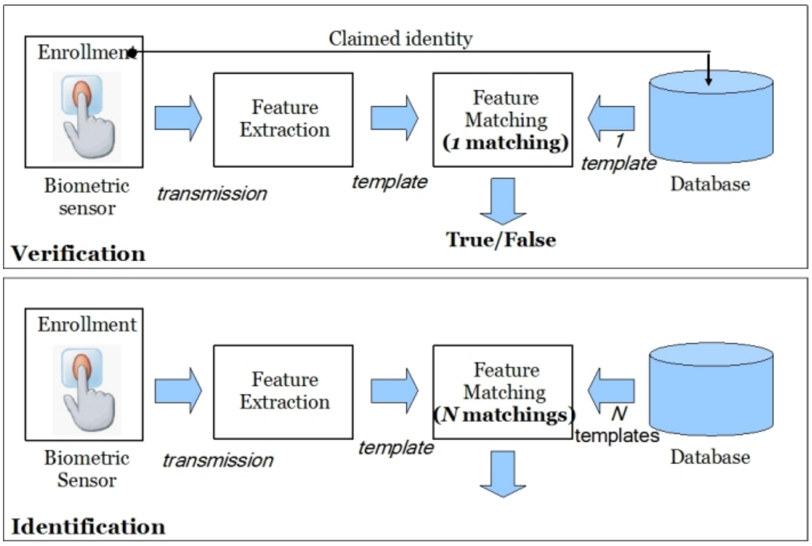


Figure 2 Biometric Systems (a) Verification, (b) Identification [4]

Biometrics are different types to extrapolate information from the human body, but it is also important to understand that relying on a specific feature is certainly necessary to build a good system.

1.3 Biometric Classifications

A general comparison between the various biometric techniques is quite necessary. Therefore, all technologies listed in Fig. 3. should be evaluated based on objective metrics so that if we want to develop any software that complies with all requirements of the work and foremost is reliable; we need an in-depth analysis of the characteristics of the application to choose the necessary technology to be used [5].

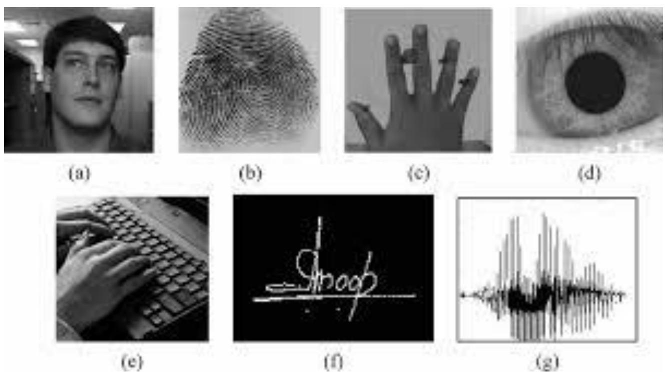


Figure 3 Biometrics System Examples are shown: (a) Face, (b) Fingerprint, (c) Hand Geometry, (d) Iris, (e) Keystroke, (f) Signature, and (g) Voice [5]

- **Hand Geometry:** Human hand is a tool used in everyday life. It is important to know that each individual possesses exclusively special hands because of their length, width, thickness, and in particular curvatures [6].

Figure 4 Hand Geometry Biometric Devices [6]

- **Iris:** Iris is one of the most accurate biometric features in humans. They also excelled in accuracy compared to using fingerprint and/or iris. Additionally, it is difficult to manipulate iris of the eye, whether this manipulation is by glasses or contact lenses or surgery of the eye. And the rest of the identification process through the iris imprint as possible and easy to process. And so this method has been adopted in many systems that require the disclosure of the identity of the person security at airports and banks in automated teller machines and the high efficiency of the iris [7].

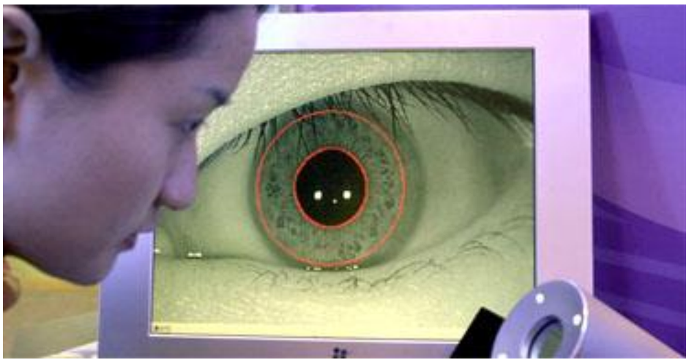


Figure 5 Iris Manipulations [7]

Iris featuring is fixed and does not change over the life time, and therefore does not require renewal scanning and updating the data stored in the security databases.

Besides, the process of scanning the iris is accurate, and efficient as the process is easy to manage through the several stages compared with the accuracy of fingerprint or palm of the hand.

- **Face:** The first thing we do is to identify the person by looking at him in the face, and we certainly are not used to analysing fingerprints or the iris of the eye. Researches show that when we look at people we tend to focus on the dominant parts such as big ears, aquiline nose, etc. It is also found that the internal characteristics (nose, mouth and iris) and (head shape, hair) are more important [8].

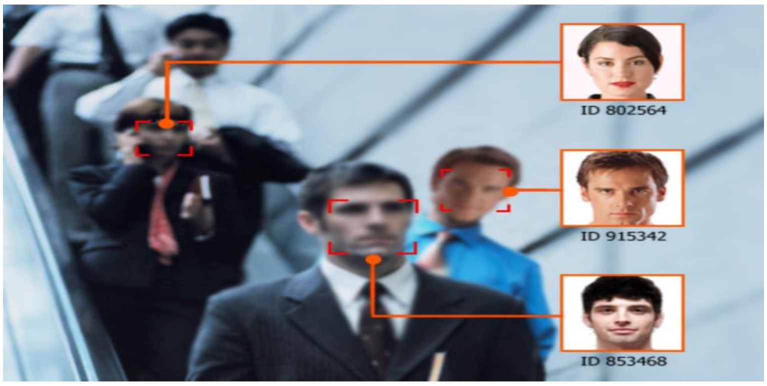


Figure 6 Face Recognition [8]

- **Voice:** Even a person's voice is considered an element of biometric recognition. Biometric feature does not have sound levels of stability [9].

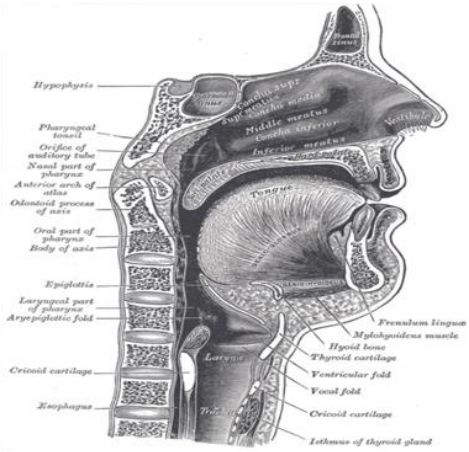


Figure 7 Vocal Apparatus [9]

These organs shown in Fig. 7. are responsible for issuing the voices of the mouth, which in fact can change from person to another and produce a sound wave when air passes from the lungs through the windpipe and vocal cords. This sound is characterized by its source through dealing with the excitement, pressure and vibration, murmur or a combination of them.

- **Fingerprints:** Fingerprint is the best characteristic to verify the identity of people. It is the most common, oldest and most widely used biological characteristic in technological applications, which depend on the lines and formations deployed on the surface of human skin at the fingertips. Readers can utilize these lines and formations to analyse and identify people and store in computerized security systems [10].

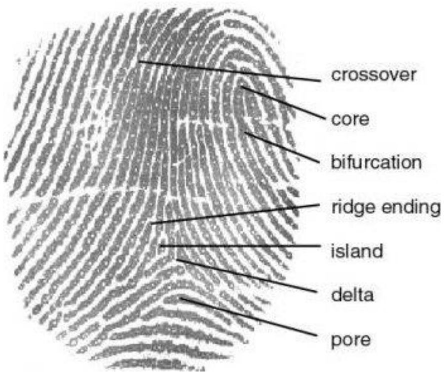


Figure 8 Fingerprint Minutiae [10]

- **Signature:** There is always a difference in every sample of that person's signatures resulting from the movement of the hand in the way of drawing the letters of the name or in the way of drawing a certain curve or certain angle or certain lines in the signature itself. Those differences may affect the results [11].

Figure 9 Electronic Tablets [11]

- **DNA:** Deoxyribonucleic Acid (DNA) it is a unique code for one's individuality for one-dimensional ultimate, the identical twins has identical DNA patterns except for the fact. The forensic applications for person recognition [12] used currently context.

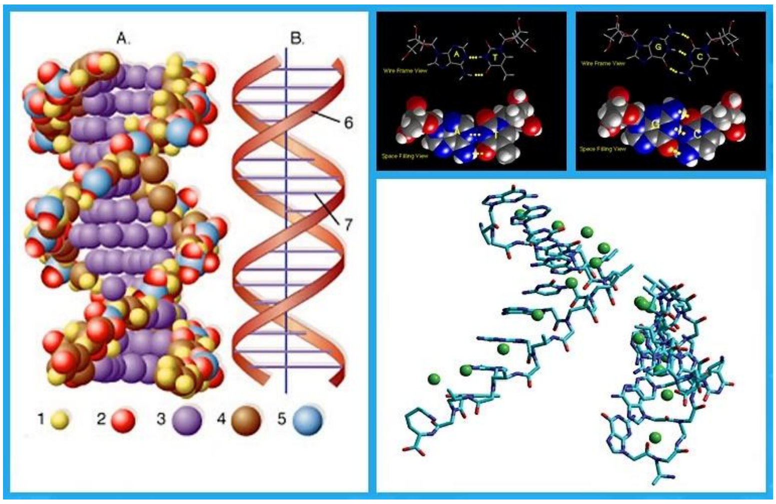


Figure 10 DNA Recognition [12]

Factors → / Biometric identifier ↓	Universality	Distinctiveness	Permanence	Collectable	Performance	Acceptability	Circumvention
Hand Geometry	**M**	**M**	**M**	**H**	**M**	**M**	**M**
Iris	**H**	**H**	**H**	**M**	**H**	**L**	**L**
Face	**H**	**H**	**M**	**H**	**L**	**H**	**H**
Voice	**M**	**L**	**L**	**M**	**L**	**H**	**H**
Fingerprint	**M**	**H**	**H**	**M**	**H**	**M**	**M**
Signature	**L**	**L**	**L**	**H**	**L**	**H**	**H**
DNA	**H**	**H**	**H**	**L**	**H**	**L**	**L**

Table 1 Biometric Technologies Comparison, Data Based On the Authors. High, Medium, and Low are Denoted by H, M, and L, Respectively [13]

1.4 Summary

The feature of vital physiological characteristic of every human, such as fingerprint, iris, face, hand, voice and signature have achieved significant improvement in personal identification. The extracted feature of this biometrics has made a significant achievement in reducing many of the problems and weaknesses that faced with the traditional way of verifying the identity (persons) using passwords. Despite the degree of high security achieved by these techniques the accuracy recognition systems did not reach to 100% yet. For this reason the design of new techniques for feature extraction and image recognition become important computer science.

CHAPTER 2

PREVIOUS WORKS

2.1 Overview

In this chapter we will discuss certain previous works related to the subject of this thesis form three attitudes:

2.1.1 Discrete Wavelet Transform (DWT)

There are different types of texture features already exist. Texture feature will be good when allows one to determine similarities and dissimilarities in intensity variation patterns present in different area in the image. The texture of regions cannot be characterized by intensity statistics only as mentioned B. Julesz, et al [14], but When a digital image contains regions of distinctly different texture, can be possible to segment the image into its constituent parts based on texture features. To represent this features statistical as well as structural characteristics of the texture we must using any mathematical measure or use some different rules in this matter. The most of popular texture methods are based on gray level co-occurrence statistics, probability density functions on N. Saito, et al [15].

Others papers K. Muneeswaran, et al [16], combined invariant feature (CIF) that contains crude wavelet integration like Gaussian, Mexican Hat and orthogonal wavelets like Daubechies to product the high quality scale and rotation invariant, used the fractal dimension (FD) with first and second order statistical parameter. Fig. 11. show the different Gaussian wavelet with derivatives.

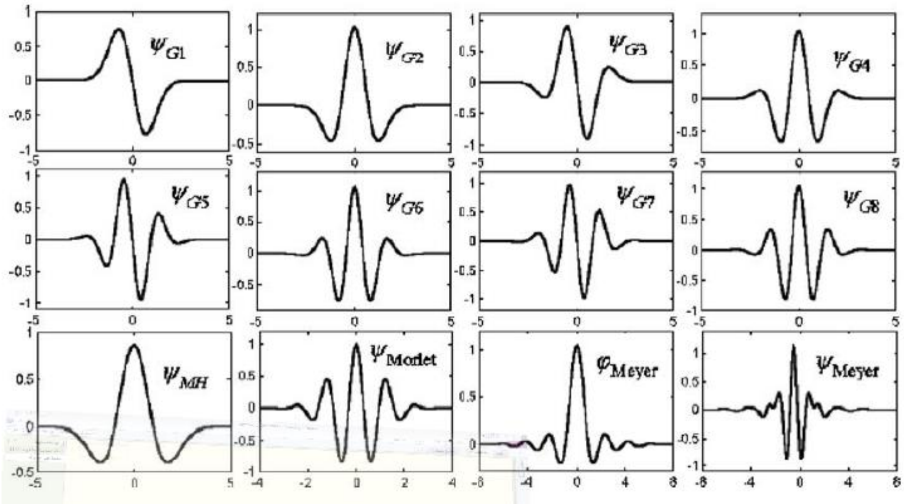


Figure 11 Shows the Subscript for the Different Gaussian Wavelet Obtain From Mexican Hat Wavelet and the Order of This Derivative

The images characteristics used wavelet co-efficient to found the statistical properties and that lead to the good result in image classification, and in this matter there are many energy measures improved the features quality extraction, form this energy measures are:

1- Standard deviation and can defined in this equation:

$$E1 = \sqrt{\frac{1}{N^2}\sum_{k=1}^{N}(C_k - \mu)^2} \tag{2.1}$$

2- Entropy and defined with this equation:

$$E2 = -\frac{1}{N^2}\sum_{k=1}^{N}|C_K|^2 . \log|C_K|^2 \tag{2.2}$$

3- Average residual and it is defined as:

$$E3 = \sum_{k=1}^{N}(C_k - \mu)^2 \tag{2.3}$$

4- Energy Norm-2

$$E4 = \frac{1}{N^2}\sum_{k=1}^{N}|C_K|^2 \tag{2.4}$$

5- Energy Norm-1

$$E5 = \frac{1}{N^1}\sum_{k=1}^{N}|C_K| \tag{2.5}$$

Where N is represent the size of the image.
Finally computed the statistical properties of orthogonal form by:

$$O(x, y) = [E1 \quad E2 \quad E3 \quad E4 \quad E5] \tag{2.6}$$

One of the necessary desired property in several application is feature insensitively to different image transformation, and this method is good for classification and conventional methods when image scaling and rotation.

Zhou Weina, et al [17], proposed modern method for fingerprint verification with application of wavelet transformation and prewitt operator, the wavelet transformation is noise resistance and prewitt operator is invariant to rotation, scale and translation and by used this method they improved that result is definitely effective and low computation complexity. Wavelet image in fact consists of four sub–image each quarter from the original area and Fig. 12. show the low frequency located in up left sub–image and called approximate area and the remaining three images, the high frequency consist of vertical and horizontal (down left and up right) respectively and in the both direction high frequency (down right) it is contain all the details image, and all this three sub–image contain the whorl information and ridge orientation which effected on the classification on the image.

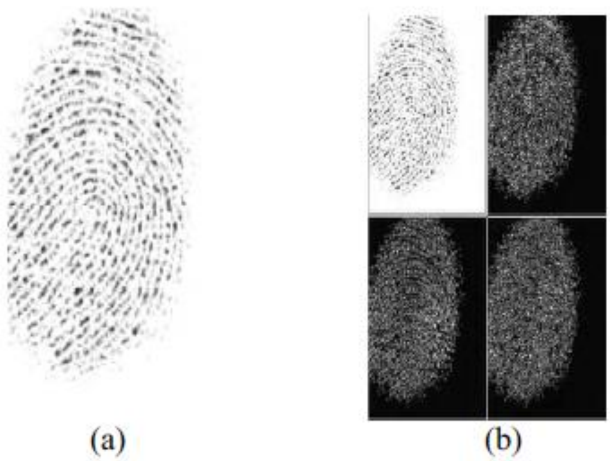


Figure 12 (a) Shows The Original Image and (b) The Sub One Level Image Decomposition Wavelet Transform

After applied the combining wavelets transform on the image to get the details information and prewitt to get the edge detection for the same image, the verification accurate was 100% after used different circumstances like dirty/dry fingerprint, distorted fingerprint and wet/heavy pressed fingerprint. This method consider low cost implementation because no preprocessing methods and very simple computation.

Jing-Wein Wang, et al [18], proposed new algorithm that contain from two stages, the first is decomposing the fingerprint image input in two dimension DWT with four sub–bands levels, and the second compensated image to obtain the compensation image for each sub–band depending on Gaussian template, with this method indicated that the compensated image quality can be high compared with the original image. The Most of information in the fingerprint image can be obtained in the low frequency sub–band, the ridge information structure can be obtained in the middle frequency sub–band, while the noise distribution was observed in the high frequency sub–band. Singular Value Decomposition of a Fingerprint Image (SVD) is widely used in image processing without losing of generality, all the SVD in the Fig. 13. show that Fig. 13. (a) multiplied by two and the reconstructed the fingerprint image again, the fingerprint image foreground ridge represent by Fig. 13. (d), so the SVD can be used to enhanced the fingerprint image ridge and noise removing in the same time, to calculated the SVD for each sub–band coefficient fingerprint image matrix with Gaussian template can represent by:

$$A = U_A \sum_A V_A{}^T \qquad (2.7)$$

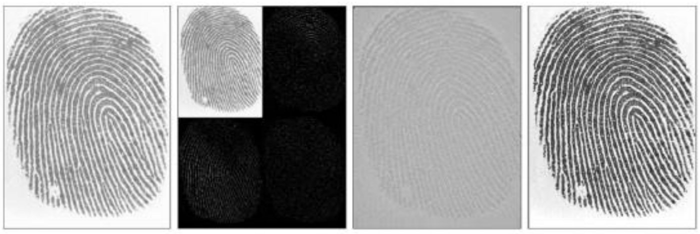


Figure 13 (a) The Original Image Fingerprints. (b) After Using 2–D DWT First Level Four Sub–Bands. (c) All The SV in (a) Equal to One to Reconstructed Image. (d) Multiply All SV in Fig. 13 (a) with Two to Reconstructed Fingerprint Image Again

The compensation coefficient increased when the image was dark and the if image was too bright the compensation coefficient decreased, this method applied in many different fingerprint database like FVC 2002 DB1, FVC 2002 DB2, FVC 2002 DB3, FVC 2002 DB4 and NIST–4 database. The Fig. 14. shows these types in fingerprint database the results obtain by using this method.

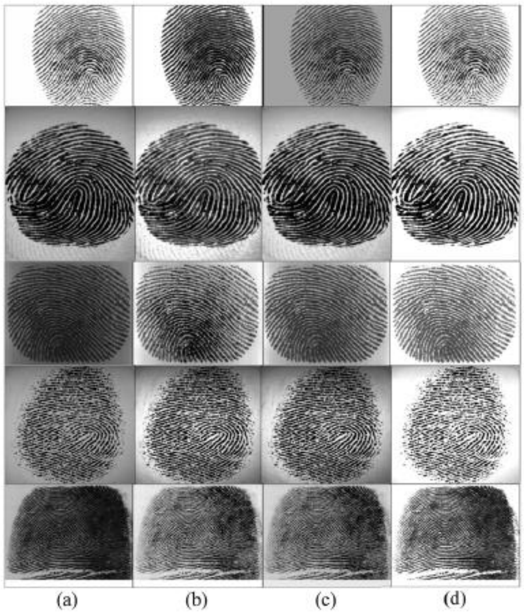


Figure 14 (a) Top to Bottom: FVC 2002 DB1, FVC 2002 DB2, FVC 2002 DB3, FVC 2002 DB4 and NIST 4 where: (a) Fingerprint Original. (b) Images Form HE [19]. (c) Bennet and Perumal's Images. (d) Proposed Method

Priyadarshan S. Ohabe, et al [20], they approach extract the features from the image without need for any preprocessing and Gray scale has rich information that can give us many details for image, Haar algorithm wavelet used to extract characteristics and verifications from images. Hierarchically decomposes used to on Multi–resolution Analysis (MRA) and divided the image into two frequency, high frequency and low frequency from the Mother wavelet given in (2.8) where a is the scaling and b is the shifting parameter.

$$\Psi_{a,b}(t) = \frac{1}{(\sqrt{a})} \Psi[(t-b)/a] \tag{2.8}$$

The Haar transform calculated the set of the wavelet coefficients and set of average coefficient, and the Haar wavelet given by the (2.9), (2.10) equations, where N is average and M is the differencing, S_0, $S_{n\pm1}$ are data image.

$$N = (S_i + S_{i+1})\ /2 \tag{2.9}$$

$$M = (S_i + S_{i+1})\ /2 \tag{2.10}$$

Figures below Fig. 15 shows the first level, second level and third level respectively decomposition of Haar wavelet transform.

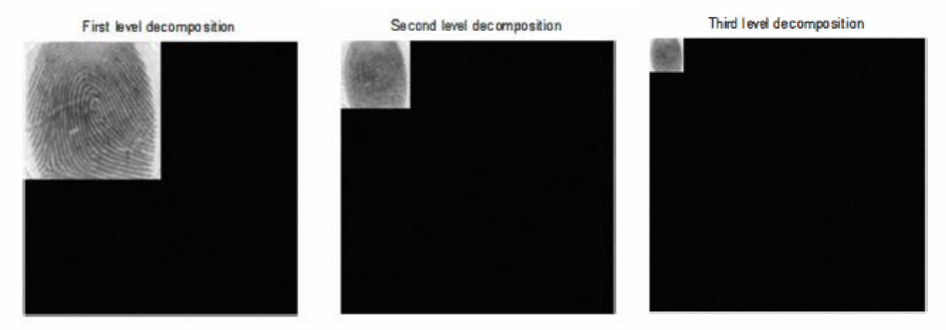


Figure 15 The First Level, Second Level and Third Level Decomposition Respectively.

The achieved verification rate equal to 82.08 even rotation each fingerprint image angles 0^0, 360^0 with steps 10^0 with (0.5) False Acceptance Rate (FAR) and 0.58sec for feature extraction time per each fingerprint image.

2.1.2 Discrete Cosine Transform (DCT)

As it is mentioned by T. Amornraksa, et al [21], the DCT coefficient proposed by extract the informative features from a fingerprintimage, the image is first cropped to a 64_64 pixel region,then found the centered at the reference point, and then quartered to obtain four non-overlappingsub-images of size 32_32 pixels as Fig. 16.

(a) (b)

Figure 16 (a) Fingerprint Image &(b) Four 32_32 Pixel Sub-Images

The applied of DCT for each sub image get a block of 32×32 coefficient, end of standard deviation DCT coefficients found to 6 predefined areas. Fig. 17. explain this clearly.

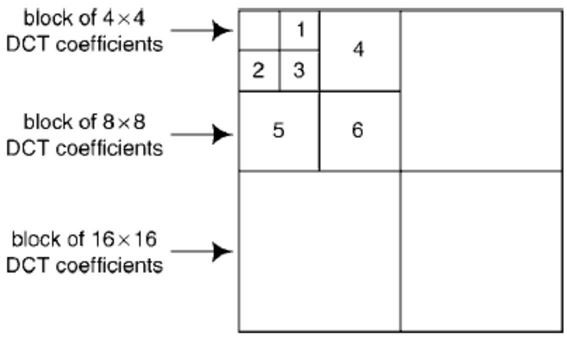


Figure 17 The Areas 32×32 DCT Coefficients It is Used to Extract Features Informative Form Six Region

In this paper the image fingerprint database contains from 104 greyscale fingerprint image size 256×256 pixel, where each finger contains form eight image and 13 individual sample, after all that use K-NN for classification.

The features used for fingerprintmatching can be directly extracted, with no preprocessing and the results verified its efficiency from a higher recognition rate anda lower complexity.

M. P. Dale, et al [22], The much helpful information using Discrete Cosine Transform (DCT) based on feature vector for fingerprint representation and matching, this method does not need to any reprocessing, dividing image transformed into various blocks, standard deviation will form the feature vectors for mid and high frequency and calculated for each blocks with different thresholds value. For each person used eight images captured for 15 training set and individual of k image from one to eight. Represent the result in term Falsely accepted and Truly accepted for each persons. And finally calculated the recognition rate with many numbers value of thresholds.

As previous methods [21], this methods used coefficients sub image size 64×64 calculated without any preprocessing and distributed in many type of frequency domain but after that must resize the image to 64 with considered variation in scale, position and rotation angle as Fig. 18.

Figure 18 (a) The Original Image with Size 248×292

Figure 18 (b) The Image with Zoomed Out of Size 64×64

This method proofed that the performance will be same and remains after training the images 4 to 6 times, gives better performance in recognition rate and gives negative contribution to FFR with poor quality images in matching fingerprint, In case of noisy images can extended this approach for multiple finger print to get better result.The DCT frequency bands with favorable linear discriminative features of Fisherface method and performs Xiao-Yuan Jing , et al [23], the two dimensional separability judgment select and using the reduce the dimension of feature space and cost little computing time can significantly improve the recognition rates for face and palmprint. In this approach description present 2-D separability judgment by perform a two dimension DCT on each image in this equation:

$$F(u,v) = \frac{1}{\sqrt{MN}} \alpha(u)\alpha(v) \sum_{x=1}^{M} \sum_{y=1}^{N} f(x,y).x \cos\left[\frac{(2x+1)u\pi}{2M}\right].\cos\left[\frac{(2y+1)v\pi}{2N}\right] \quad (2.11)$$

Where:

x1, x2 test sample sets for image training, MN matrix size for gray image and represent with $f(x,y)$.

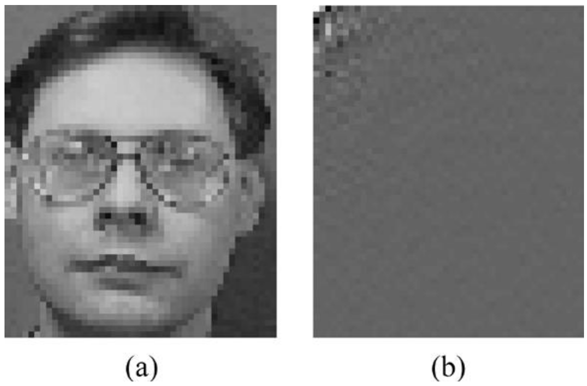


Figure 19 The Facial Image and Its DCT Image Transformed

Fig. 19. (a) the facial image and (b) the energy of the image is concentrated in the left up corner, which is mean low frequency band. While the figure 20 show the different DCT frequency band.

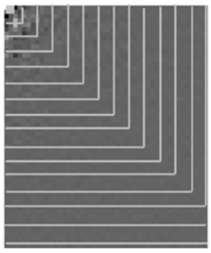


Figure 20 DCT Frequency Bands Expression Ways

The α(w) defined as:

$$\alpha(w) = \begin{cases} \frac{1}{\sqrt{2}} & , \quad w=1 \\ 1 & , \quad otherwise \end{cases} \tag{2.12}$$

Where: F(u,v) is sized M×N

In this paper the direct extracted DCT feature from facial image and achieved the similar classification and select the entire appropriate frequency band with linear separability and there are little correlation between different bands by using the DCT linear orthogonal transform. The results for this paper experiment are compared with 4 conventional linear discrimination methods: Fisherface, Eigenface, discriminant wavelet face and DLDA. The result for this paper experiment improved that it is given little computing time cost and reducing the dimension of feature space and given the average recognition data rates for four conventional methods respectively by 13.33%, 13.65%, 16.13% and 15.21%.

A fingerprint Matching method using DCT features [24], the extract and matching informative features fingerprint are performed by calculating the coefficients in predefined areas, evaluated and classifier the recognition rate using K-NN. Finally the result compared to the existing method based on the wavelet features and matching processes between two approaches, in the same time with used this method can achieved the lower complexity and high recognition rate.

This method used 12 wavelet sub-images for future extraction in DCT as show in Fig. 21.

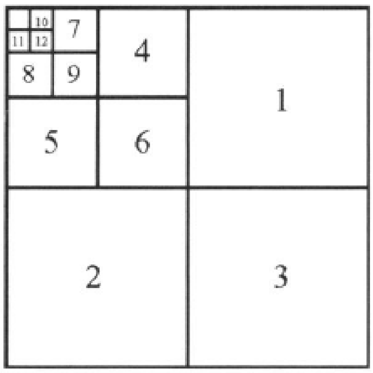
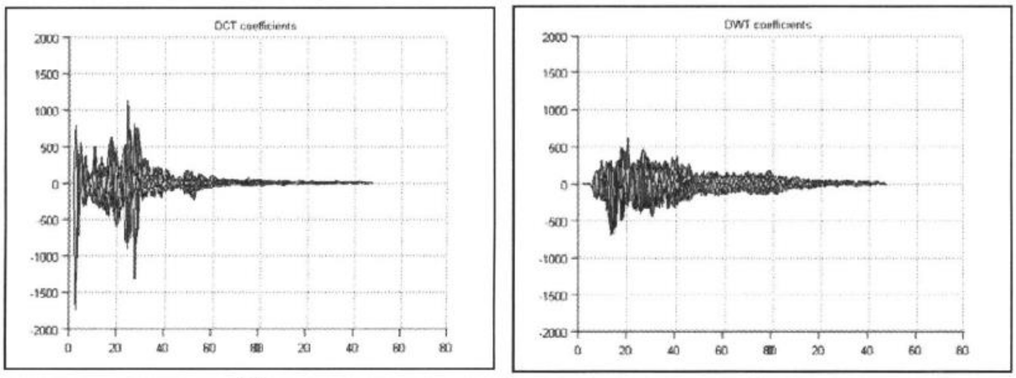


Figure 21 Feature Extraction for Twelve Sub Images Arrangements

From the Fig. 22. we notice that the DCT have more variation than DWT, and the DCT coefficient in middle and high frequency are smaller than DWT.



(a) (b)

Figure 22 (a) DCT (b) DWT Distributed Coefficients

In this paper the author show that the DCT fingerprint image extraction is better than DWT in middle frequency channels, and could achieved high recognition in lower complexity.

2.1.3 Minutiae Extraction and Matching

Lavanya B N, et al [25], proposed Minutiae feature Extraction and post processing by using gray-level fingerprint image 500 dpi with size N×N, then test the Minutiae Extraction in Fingerprint using Gabor Filter Enhancement (MEGFE) algorithm, Fig. 23. shows the block diagram for this algorithm.

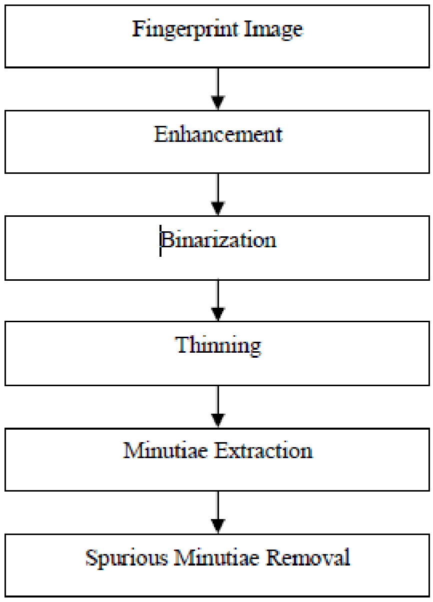


Figure 23 MEGFE Block Diagram

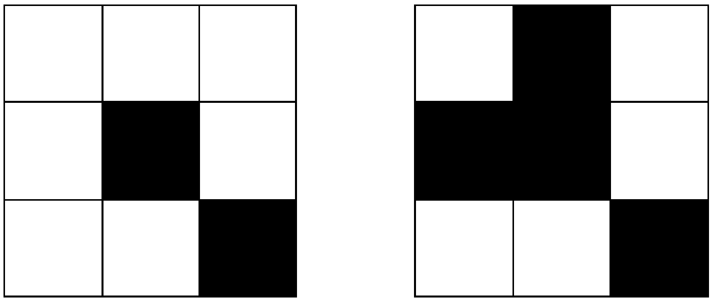
First, low pass filter enhancement image quality and removing the noise, the frequency and orientation effectively remove undesired noise and improved the true ridge by using the mask for each block classification in the fingerprint image, if the percentage of recoverable regions is smaller than a threshold, the fingerprint image is rejected, then grayscale image converted into binary image by using threshold value, where the pixels ridge converted to white pixel and the background converted to black pixel, the equation (2.13) show how the Binarization method represented:

$$BW(x,y)=\begin{cases}1 & if\ I(x,y)\geq T_P \\ 0 & otherwise\end{cases} \qquad (2.13)$$

Where T_P is the threshold value and $I(x,y)$ intensity grayscale image value.

Next step using the Thinning for faster processing reduced the complexity and less time computation by converted image to the one pixel width. The next step in this algorithm is minutiae extraction, the local minutiae extractions are Ridge ending and Ridge bifurcation, using 9- pixel neighborhood method to extract the minutiae. Finally the Spurious Minutiae are removed and true minutiae points are imposed on image; one of the feature works for this paper is combining discreet wavelet transform (DWT) with the MEGFE method.

Yin Li-qiang, et al [26], paper discuss how correctly extraction fingerprint feature point based on the thin ridge ending and ridge bifurcation current point in fingerprint image, used 8-neighborhood pixel coding, these methods improve speed feature extraction by less time processing and eliminate pseudo minutiae, Fig. 24. show the local minutiae.



(a) (b)

Figure 24 Fingerprint Local Minutiae, (a) Ridge Ending, (b) Ridge Bifurcation

The main basic to extraction the local minutiae feature form the fingerprint image it has 1 gray spot level (black) around the ridge ending and the others is 0; while the bifurcation ridge has 3 gray spot level (black) around it and the others is 0, so the time for the variation different completely. Before get the feature point for image first must remove the false minutiae by certain threshold and calculate the distance between the two ridges ending if they can in the same direction and less than threshold then must close and represent that the false minutiae, Fig. 25. show this idea.

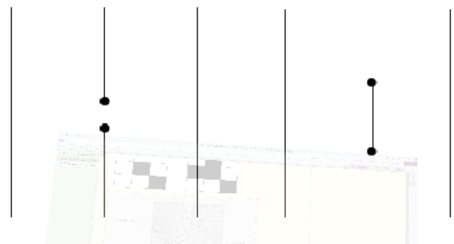


Figure 25 Show The Calculate False Ridge Minutiae with Distance of Threshold

On the other hand to eliminate the bifurcation false minutiae must have three ridge lines from the ridge bifurcation, Fig. 26. show eliminate bifurcation false minutiae.

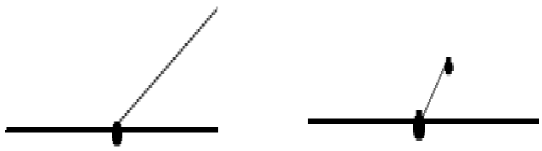


Figure 26 Eliminate The False Bifurcation Minutiae Features

Fig. 27. shows the result the feature point minutiae extraction form the fingerprint after removing the false minutiae.

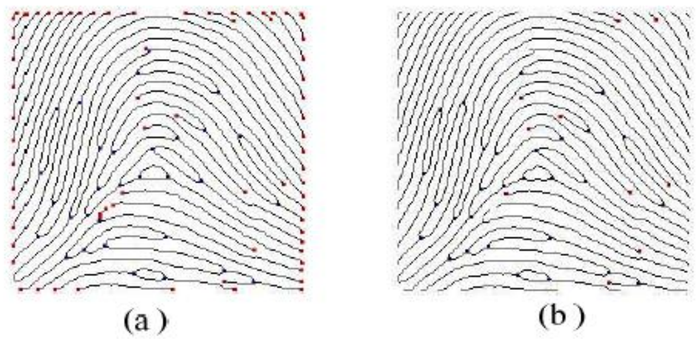


Figure 27 Feature Point Minutiae Extraction, (a) Before False Minutiae Eliminate, (b) After False Minutiae Eliminate

Zin Mar Win, et al [27], developed fingerprint recognition system depending on fingerprint image on Myanmar National Registration Cards (NRCs), all the approach for fingerprint identification based on minutiae based and correlation base, the minutiae base more popular, by using the correlation based can identification low quality images by calculated the mean value of factor correlation, compared the value of factor between the input image and the template image in database and using the threshold value for matching if it can positive of negative process, using the Gabor filter to enhancement the bad images before calculated the correlation factor, so this method using for bad and good quality images, by using the integration the Gabor filter and two pass thinning can obtain the good ridge features and before using the Gabor filter must detected the orientation line ridge direction and to obtain the reference core point must calculate the correlation values and determine the two images correlation scores, Fig. 28. show the all previous steps.

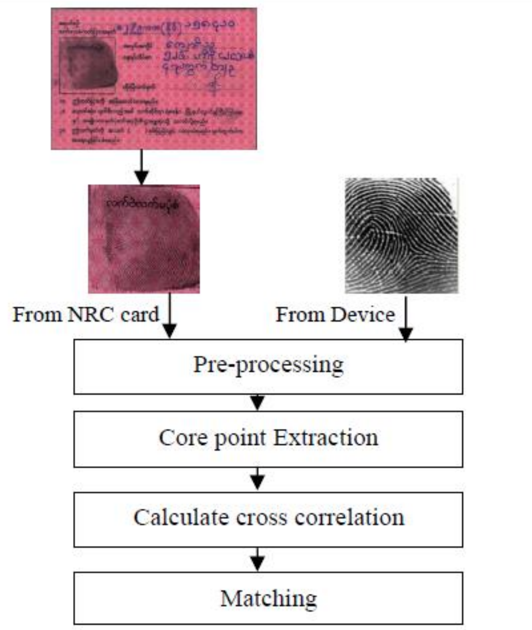


Figure 28 System Model

The experimental using images with 256×256 inkless fingerprint database images size and use the low quality images and NRC images card. This proposed is simple as compared with the matching of minutiae point, by using the Gabor filter can obtain the low quality of impression from print paper not only form image device.

Vijayaprasad P, et al [28], using input image 8-bit grayscale, 500 dpi, standard database images FVC 2004 with 256×256 image size, proposed method using first the fuzzy technology to enhancement image with 10 complex filter to get better result, then find the region of interest (ROI) and this point represent the maximum curvature of the concave ridges in image, after finding the ROI the image is sectored, then normalized image to remove the effect of noise form the pressure and sensor after that the Gabor filter is applied to remove the noise to improve the true ridge and valley, finally calculated the feature vector to indicated the ridge activity that it is useful for fingerprint classification. Fig. 29. show the flowchart for this method.

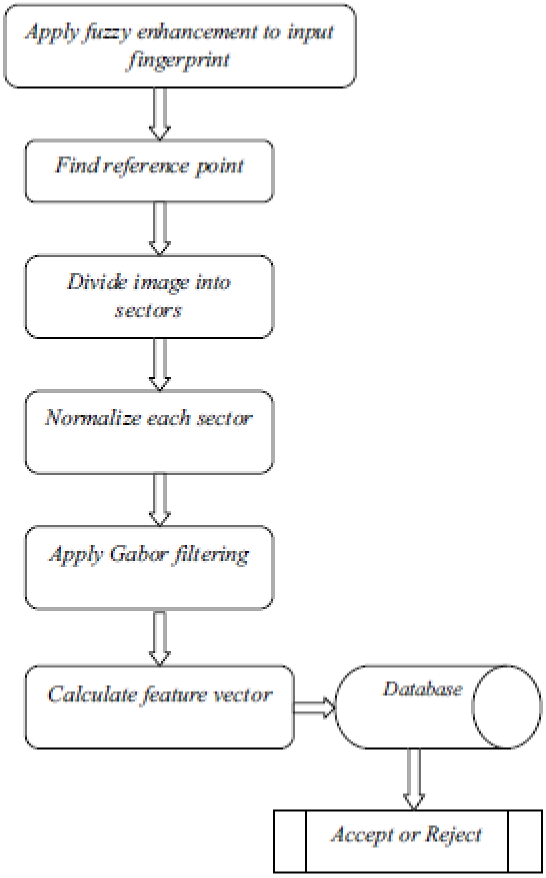


Figure 29 Show The Block Diagram Method For The Proposed System

Euclidean distance used to matching the fingerprint template in database with the image enrolled, this approach don't success to improve the performance with other minutiae based, so filter bank maybe better choice to compare local minutiae based.

CHAPTER 3

TEXTURE ANAYLSIS EXTRACTION

3.1 Overview

This part is based on my proposed method for M.Sc. thesis and for the fingerprint identification; Discrete Wavelet Transform (DWT) and texture analysis will be used as based for my work, where we have two stage: First, apply DWT on the Gray scale image in one level decomposition, this level are four sub-band levels (HH,HL,LH,LL) and the second stage: the texture analysis used to refer to the characteristics of region in the image by using their texture contents such as Angular Second Moment, Contrast, Correlations, Dissimilarity, Entropy, Homogeneity, Maximum probability, Average and all used attempts to the quality described, in the same time the texture analysis used to find the texture boundaries that is called texture segmentation. The texture analysis has many various applications, like fingerprint identification, medical image processing, document processing and remote sensing.

Compared with methods described in chapter 2 in 2.1 Discrete Wavelet Transform (DWT) Identification Technology, texture analysis image filter used the standard statistical measurements and these texture characteristics images provide information for the local intensity value of the pixel in the images. Table 2 shows used this functions and description:

Function	**Description**
Entropy	Used to represent the grayscale pixel values of image to (8) unite and calculated the histogram count.
Graycomatrix	Create gray–level co–occurrence matrix from binary image (GLCM) and contain form 2 gray level (0,1).
Graycoprops	Calculated the specific properties of image statisticaly from three dimension M×N×P and obtain the result from statisticaly for each GLCM.

Table 2 Standard Functions Texture Analysis For GLCM

3.2 A Brief Discussion of Wavelets

Discrete wavelet transform becomes one of the most important mathematical wavelet analysis techniques and powerful tools representation of signals, there are many applications that have been used like signal processing, compression of data and image processing, this paper will discuss the basic concept of Discrete Wavelet Transform. The wavelet signal $f(x)$ can decomposition by convolution the signal with basic family function:

$$\left\langle f(x), \psi 2^{s}, t^{(x)} \right\rangle = \int_{-\infty}^{\infty} f(x) \psi 2^{s}, t^{(x)dx} \qquad (3.1)$$

Where (s, t) are referred respectively, translation and dilation parameter. Wavelet decomposition has two pairs of filter, high pass and low pass filter used to calculate the wavelet coefficients [29] as Fig. 30. below:

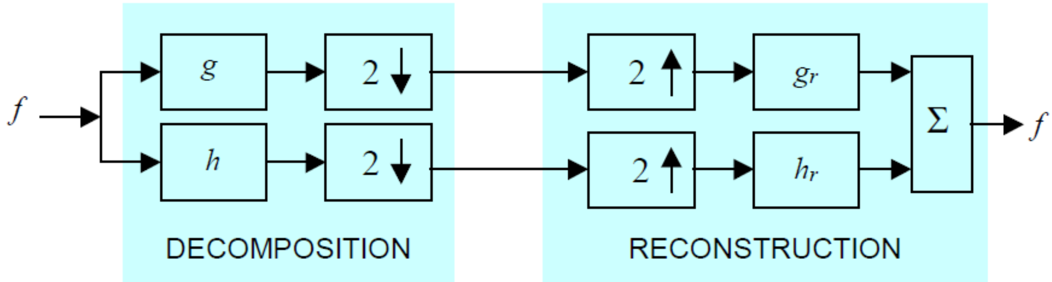


Figure 30 Shows The Low Pass Filter and High Pass Filter with Decomposition and Reconstruction, where g, gr Represents The Low Pass Filter and h, hr Represent High Pass Filter

The image can be frequency analysis and decomposition by using the wavelet transformer, the high frequency in both directions–corners (HH) when applied (DWT) on the image called diagonal details, while the vertical edges represent the horizontal high frequency (HL), in the same way the horizontal edges represent the vertical high frequency (LH), finally the LL represent the low frequency in the image, Fig. 31. shows this method:

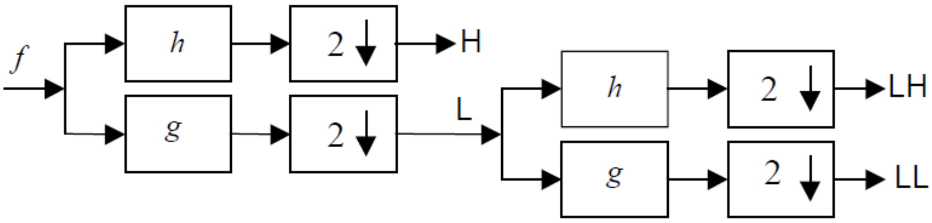


Figure 31 Two Level Decomposition Signal Analysis where H Represents The Detail Components and L Represents The Approximation Components

The upper left corner using the subsequence analysis scale (LL) decomposition again with the same g and b filters, the Fig. 32. show this way clearly:

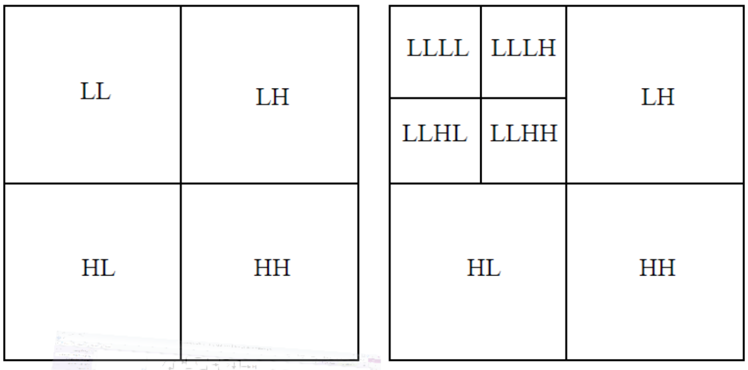


Figure 32 (Left) 1-Scale Wavelet Decomposition, (Right) 2-Scale Wavelet Decomposition

When used the 3 scale level we can obtain the 10 channels frequency as show in the Fig. 33.

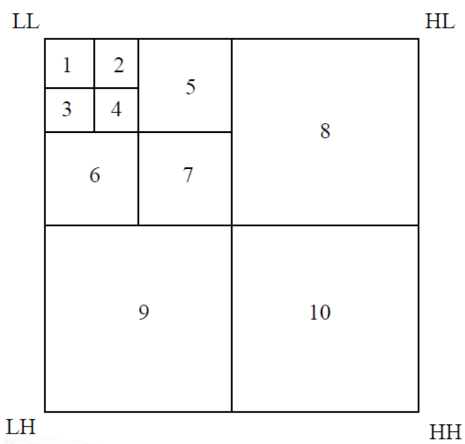


Figure 33 Three Scale Level Wavelet with 10 Channels Decomposition

Can calculate the magnitude of wavelet coefficients to obtain the energy of each channel as show in this equation (3.2) [30]:

$$C_n = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left|w(x,y)\right| \tag{3.2}$$

Where M×N represents the dimension of the channels and usually M=N, w is the wavelet coefficient to this channel, the low and middle frequency contains the almost energy for the image texture.

3.3 Texture Analysis

There are no formla definition exists for the texture, texture content approach the quantify descrpition region, the somoothness, regularity and coarseness, all are the properties measures descriptor [31]. The approaches that principal used in image processing describe for texture can divided into the types [32]:

1- Sturctural
2- Statistical
3- Model–based
4- Transform

The structural defined by [33] [34] in two ways, primitive and hierarchy. The primitive put the particular region of function near of the location, the feature of used the structural gives us the good description analysis of symbolic image. On the other hand the statistical method deal with the distribution properties of relationship gray levels of the image of pair of the pixel [35], can be derived the co–occurrence matrix to obtain the second order feature texture analysis as [36], the texture classification applied by [37] which based on the co–occurrence multidemensional matrices. Fractal and stochastic is represent the model– bsed texture analysis [38] by using the image model to enterprter the image texture, then calculated the parameter for image analysis, the primary problem in the stochastic is the complexilty for computational analysis, so the fractal model is useful for discrimination and texture analysis [39] [40] [41] [42]. Finally the transform model for the analysis of texture represents the image on the space, which depends on the cordinate system that it obtain the characteristics of the texture image such as frequency or size [43] [44], in many specific application the wavelet transform have best suitable texture analysis like segmentation but it is have problem with the invariant translation [45], there are many advantages of wavelet featrues transform:

1- Wide range wavelet analysis function in specific applications.
2- Many change special resolution that is allow represetn texture for more suitable scale applications.

3.4 Texture Analysis Functions

In this thesis i used six types of functions for the texture analysis, entropy, entropyfilt, rangefilt, stdfilt, graycomatrix and graycoprops [46]. we will discusses each one and how it works.

3.4.1 Entropy

This function of grayscal image in Matlab [47] used to represent the pixel values and corresponding it to bin values by convert and support the class logical values or any other class (unit 8, unit 16 or double and must be real, nonsparse and nonempty) to unit 8 and calculated histogram count, entropy used 2 bins default for logical arrays and 256 bins for unit 8, unit 16 or double. The syntax for this function is:

$$E = entropy \quad (I)$$

Where the I return the value for E that is represent the scalar value grayscale image entropy, by using the characterize of the texture image can measure the statistical entropy randomness and this equation in Matlab can represent as:

$$-sum(p.*\log 2(P))$$

From imhist in Matlab histogram counts returned that contains of P, entropy deal with the grayscal image as a multidimensional image not as RGB image, the entropy code represent in Matlab as this syntax:

```
I = imread('circuit.tif');
J = entropy(I)
```

3.4.2 Graycomatrix

(GLCM) mean brief the a Gray Level Co-occuurrence Matrix for image (I) in the syntax [glcm=graycomatrix(I)], from the scale type of image can GLCM calculated the graycomatrix [46] [48], where the image can be binary image that means graycomatrix image contain from 2 gray level (1,0) or image can be intensity image and that is mean the graycomatrix image contain form eight gray level by default or can specific the gray level for the intensity image by used the parameter in syntax (NumLevels) number of levels, the syntax below show how can used the number of gray levle used:

```
glcm = graycomatrix(I)
glcms = graycomatrix(I, param1, val1, param2, val2,...)
[glcm, SI] = graycomatrix(...)
```

where the value of (va11, val2, ...) represnt how many gray level co-occurrence values should be return depending on the number of the values. There are many parameters used in this syntax [48], table 3 explain it brief:

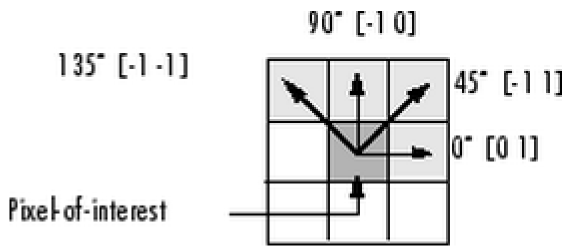
Parameter	Description
‘NumLevels’	The integers gray level co-occurrence intensity image between 1 to 8 if the use ‘NumLevels’ is 8 (numeric), and 2 when use the binary image, ‘NumLevels’ determine the number of gray level co-occurrence image.
‘GrayLimits’	This parameter have two specific range element by class (Minimum & Maximum) and the range divided into N, double [1 0] and int16 [-32768 to 32768], the limits value [min(I(:)) max(I(:))] use graycomatrix grayscale in (I) image.
‘Symmetric’	True of false Boolean value, the graycomatrix count 1,2 and 2,1 when ‘Symmetric’ true calculated the numbers of repeated 1 approach to the numbers of 2, when ‘Symmetric’ false and depending on the 'Offset' the graycomatrix count 1,2 or 2,1 graycomatrix(I, 'offset', [0 1], 'Symmetric', true) graycomatrix(I, 'offset', [0 1], 'Symmetric', false)
‘Offset’	Calculated the distance between the interest pixel and the it's neighbor, the specific 'Offset' represent 2 elements vector in each row in array, [row_offset, col_offset], the 'Offset' represent always as angle with 4 levels (0, 40, 90, 135)  Each angles in the 'Offset' represents with 2 digit in array Offset =[0 1; -1 1; -1 0; -1 -1]

Table 3 Gray Level Co-occuurrence Matrix Parameters

The (SI) in the syntax parameter value [glcm, SI] = graycomatrix(...) represents between 1 and NumLevels, so it is used to to calculate the scaling image

3.4.3 Graycoprops

From the matrix of gray level co-occurrance can calculate the specific properties of image statisticaly [49], the matrix contain form three dimension M×N×P and can obtain the result statisticaly for each glcm, the Matlab syntax below:

```
stats = graycoprops(glcm, properties)
```

There are string list type of properties can be obtained from the graycoprops syntax as show example belwo:

```
I = imread('circuit.tif');
GLCM2 = graycomatrix(I,'Offset',[2 0 ; 0 2]);
stats = graycoprops(GLCM2,{'contrast','Correlation','Energy','homogeneity'})
```

Each properties from this list has structure feild, if properties of energy GLCM2 contaion from 8×8×3 array, then the stats of structure field which contaion a 1×3 array. The table 4 belwo show the description and formula for each property:

Property	Description	Formula
‘Contrast’	For the whole image this property return the and measure the intensity contrast between the pixel image and the neighbor for this image Range = [0 (size(GLCM,1)-1)^2] 0 is representing the constant number for the image, Contrast called also inertia and variance.	$\sum_{i,j} \lvert i-j \rvert^2 p(i,j)$
‘Correlation’	For the constant image the correlation is NaN, that is mean the specific number of correlation is 1 or -1 where return and measure the correlation for neighbor pixel over the all image. Range=[-1 1]	$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$
‘Energy’	Calculated the squared elements and then found the summation as the equation in formula, the Energy called also Uniformity and angular. Range=[0 1]	$\sum_{i,j} p(i,j)^2$
‘Homgeneity’	Calculated the percentage between the GLCM diagonal and GLCM distributed elements. Range=[0 1]	$\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j \rvert}$

Tabel 4 Shows the Property With Description and Formula for Gray Level Co-occurrance Matrix Properties

CHAPTER 4

PROPOSED METHOD AND EXPERIMENTAL RESULT

4.1 Proposed Method

In this thesis we used wavelet transformation based on Daubechies wavelets one for image compression. Here the first level of wavelet transformation is taking and from the result of wavelet we take the gray level co-occurrence matrix GLCM. We used 8 global features for feature extraction. These features are used for every image. For training images we used 1 – 7 images for each person in database then used the image 8 for testing. The result is shown in table 5 the proposed method is arranged below.

4.2 Gray-Level Co-occurrence Matrix

Our observation of fingerprint image is to be allocated to regions with normal tissues. Using co-occurrence matrices so that in normal tissues need to represent; as in the Fig. 34. The degrees 0 °, 45 °, 90 ° and 135 ° from the co-occurrence matrix is used [50].

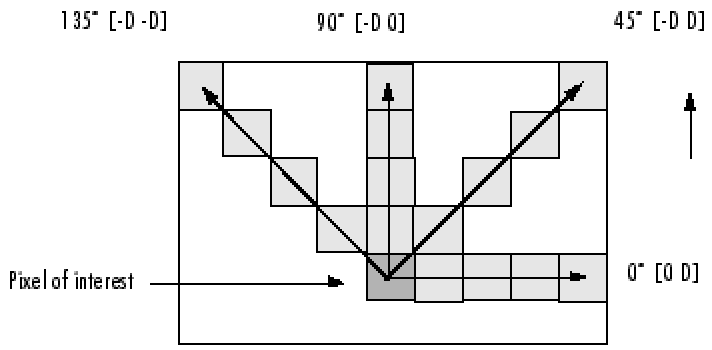
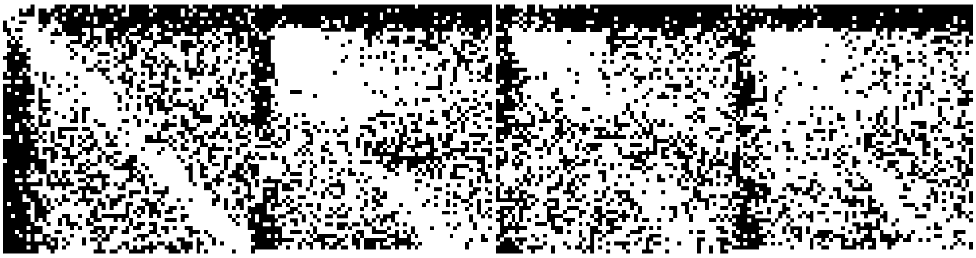


Figure 34 Gray-Level Co-occurrence Matrix

The Gray-Level Co-occurrence matrix angle θ = 0 °, 45 °, 90 ° and 135 ° constant and calculated, the (d) in GLCM represent the distance between the pixel of interest and its neighbor and in this thesis we used the value of d = 3, So there are four co-occurrence matrices directions.



(a) (b) (c) (d)

Figure 35 The Result of Co-occurrence Gray Level Co-matrix for Four (a=0 °, b=45 °, c=90° and d=135 °) Directions

4.3 Feature Extraction

According GLCM in each computer, the successful co-occurrence matrix, which characterizes the behavior of the statistical property, is obtained 8 features: Angular Second Moment, Contrast, Correlations, Dissimilarity, Entropy, Homogeneity, Maximum probability, Average. The equations of these features are below:

1- Angular Second Moment:

$$f_1 = \sum_i \sum_j p(x, y)^2 \tag{4.1}$$

2- Contrast:

$$f_2 = \sum_i \sum_j (i - j)^2 p(x, y) \tag{4.2}$$

3- Correlation:

$$f_3 = \sum_i \sum_j \frac{(i - \mu_x)(j - \mu_y) p(x, y)}{\sigma_x \sigma_y} \tag{4.3}$$

4- Dissimilarity:

$$f_4 = \sum_i \sum_j |i - j| p(x, y) \tag{4.4}$$

5- Entropy:

$$f_5 = \sum_i \sum_j \left(\frac{p(x,y)}{\log\, p(x,y)} \right) \tag{4.5}$$

6- Homogeneity:

$$f_6 = \sum_i \sum_j \left(\frac{p(x,y)}{1+|i-j|} \right) \tag{4.6}$$

7- Maximum probability:

$$f_7 = \max\left(\frac{p(x,y)}{i*j} \right) \tag{4.7}$$

8- Mean:

$$f_8 = \frac{\sum p(x,y)}{i*j} \tag{4.8}$$

Where x and y is coordinate of pixel. $p(x,y)$ is intensity of output gray level co-occurance matrix. *i* and *j* is the length of row and coloumn of image [50].

4.4 Euclidean Norm

In Cartesian coordinates, if i = (i_1, i_2,..., i_n) and j = (j_1, j_2,..., j_n) are two points in Euclidean *n*-space, then the distance (d) from i to j, or from j to i is given by the Pythagorean formula:

$$\begin{aligned} d(i,j) = d(j,i) &= \sqrt{(i_1 - j_1)^2 + (i_2 - j_2)^2 + \ldots + (i_n - j_n)^2} \\ &= \sqrt{\sum_{k=1}^{n} (i_k - j_k)^2} \end{aligned} \tag{4.9}$$

The position of a point in a Euclidean *n*-space is a Euclidean vector. So, i and j are Euclidean vectors, starting from the origin of the space, and their tips indicate two points. The Euclidean norm, or Euclidean length, or magnitude of a vector measures the length of the vector:

$$\|I\| = \sqrt{i_1^2 + i_2^2 + \ldots + i_n^2} = \sqrt{I.I} \tag{4.10}$$

Where the last equation involves the dot product.

In this thesis we used the standard UPEK Fingerprint Database. The example of this database for first person is in Fig. 36.

These images are 256×256 dimensional and RGB colored images and the all images are bit map format. In preprocessing step we must to convert this image to gray scaled image, because the co-occurrence matrix need for gray level images.

Figure 36 The Database UPEK Used in This Thesis (First Person)

		Number of training Image in each person						
		1	2	3	4	5	6	**7**
Number of persons	1	100	100	100	100	100	100	**100**
	2	100	100	100	100	100	50	**100**
	3	66.6667	66.6667	33.3333	33.3333	100	33.3333	**100**
	4	75	50	50	50	100	50	**100**
	5	60	60	40	60	80	40	**100**
	6	50	50	33.3333	50	66.6667	33.3333	**100**
	7	57.1429	42.8571	28.5714	57.1429	71.4286	42.8571	**100**
	8	50	37.5000	25	62.5000	75	37.5000	**100**
	9	55.5556	33.3333	22.2222	55.5556	77.7778	33.3333	**100**
	10	60	40	30	60	80	40	**100**
	11	63.6364	45.4545	36.3636	54.5455	81.8182	45.4545	**90.9091**
	12	58.3333	50	33.3333	50	83.3333	50	**91.6667**
	13	53.8462	53.8462	38.4615	53.8462	76.9231	46.1538	**84.6154**
	14	50	57.1429	42.8571	50	71.4286	50	**85.7143**
	15	46.6667	53.3333	46.6667	46.6667	73.3333	53.3333	**86.6667**
	16	37.5000	43.7500	43.7500	43.7500	68.7500	56.2500	**87.5000**
	17	41.1765	41.1765	47.0588	47.0588	58.8235	47.0588	**88.2353**
	18	38.8889	38.8889	50	44.4444	61.1111	50	**88.8889**
	19	42.1053	31.5789	47.3684	42.1053	52.6316	52.6316	**84.2105**
	20	40	35	45	45	55	55	**85**
	21	42.8571	38.0952	47.6190	47.6190	57.1429	52.3810	**85.7143**
The average		56.63693	50.88683	44.8066	54.9318	75.7699	48.5057	**93.2914**

Table 5 All Number in Table Represents Accuracy (Identical in Percent)

In table 5 as seen in the columns represent the number of training Image and in the rows represent the number of person, in column 7 image selection we have good accuracy results. Here we have 21 persons in database for each one we select the 7 images for training and last image for testing. This state is shown in Fig. 37. minimum accuracy is 84.2105 and obtained in 19 person selection, also the maximum accuracy is 100 and obtained in 1-10 person selection. The average accuracy for the 7 image for 21 person is 93.2914 and that good result. Fig. 37. shows the all steps flowchart algorithm for new fingerprint proposed.

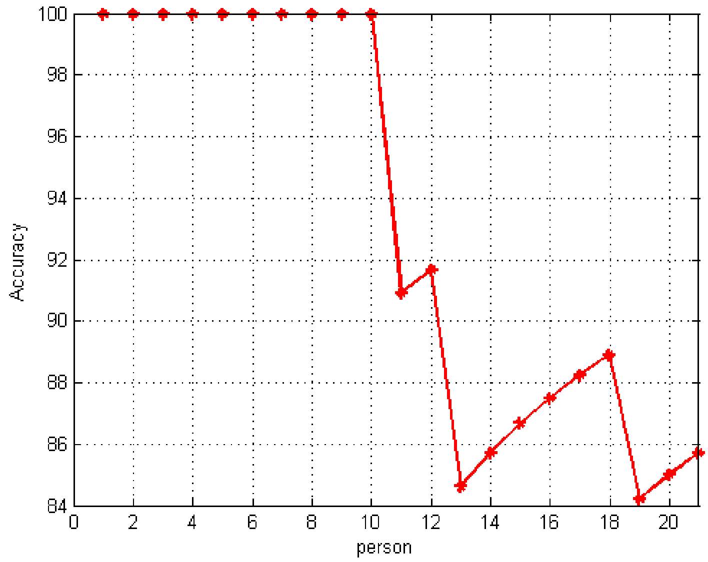


Figure 37 Accuracy When 7 Image Selected for Each Person

Also in column 6 image selection in table 5, we have not better than column 7 selection image. This state is shown in Fig. 38. minimum accuracy is 33.3333 and obtained in 3, 6 and 9 person.

Also the maximum accuracy is 100 and obtained in 1 person selection.

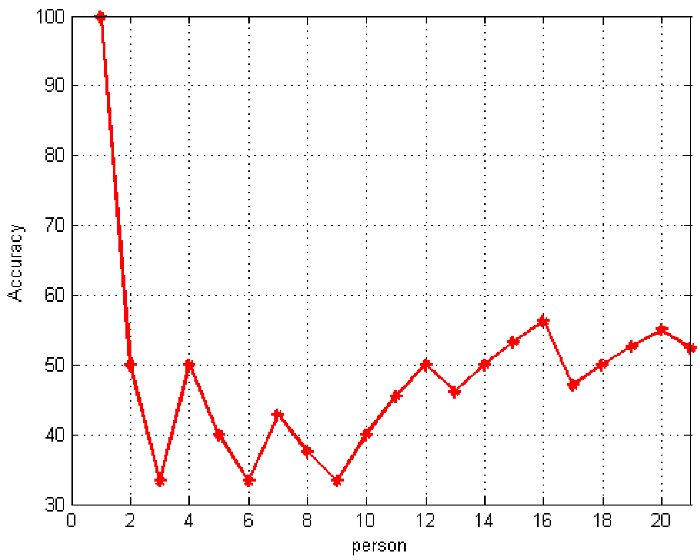


Figure 38 Accuracy When 6 Image Selected for Each Person

The Fig. 39. shows the accuracy of fingerprint identification vs Image, as seen in 7 images we have highest accuracy and this value is shown on table 5 last row (average row) and equal to 93.2915 and this figure give us a fact that if we use more image training for the person we will get high accuracy.

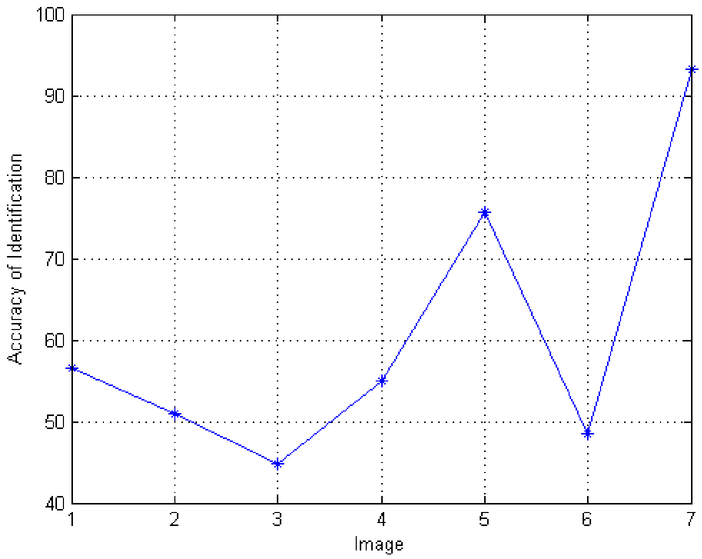


Figure 39 Accuracy of Fingerprint Identification vs Image

The Fig. 40. as below give us declare imagination for the algorithm that it is used in this thesis and how we write the code in Matlab depending for this algorithm.

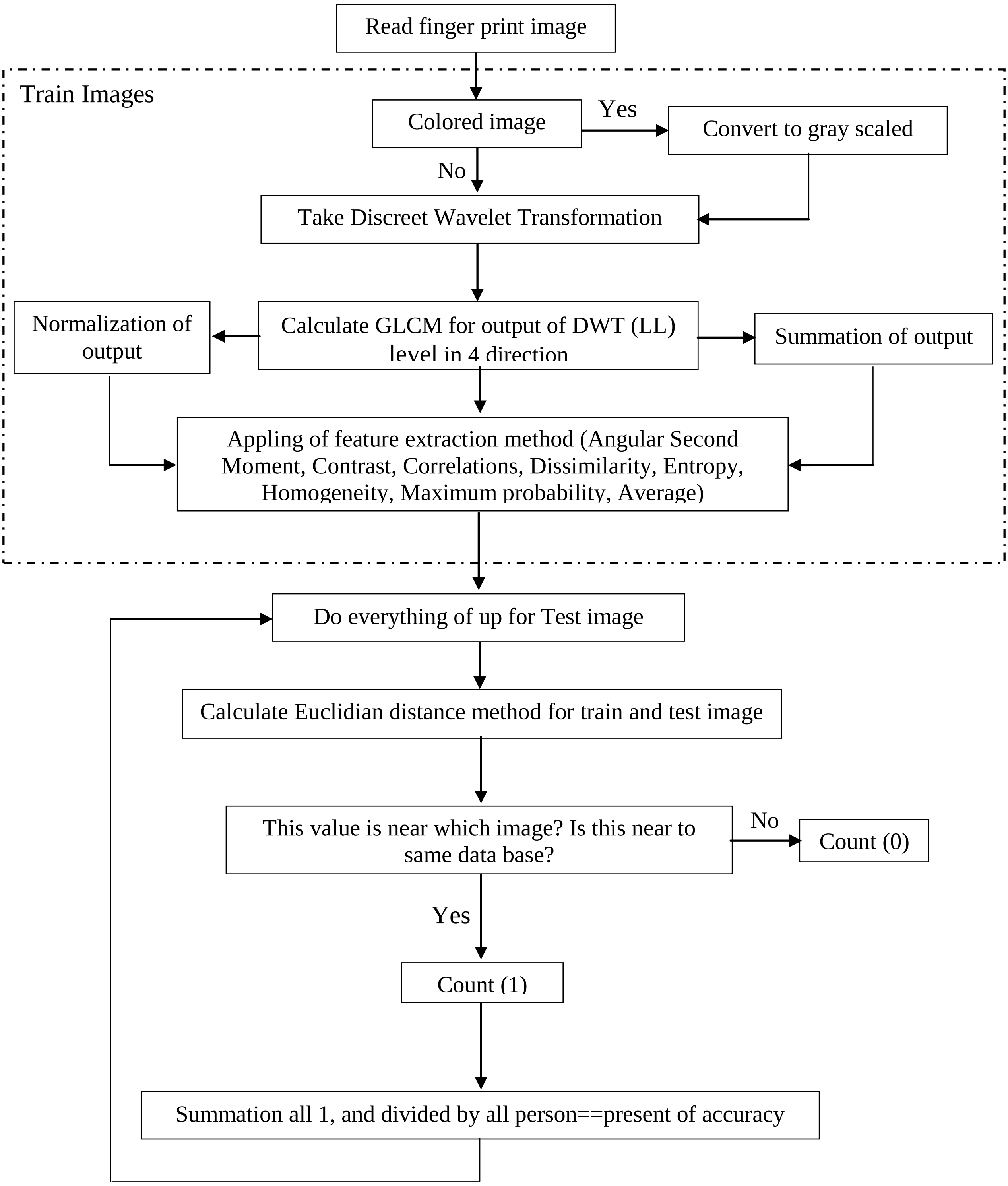


Figure 40 Flowchart of The Algorithm for Thesis

Figure 41 Wavelet Transformation Result (First Level)

In this thesis we used second level of wavelet transformation but we didn't get good result, Because in second level wavelet transformation we loss a lot of information. The second level is shown if Fig. 42.

Figure 42 Wavelet Transformation Result (Second Level)

The Fig. 43. shows how the software program in Matlab found and it appears the identified image when used test image (Test Image = Identified Image) and get the same image number in database (database: 011) and this put True number (1) in the person (1,3,4 to 12) as in Fig. 45.

Figure 43 Test Image From 011 Database and Indentified Image From Same Database

In Fig. 44. The software matlab program doesn't discriminate the test image with the database image and put False number (0) in the person (2,13) and that shows in Fig. 45.

Figure 44 Test Image From 013 Database and Indentified Image From 012 Database

The Fig. 45. Shows how calculate the accuracy of identificaion in person 19 with 7 image training (84.2105) in table 5, the True (1) represent the identification and False (0) for don't discriminate, where the accuracy of identification fingerprint calculate by used this simple equation in matlab (accuracy of Identification = 100 × (sum (Percent) / Person).

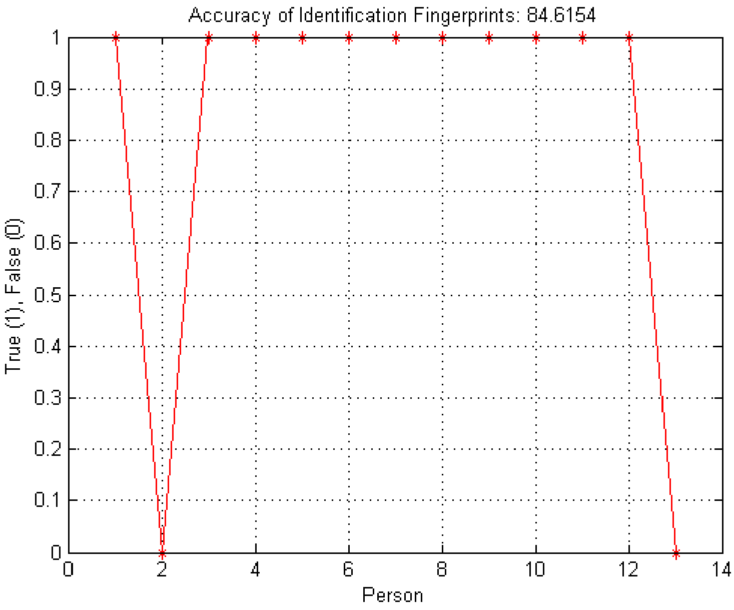


Figure 45 Accuracy of Identification Fingerprint

CHAPTER 5

CONCLUSION AND FEATURE WORKS

5.1 Conclusion

In this study we have proposed a method for finger print identification. The ability of the proposed method to determine a person's identity is of significant importance. In proposed method fingerprint identification has been processed and implemented using MATLAB software and the results have proved the ability of the proposed method. Feature extraction is performed using Co-occurrence matrix. Extracted features of the fingerprints are grouped in a vector and compared with many variants of sample data from the standard databases.

For 7 images in training we obtained the best identification accuracy by 100% from 1 person to 10 persons of database. However, the processing time to reach this accuracy level is relatively high. Table 5 in this study shows performance of the proposed algorithm compared with the similar reported methods. Different scenarios can be used to improve the accuracy of identification in order to increase the algorithm's performance. Also the detection of fingerprint images not present in the database has been increased.

5.2 Future Works

1. In the future we can to employee this algorithm on hardware, the advantage of our method is fast and also the complexity of our method is very low, for this reason we can use in hardware systems.
2. We used discrete wavelet transformation, in the future we can test and use the Fourier transformation for compression and also use discrete cosine transformation.
3. We used 8 type of feature extraction. In future we can use less number of features preserving the high level of accuracy. Smaller number of features will increase the speed of processing and decrease the time needed.

REFERENCES

1. **Lenchik L., Rogers L. F., Delmas P. D., Genant, H. K., (2004),** "*Diagnosis of Osteoporotic Vertebral Fractures: Importance of Recognition and Description by Radiologists*", American Journal of Roentgenology, vol. 183, no. 4, pp. 949-958.

2. **Zdobnov E. M., Apweiler R., (2001),** "*InterProScan–an Integration Platform for the Signature-Recognition Methods in InterPro*". Bioinformatics, vol. 17, no. 9, 847-848.

3. **Snelick R., Indovina M., Yen J., Mink A., (2003),** "*Multimodal Biometrics: Issues in Design and Testing*", In Proceedings of the 5th international conference on Multimodal interfaces, pp. 68-72

4. **Jain A. K., Dass S. C., Nandakumar K., (2004),** "*Soft Biometric Traits for Personal Recognition Systems*". In Biometric Authentication, Springer Berlin Heidelberg, pp. 731-738.

5. **Jain A. K., Ross A., Pankanti S., (2006),** "*Biometrics: A Tool for Information Security*", Information Forensics and Security, vol. 1, no. 2, pp. 125-143.

6. **HuopioS.,(1988).,**"*Biometricidentification Eye*", 3,1.http://www.tml.tkk.fi/Opinnot/Tik-110.501/1998/papers/12biometric/biometric.htm (Download Date: 3-11-2014)

7. **Kolb H., Fernandez E., Nelson R., (2005),** "*Gross Anatomy of the Eye*", http://www.ncbi.nlm.nih.gov/books/NBK11534/ (Download Date: 4-9-2014)

8. **Kroeker K. L., (2009),** "*Face Recognition Breakthrough. Communications of the ACM*", 52(8), 18-19. http://dl.acm.org/citation.cfm?id=1536623 (Download Date: 4-12-2014)

9. **Fitch W. T., Hauser M. D., (2003),** "*Unpacking "Honesty": Vertebrate Vocal Production and the Evolution of Acoustic Signals*". In Acoustic communication, pp. 65-137.

10. **Jiang X., Yau W. Y., (2000),** "*Fingerprint Minutiae Matching Based on the Local and Global Structures*". In on Proceedings of 15th International Conference Pattern Recognition, vol. 2, pp. 1038-1041.

11. **Merkle R. C., (1990),** "*A Certified Digital Signature*". In Proceedings of Advances in Cryptology—CRYPTO'89, pp. 218-238.

12. **Rohs R., West S. M., Sosinsky A., Liu P., Mann R. S., Honig B., (2009),**"*The Role of DNA Shape in Protein–DNA Recognition*", Nature, vol. 461, no. 7268, pp. 1248-1253.

13. **Yun Y. W., (2002),** "*The '123'of Biometric Technology*", Synthesis Journal.

14. **Julesz B., Gilbert E.N., Victor J.D., (1978),**"*Visual Discrimination of Textures with Identical Third Order Statistics*", Biol. Cybern. vol 31, pp. 137–140.

15. **Saito N., Coifman R., Geshwind F.B., Warner F., (2002),**"*Discriminant Feature Extraction Using Empirical Probability Density Estimation and A Local Basis Library*", Pattern Recognition, vol 5, pp. 2841–2852.

16. **Muneeswarana K., Ganesan L., Arumugam S., RubaSoundar K., (2005)**"*Texture Classification with Combined Rotation and Scale Invariant Wavelet Features*", in pattern recognition society, published by Elsevier Ltd. vol 38, pp. 1495–1506.

17. **Zhou W., Han J., Zeng X., Yan W., (2009),**"*Fingerprint Verification Based on Wavelet and Edge Detection*", IEEE Trans,The Ninth International Conference on Electronic Measurement & Instruments, pp. 1001–1004.

18. **Jing-Wein W., Ngoc T.L., Chou-Chen W., Jiann-Shu L., (2015),**"*Enhanced Ridge Structure for Improving Fingerprint Image Quality Based on a Wavelet Domain*", IEEE Trans. Image Process., vol. 22, no. 4.

19. **Gonzalez R. C., Wood R. E., (2007),**"*Digital Image Processing*", 3rd ed.Upper Saddle River, NJ, USA: Prentice-Hall.

20. **Priyadarshan S. O., Priti S. S., (2010),**"*Fingerprint Verification Using Haar Wavelet*", Biol. Cybern., vol. 3, pp. 361-365.

21. **Amornraksa T., Tachaphetpiboon S., (2006),**"*Fingerprint recognition using DCT features*", in:Electronic letters, vol. 42, no. 9, pp. 103.

22. **Dale M. P., Joshi M. A., Sahu M. K., (2007),**"*DCT Feature Based Fingerprint Recognition*", in international conference on intelligent and advanced system, pp. 611–615.

23. **Xiao-Yuan J., David Z., (2004),**"*A Face and Palm Print Recognition Approach Based on Discriminant DCT Feature Extraction*", in: IEEE Transaction on system, Man and Cybernetics-part B: Cybernetics, vol. 34, No. 6, pp. 107.

24. **Tachaphetpiboon S., Amornraksa T., (2005),**"A Fingerprint Matching Method Using DCT Feature", in: proceedings of ISCIT, pp. 446–449.

25. **Lavanya B.N., Raja K.B., Venugopal K.R., Patnaik L.M., (2009),** "*Minutiae Extraction in Fingerprint Using Gabor Filter Enhancement*",Advances in Computing, Control, and Telecommunication Technologies, pp. 54–56.

26. **Yin L-Q., Gao L., (2012),** "*Feature Extraction of Fingerprint ImageBased on Minutiae Feature Points*", Computer Science and Service System, IEEE CONFERENCE PUBLICATIONS, pp. 1737–1740.

27. **Zin M. W., Myint S., (2011),** "*Fingerprint Recognition System for Low Quality Images*", SICE Annual Conference, pp. 1133–1137.

28. **Vijayaprasad P., NasirSulaiman M. d.., Norwati M., Rahmita R., (2011),** "*Feature-Based Technique for Partial Fingerprint Matching*",*7th International Conference on IT in Asia (CITA*), pp. 1–4.

29. **Mallat S., (1989),** "*Multifrequency Channel Decomposition of Images and Wavelet Models*", IEEE Trans. Acoustic, Speech and Signal Processing, vol. 37, no. 12, pp. 2091-2110.

30. **Porter R., Canagarajah N., (1996),** "*A Robust Automatic Clustering Scheme for Image Segmentation Using Wavelets*", IEEE Trans. Image Processing, vol. 5, no. 4, pp. 662-665.

31. **Gonzalez R. C., Wood R. E., (2003),** "*Digital Image Processing*", Third edition, pp. 894.

32. **Materka A., Strzelecki M., (1998),** "*Texture Analysis Methods – A Review*", Technical University of Lodz, Institute of Electronics, COST B11 report, Brussels.

33. **Haralick R., (1979),** "*Statistical and Structural Approaches to Texture*", Proc. IEEE, vol. 67, no. 5, pp. 786-804.

34. **Levine M., (1985),** "*Vision in Man and Machine*", McGraw-Hill.

35. **Weszka J., Deya C., Rosenfeld A., (1976),** "*A Comparative Study of Texture Measures for Terrain Classification*", *IEEE Trans. System, Man and Cybernetics*, vol. 6, pp. 269-285.

36. **Haralick R., (1979),** "Statistical and Structural Approaches to Texture", Proc. IEEE, vol. 67, no. 5, pp. 786- 804.

37. **Valkealathi K., Oja E., (1998),** "*Reduced Multidimensional Co-Occurrence Histograms in Texture Classification*", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 20, no. 1, pp. 90-94.

38. **Strzelecki M., Materka A., (1997),** "*Markov Random Fields as Models of Textured Biomedical Images*", Proc. 20th National Conf. Circuit Theory and Electronic Networks KTOiUE '97, Kołobrzeg, Poland, pp. 493-498.

39. **Pentland A., (1984),** "*Fractal-Based Description of Natural Scenes*", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 6, no. 6, pp. 661-674.

40. **Chaudhuri B., Sarkar N., (1995),** "*Texture Segmentation Using Fractal Dimension*", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 17, no. 1, pp. 72-77.

41. **Kaplan L., Kuo C-C., (1995),** "*Texture Roughness Analysis and Synthesis via Extended Self- Similar (ESS) Model*", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 17, no. 11, pp. 1043-1056.

42. **Cichy P., Materka A., Tuliszkiewicz J., (1997),** "*Computerised Analysis of X-ray Images For Early Detection of Osteoporotic Changes in the Bone*", Proc. Conf. Information Technology in Medicine TIM '97, Jaszowiec, Poland, pp. 53-61.

43. **Bovik A., Clark M., Giesler W., (1990),** "*Multichannel Texture Analysis Using Localised Spatial Filters*", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12, pp. 55-73.

44. **Lu C., Chung P., Chen C., (1997),** "Unsupervised Texture Segmentation via *Wavelet Transform*, Pattern Recognition", vol. 30, no. 5, pp. 729-742.

45. **Lam W-K., Li C-K., (1997),** "*Rotated Texture Classification by Improved Iterative Morphological Decomposition*", IEE Proc. – Visual Image Signal Processing, vol. 144, no. 3, pp. 171-179.

46. http://www.mathworks.com/help/search.html?qdoc=texture+analysis+functions (Download Date: 20-2-2015)

47. **Gonzalez R.C., Woods R.E., Eddins S.L., (2003),** "*Digital Image Processing Using MATLAB*", New Jersey, Prentice Hall, Chapter 11.

48. **Haralick R.M., Shapiro L.G., (1992),** "*Computer and Robot Vision*", vol. 1, Addison-Wesley, pp. 459.

49. **Haralick R.M., Shanmugan K., Dinstein I., (1973),** "*Textural Features for Image Classification*", IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-3, pp. 610-621.

50. **Albregtsen F., (2008),** "*Statistical Texture Measures Computed from Gray Level Coocurrence Matrices*", Image Processing Laboratory Department of Informatics University of Oslo, pp. 1-14.

CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Sultan, Thaer

Date and Place of Birth: 08 January 1973, Mousl

Marital Status: Married

Phone: +90 5382500166

Email: tha.aljuburi@gmail.com

EDUCATION

Degree	Institution	Year of Graduation
M.Sc.	Çankaya Univ., Computer Engineering	2015
B.Sc.	Technical Education., Computer Engineering	2006
B.Sc.	Mosul Univ., Science of Chemistry	2005
High School	Al-Mothana High School – Mosul	1990

LANGUAGES

1. Mother Language (Arabic)
2. Advanced English

HONOURS

3. Letter of Appreciation from the Rector of the Tikrit University for Ending the Course of CISCO International Academy in 16/11/2008.
4. Letter of Appreciation from the Dean of Faculty of Computer Science of the Tikrit University for Outstanding work in 12/03/2009.
5. A Certificate of Appreciation from the Rector of the Tikrit University for Ending Electric Government project in Tikrit University in 15/03/2000.
6. Letter of Appreciation from the Dean of Faculty of Computer Science of the Tikrit University for Outstanding work in 25/05/2009.
7. Letter of Appreciation from the Dean of Faculty of Computer Science of the Tikrit University for Outstanding work in 09/09/2009.

8. Letter of Appreciation from the Rector of the Mosul University for the Complete the Project of Mosul Website in 21/11/2010.
9. Letter of Appreciation from the Dean of Faculty of Computer Science of the Tikrit University for Outstanding work in 16/03/2011.
10. Letter of Appreciation from the Dean of Faculty Science of the Tikrit University for Outstanding work in 24/10/2011.
11. Letter of Appreciation from the Assistant Rector of the Tikrit University for Outstanding work in 15/11/2011.

HOBBIES

Running, Football, Books, Travel, Fitness