



FINAL YEAR PROJECT

FINAL REPORT

Fingerprint Recognition using GLCM and DWT.

By

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(ELECTRICAL & ELECTRONICS ENGINEERING)

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ABSTRACT

Author is thoroughly investigated regarding the fingerprint recognition techniques. This is because the world of security had become more essential. Thus, fingerprint recognition is one of the security enforcement and needed to be developed essentially. This project is focused on the effectiveness of the Gray-Level Co-occurrence Matrices (GLCM) and Discrete Wavelet Transform (DWT) techniques for fingerprint recognition. As in the chapter one, author discusses regarding the background of the GLCM and the DWT as well as the reason of this project was initiated. Other than that, author also discuss regarding the problem that had been faced previously in order to recognise fingerprint optimally. Author also discusses the objectives and the limitation of this project in this chapter. On the next chapter, history regarding the GLCM as well as DWT had been widely discuss that made the fingerprint recognition system becomes more popular nowadays. The definition of term, equation and equation related to the GLCM and DWT also had been explained. Moreover, some previous related study will also be discussed. On the third chapter, author reviews the method that will be approached for the project for the entire eight months' timeframe. As for the last chapter, several initial conclusions had been made regarding the fingerprint recognition techniques. From the result obtained at the chapter four, it shown that the higher the noise value applied, the higher the dissimilarity. In correspond to that, the value of dissimilarity of DWT is higher and more sensitive compare to GLCM.

Keywords: GLCM, DWT, fingerprint recognition, MATLAB, noise

CHAPTER 1: INTRODUCTION

1.1 Background of Study

Fingerprint is one of the most commonly used biometric identification. Because of their uniqueness and consistency over time, fingerprints have been used for identification for over a century. Fingerprint identification is popular because of the inherent ease in acquisition, and their established use and collections by law enforcement and immigration. Apart from that, authentication of personnel identification also important for the existing life as it is a commercial way of large number of security system throughout the world. In correspond to that, unreliable recognition system may lead to the devious of the system and exposed to the irresponsible people. This application will be extremely essential for the security and protection for any of peculiar data [1].

The first approach for the fingerprint recognition will be done via the Gray-Level Co-occurrence Matrices (GLCM). This is because this method is proven to be one of the most suitable implementation for the texture imaging segmentation [2]. For the past years, the GLCM is limited by the pixel-by-pixel image processing. This method had cause burden for the user. Thus, new GLCM method provides a simpler technique by implementing combined image in a matrix form. Generally, this technique can process grain included in image by showing a repeating array of local variation of intensity [3].

The second approach for the fingerprint recognition is based on the Discrete Wavelet Transform (DWT). This is a specialised linear algebra for area of image compression as well as recognition. This technique is done by factoring a single matrix into three new matrices [4]. This technique will be done by using several of terms and will be implemented in MATLAB for high performance computation integration, visualisation as well as programming. By using this technique also allow author to simplify several sets of values, thus preserve a very powerful features of the original sets of database. In correspond to that, large amount of space of memory can be saved by using the compression method, but still preserve the quality of the image of the database data.

1.2 History

Throughout the centuries, fingerprint or thumbprint matching had been used by the law administration for security purpose. The technology nowadays has develop a new approaches in correspond to the identity management as well as access control regarding the fingerprint or thumbprint identification or rather, recognition. Moreover, our palms have a curve-like pattern which make every single person on the world has specific and unique signature. In correspond to that, our fingerprints also have this unique trait. This surface texture which somehow called as “Friction Ridge Patterns” that make everyone has different fingerprint signature [5].

During the early 20th century, several conventional scientists such as Henry Faulds, Francis Galton as well as Edward Henry started to develop the fingerprint recognition approach for the knowledge development intention. Among the early development are homicides, crimes and offenders identification foundation by using the fingerprint recognition [5].

Nevertheless, at the late 20th century, the largest fingerprint recognition system had emerged and had been developed by Integrated Automated Fingerprint Identification System (IAFIS). This firm had gathered and store nearly around half of hundred millions fingerprints from around the world. The gathered information is included with the demographic statistics as well as complete with 10 fingerprints index [5].

Grey-level co-occurrence matrices (GLCM) have been on the scene for almost forty years and continue to be widely used today. In author we present a method to improve accuracy and robustness against rotation of GLCM features for image classification. Some approaches of co-occurrences are computed through digital circles as an alternative to the standard four directions [10].

1.3 Problem Statement

Feature extraction of fingerprint is a critical stage of a fingerprint recognition system. In this work, author will investigate a fingerprint recognition system that fused two feature extraction techniques, namely Gray-Level Co-occurrence Matrices (GLCM) as well as Discrete Wavelet Transform (DWT). The extracted features of trained images are to be fed into support vector machine for recognition process. The final stage is to evaluate the performance of the system measured in terms of correct detection. Then the system will be optimized with the rejection rate.

1.4 Objectives

The main objective for this particular project is to develop a fingerprint recognition system based on:

- I. Fingerprint recognition using minutiae details.
- II. Fingerprint recognition using image correlation.
- III. Fingerprint recognition using texture Analysis.

1.5 Scope of Study

The Scope of study for the project entitled “Fingerprint Recognition using Gray Level Co-Occurrence Matrices and Discrete Wavelet Transform” are as followed:

- I. Understanding the concept of Gray-Level Co-occurrence Matrices (GLCM) technique.
- II. Understanding the concept of Discrete Wavelet Transform (DWT) technique.
- III. Understanding the application of the MATLAB.
- IV. Applying GLCM and DWT techniques with MATLAB.

- V. Analysing fingerprint database by using MATLAB with GLCM and DWT techniques.
- VI. Apply and optimising the fingerprint recognition with correct detection technique and rejection rate technique.

1.6 Relevancy of Study

- I. As an alternative method for fingerprint recognition
- II. Select the best and fastest method for fingerprint recognition

1.7 Feasibility of Study

- I. The research of fingerprints recognition has been done previously in UTP by the students and lecturers.
- II. The software for testing the method is available to carry out the project.
- III. Improvement of one of the previous final year project regarding GLCM and DWT methods.

CHAPTER 2: LITERATURE REVIEW

2.1 Definition

The GLCM was formerly known as Gray Level Co-Occurrence Matrices also known as Grey Tone Spatial Dependency Matrix. The GLCM is a technique where various combinations of pixel Contrast values appear in the captured image are formulated.

Order is defined as the degree of the equation. First order texture covers statistic calculated from original image values such as variance and standard deviation value. Second order covers the relationship between pixels and the original images while the third order texture covers higher value of pixels. Nevertheless, the third order texture are impossible to be implemented because the complications in time constrain and understanding of calculation.

2.2 GLCM

Most likely, GLCM is highly recommended for the second order texture measurement. Some of the steps, methods and applications of GLCM are discussed as below. The various figures of texture files can be refer at the appendices section.

The GLCM technique can also classify the tea healthiness. The paper that did research regarding this experiment found that the GLCM could be used for outlining the effectiveness tea patches at different resolutions. Assessment of tea health, as well as early detection of crop infestations, is critical in ensuring good tea productivity. Stress related can be sensed early enough to provide a chance for mitigating. This experiment had been done at various places such as Indonesia, China, Bangladesh, Sri Lanka as well as Kenya. Some function of GLCM is to define illness and pests infested areas in tea gardens. To do so, the paper uses texture and tonal variations from satellite imagery of tea growing areas and investigate whether texture based classification could be utilised for disease and pests detection in tea plantation. Moreover, the diseased patches were delineated using both texture and the

classified based images. Supervised and unsupervised classifications were carried out using the maximum likelihood classifier on all the images. Then, the classified images can be calculated averagely.. Classifying the remotely sensed images had been done by using texture analysis [9].

“In addition to that, GLCM also been used as discrete Fourier transform normalization to convert rotation dependent features into rotation invariant ones and tested on four different datasets of natural and synthetic images. The objective can be achieved by considering all pixels that are located approximately at a given distance from it, extract rotation dependent features for each direction defined by the neighbourhood and convert the rotation dependent features into rotation-independent ones” (Francesco Bianconi, 2014) [10].

GLCMs texture can be also categorize into fourteen features. Many quantitative measures of texture are found and used 3D co-occurrence matrices in CBIR applications. Kovalev and Petrov [12] used special multidimensional co-occurrence matrices for object recognition and matching. The objective of the related paper works is to generalize the concept of co-occurrence matrices to dimensional Euclidean spaces and to extract more features from the matrix. The new features are found to be useful in CBIR applications [11].

2.3 DWT

In numerical analysis and functional analysis, a Discrete Wavelet Transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time).

Discrete Wavelet Transform has the properties that other tools of analysis do not have. The properties are decomposition properties, its time-scale localization. These properties make the wavelet as a strong and reliable analysis tool. These characteristics owned by the wavelet thus gives relevancy to the analysis of non-stationary systems. Problems of non-station are solved by applying wavelet analysis through the process of performing a local time – scale decomposition of the signal [8]. Variety of scales related to the periodic components of the signal switch over time and this can be identified using this approach of wavelet analysis. There is no possible way to completely eliminate the edge effects, and the region affected by edge effects also known as “cone of influence”. It is stressed that the spectral information within this cone is likely to be less accurate [8]. Thus, when choosing the wavelet analysis as an approach for a research, the major consideration is the trade – off between strong localization that is good in the analysis of sharp transients and weak localization which includes more precise isolation of dominant frequencies.

Gray scale invariance is significant for texture similarity assessment. It was done by using the order of the gray values to increase the salvage of accuracy. Many image processing tasks were used for ordinal measurement by a novel method. To build the features, fundamental element pixel pairs are used [13].

Texture is an apparently paradoxical notion. Nevertheless, for practical classification is commonly used in the early processing of visual information. Texture descriptors computation should be included in the multi-level structures estimation [14].

The Haar wavelet is useful for explanations because it represents a simple interpolation scheme. If the signal is reconstructed by an inverse low-pass filter of the form then the result is a duplication of each entry from the low-pass filter output. This is a wavelet reconstruction with $2\times$ data compression. Since the perfect reconstruction is a sum of the inverse low-pass and inverse high-pass filters, the output of the inverse high-pass filter can be calculated.

The first stage involved understanding the computation involved in a multi-dilation wavelet transform, and to determine the best structure for the SPROC chip, a digital signal processing chip utilizing parallel processing and pipelining for efficiency. The SPROC chip is basically a RISC processor with an instruction set geared toward DSP applications [15]. MATLAB were chosen as simulation environments. Although it seemed fairly certain that the final version of the wavelet transformer would be a lattice filter, matrix methods were studied in order to gain a basic understanding of wavelets, the results of which are presented in the discussion of Chapter 4. A number of MATLAB programs were available which perform lattice filter functions, some of this code being directly related to the VLSI wavelet processor which has been implemented

CHAPTER 3: METHODOLOGY

3.1 Project Activities

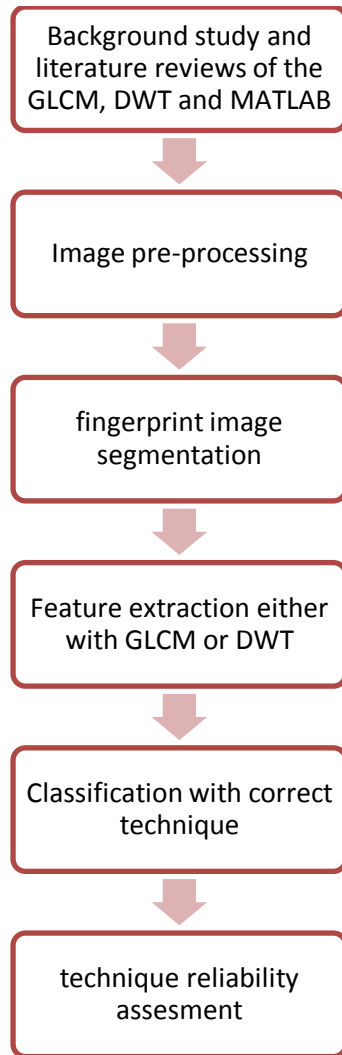


Figure 1 Flow chart of project activities

First of all, the GLCM is divided into two main frameworks. The first one is the '*spatial relationship between two pixels*'. GLCM texture must consider the relation between two pixels (at least for the second order). They are known as reference and neighbour pixel. They are also known as (1, 0) relation where a pixel is moving toward x – axis and none pixel is

moving towards y – axis. Initially, at the upper left corner every single pixel in the frame will be noted as reference pixel, then moving towards the lower right. The second one is the ‘separation between two pixels’. It is more recommend to use a larger offset compare to (1, 0) because there is not much difference in calculating. If the number of spatial combination is big, then a larger and more accurate GLCM can be conducted.

Table 1 Diagonal table of combinations of Grey Levels

neighbour pixel value ->	0	1	2	3
ref pixel value:				
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

For texture measuring, there are several groups specified for the ease of the calculation. There are **Contrast group**, **Orderliness group** and **Stats Group**. Seldom, the texture is measured by weighted averages of the normalized GLCM contents. Total and division of the GLCM number values are done after the each value of the normalize GLCM in the cell contents are multiply by a factor [6].

Equation 1 Normalization equation

$$P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}} \quad (1)$$

Equation will be particularly used for the calculating the weightage of the pixel in the imaged captured.

This Contrast group is specified for measuring the related weight or factor contrast with relate to the distance from the GLCM diagonal. This group also emphasize numerous amount of

contrast by creating factor, thus a greater contrast can be obtained as a result of the larger value. There is no contrast created in the GLCM diagonal table, but the contrast will increase as the value getting further from the diagonal, which also affect by the increasing of the factor.

The contrast equation (2) (CON) can also be known as '*sum of square variance*'. The contrast will become zero value if the integer channel is put with either 8-bit channel or 16-bit channel, thus it must be introduced with only real numbers. It will also measure the factor increasing exponentially.

Equation 2 Contrast equation

$$\sum_{i,j=0}^{N-1} P_{i,j} (i-j)^2 \quad (2)$$

The cell diagonal will be denoted as 'i' as well 'j' respectively.

The Dissimilarity equation (3) (DIS) will measure the factors increasing linearly. As a matter of fact, this equation is considered as first degree of measurement.

Equation 3 Dissimilarity equation

$$\sum_{i,j=0}^{N-1} P_{i,j} |i-j| \quad (3)$$

The Homogeneity equation (4) (HOM) was also known as "*Inverse Difference Moment*". This equation works inversely from the equation (2).

Equation 4 Homogeneity equation

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \quad (4)$$

The Dissimilarity chi-squared equation (5) then will be used for tracking the dissimilarity between original database fingerprint as well as the captured image of the fingerprint.

Equation 5 Dissimilarity Chi-squared equation

$$\sqrt{\sum_{i=1}^k \left(\frac{X_i - \mu_i}{\sigma_i} \right)^2} \quad (5)$$

As for the DWT, there will be two filters that will be used. They are high and low pass filter respectively. This will expand a digital signal and each pixel of the image will be dilated by a decimator [15].

The pyramid algorithm operates on a finite set of N input data, where N is a power of two; this value will be referred to as the input block size. These data are passed through two convolution functions, each of which creates an output stream that is half the length of the original input. These convolution functions are filters; one half of the output is produced by the “low-pass” filter function, related to equation (6):

Equation 6 Low Pass Filter Equation

$$y_{\text{low}}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n - k] \quad (6)$$

and the other half is produced by the “high-pass” filter function, related to equation (7):

Equation 7 High Pass Filter Equation

$$y_{\text{high}}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n - k] \quad (7)$$

where N is the input block size, c are the coefficients, f is the input function, and a and b are the output functions. While, in the case of the lattice filter, the low- and high-pass outputs are usually referred to as the odd and even outputs, respectively [16]. The even or high-pass output contains the difference between the true input and the value of the reconstructed input if it were to be reconstructed from only the information given in the odd output.

Then, the high pass filter and low pass filter equation are fitted within the Discrete Wavelet Transform Equation (8). This is where the image is calculated by passing it through a series of filters

Equation 8 Discrete Wavelet Transform Equation

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n - k]$$

This decomposition has halved the time resolution since only half of each filter output characterises the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled. Then, the same equation (5) will be used to determine the dissimilarities of the image.

GLCM Feature Extraction

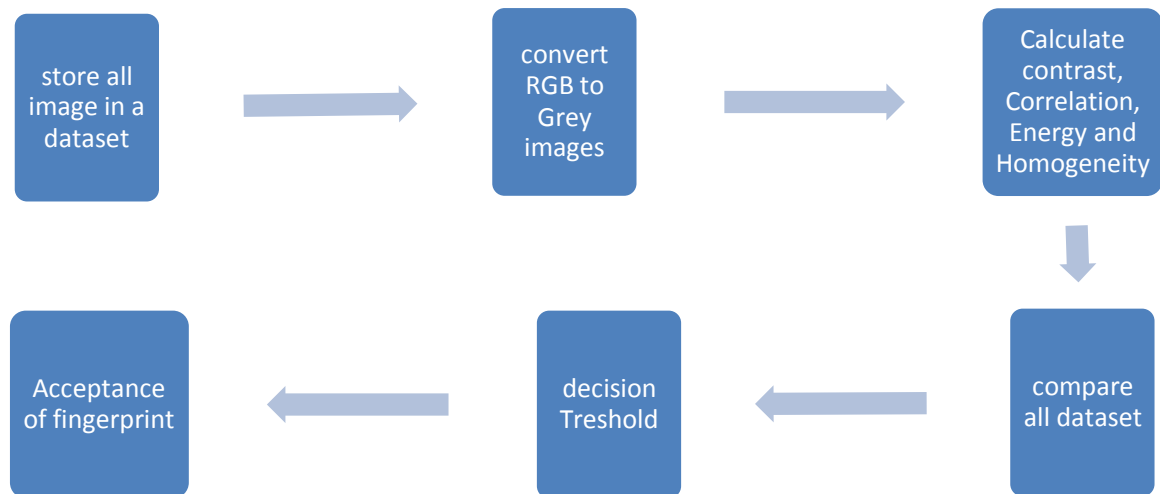


Figure 2 Block Diagram of GLCM Feature Extraction Process

The Figure 2 shows the process for the feature extraction of GLCM technique for fingerprint. For the first block, it indicates that the entire fingerprint will be store in a database in a dataset manner. This process will ensure that the fingerprints are easy to be called for the next process. Next block, it indicates that the entire fingerprint will be converted to grey in colour so that the size of the fingerprint database will be much smaller. This process also ensures that the line of the finger or finger ridge pattern can be tracked and scanned easier. Furthermore, this technique do not require for the comparison of the coloured fingerprint. Third, contrast, Correlation, Energy as well as Homogeneity of the fingerprint will be calculated and compared with each other. This will ensure that the dataset is a valid. And lastly, all the dataset will be compared with each other in order to check the dissimilarity of the fingerprint. Then, the fingerprint obtained will be compared with the set threshold and later will be decided if can be accepted or not.

DWT Feature Extraction

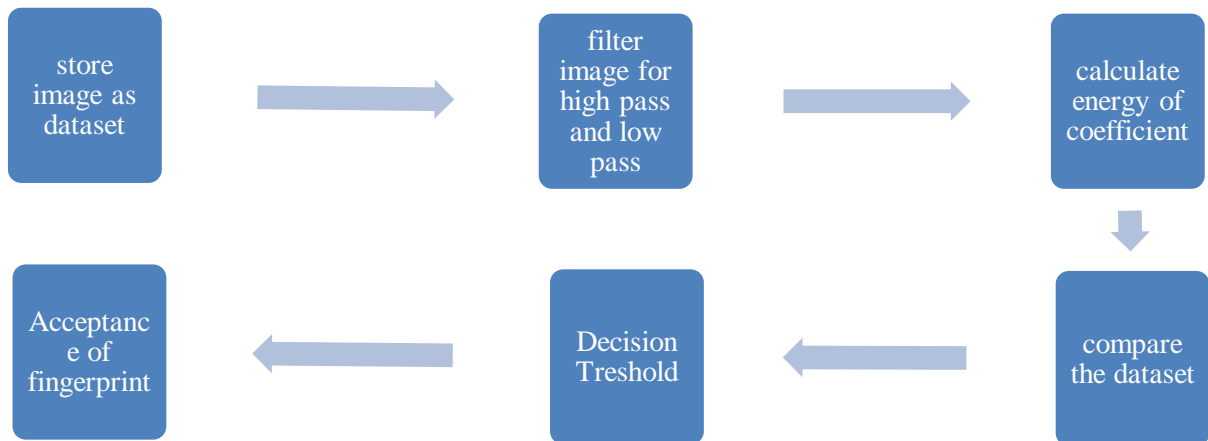


Figure 3 Block Diagram of DWT Feature Extraction Process

Figure 3 explains a flow chart for the DWT extraction process of fingerprint. First, set of the fingerprints will be store as images. Then, the image of the fingerprint will be filter as high pass and low pass in order to calculate for the next process. During the calculation process, all the approximation, horizontal, vertical and diagonal coefficient will be included. Each vector of the coefficient will be treated as column-wise storage of a matrix. Next, the comparison dataset value will be levelled with the threshold value and good fingerprint image will be selected.

3.2 Project Timeline

Please refer [Table 2](#) in the Appendices section.

3.3 Project Key-Milestone

Reliability

This project is relevant to be done using software available in UTP.

Feasibility

This similar project using GLCM method has been done previously by the senior and lecturers.

Contribution

Giving an alternative of recognizing the fingerprint detection with different approach of method.

For Flow chart of project key-milestone, please refer [APPENDICES](#) section.

CHAPTER 4: RESULTS

4.1 Result

Experiment 1: GLCM Feature Comparison with original Fingerprint with 0.1, 0.2 and 0.3 noise

Table 2, 3 and 4 below show a dataset of fingerprint of four contrast value that need to be converted into grey. Contrast 1 represent the red colour value, Contrast 2 represent Green colour value, Contrast 3 represent blue colour value and Contrast 4 represent black colour value. The higher the contrast value, the more converting process to grey colour needs to be done. Apart from that, four Homogeneity values that calculate the nearness of the distribution of fundamentals in the GLCM to the GLCM diagonal. Homogeneity 1 represent first vector value, Homogeneity 2 represent second vector value, Homogeneity 3 represent third vector value and Homogeneity 4 represent fourth vector value. Moreover, four Correlation values that calculate the joint possibility incidence of the quantified pixel pairs. Correlation 1 represent the first vector value, Correlation 2 represent second vector value, Correlation 3 represent third vector value and Correlation 4 represent fourth vector value. Lastly, four Energy values that run the sum of squared rudiments in the GLCM. Energy 1 represent the first vector value, Energy 2 represent second vector value, Energy 3 represent third vector value and Energy 4 represent fourth vector value. Nevertheless, all the 4 elements' mean is calculated and represent as in Table 2 below.

Table 2 Table of Contrast, Homogeneity, Correlation and Energy value of each fingerprint dataset with 0.1 noise

Dataset	Contrast	Homogeneity	Correlation	Energy
1	0.070383	0.089396	0.39023	0.637224
2	0.024272	0.019133	0.169521	0.339817
3	0.018137	0.021138	0.160594	0.320861
4	0.036115	0.03813	0.092428	0.198566
5	0.109873	0.129502	0.492591	0.762137
6	0.031618	0.017904	0.187856	0.354161
7	0.018972	0.011923	0.161782	0.294692
8	0.027811	0.019625	0.112209	0.221475
9	0.190899	0.20199	0.091047	0.145705
10	0.061245	0.100267	0.128921	0.278991
11	0.139216	0.147648	0.09171	0.179691
12	0.364534	0.343608	0.116606	0.210607
13	0.456262	0.461255	0.149778	0.319007
14	0.204416	0.187598	0.061594	0.178748
15	0.989206	1.042296	0.613152	0.580268
16	0.021982	0.012518	0.176738	0.323118
17	0.01756	0.01915	0.14102	0.27562
18	0.030103	0.029762	0.095548	0.210551
19	0.068307	0.071457	0.090619	0.170314
20	0.380731	0.431751	0.860628	1.191507

Table 3 Table of Contrast, Homogeneity, Correlation and Energy value of each fingerprint dataset with 0.2 noises

Dataset	Contrast	Homogeneity	Correlation	Energy
1	13.89485	0.123143	0.036566	0.427741
2	13.41305	0.148994	0.037756	0.435843
3	13.31405	0.143683	0.040379	0.438263
4	12.92645	0.156403	0.045486	0.450154
5	14.10196	0.100745	0.032878	0.41725
6	13.4985	0.159806	0.036915	0.436558
7	13.35148	0.16039	0.038775	0.440968
8	13.12395	0.184105	0.038594	0.445472
9	12.44987	0.223196	0.061616	0.484789
10	12.89184	0.125509	0.057801	0.461917
11	12.85797	0.161657	0.06246	0.473371
12	12.22146	0.243215	0.065313	0.493148
13	11.76409	0.259275	0.06882	0.500738
14	12.62958	0.225288	0.05883	0.480445
15	11.06892	0.100413	0.1002	0.514642
16	13.37954	0.159871	0.038421	0.439631
17	13.12913	0.158873	0.043195	0.446442
18	13.00992	0.162724	0.043406	0.448811
19	12.79016	0.155186	0.047066	0.451485
20	14.20803	0.029402	0.036924	0.411584

Table 4 Table of Contrast, Homogeneity, Correlation and Energy value of each fingerprint dataset with 0.3 noises

Dataset	Contrast	Homogeneity	Correlation	Energy
1	0.070383	0.089396	0.39023	0.637224
2	0.024272	0.019133	0.169521	0.339817
3	0.018137	0.021138	0.160594	0.320861
4	0.036115	0.03813	0.092428	0.198566
5	0.109873	0.129502	0.492591	0.762137
6	0.031618	0.017904	0.187856	0.354161
7	0.018972	0.011923	0.161782	0.294692
8	0.027811	0.019625	0.112209	0.221475
9	0.190899	0.20199	0.091047	0.145705
10	0.061245	0.100267	0.128921	0.278991
11	0.139216	0.147648	0.09171	0.179691
12	0.364534	0.343608	0.116606	0.210607
13	0.456262	0.461255	0.149778	0.319007
14	0.204416	0.187598	0.061594	0.178748
15	0.989206	1.042296	0.613152	0.580268
16	0.021982	0.012518	0.176738	0.323118
17	0.01756	0.01915	0.14102	0.27562
18	0.030103	0.029762	0.095548	0.210551
19	0.068307	0.071457	0.090619	0.170314
20	0.380731	0.431751	0.860628	1.191507

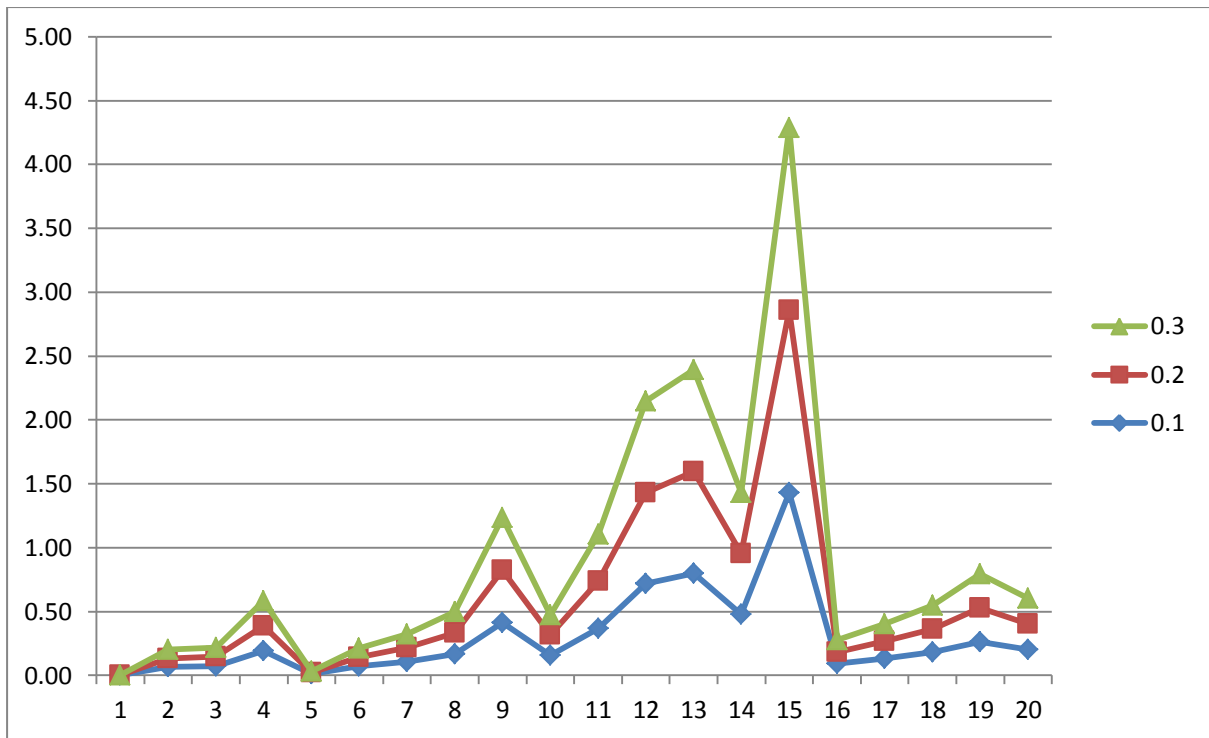


Figure 4 Comparison of Dissimilarity of GLCM Technique with 0.1, 0.2, 0.3 noise

Figure 4 above explain the value of each dataset of fingerprint is compared with each other. Zero value that the dataset comparison has zero dissimilarity. Thus, the higher the value, the higher the dissimilarity between dataset compared. Notice that there highlighted cell and has zero value. This is because the dataset are being compared to each other. Thus, no dissimilarity should be detected and these results show a correct value. Nevertheless, it show that fingerprint between dataset number 13 and dataset number 20 has the highest dissimilarity. This shows that the fingerprints are very dissimilar between each other. In this part of experiment, the result of dissimilarity obtained is more vary compare to experiment 2 and experiment 1. This is due to noise applied to each of the dataset is highest.

Experiment 2: DWT Feature Comparison with original Fingerprint with 0.1, 0.2 and 0.3 noise

Table 5, 6 and 7 below show that the value of approximation, horizontal, vertical and diagonal coefficient respectively. These values are essential for the vector column-wise storage of a matrix.

Table 5 value of approximate and detail coefficient for 0.1 noises

dataset	Ea	Eh max	Eh min	Ev max	Ev min	Ed max	Ed min
1	74.72	6.07	2.65	6.22	2.55	5.79	1.99
2	77.52	5.50	2.54	5.31	2.13	5.31	1.69
3	78.57	5.40	1.96	5.38	2.20	4.92	1.57
4	79.86	4.92	1.84	5.03	2.07	4.77	1.50
5	71.61	6.96	2.81	7.06	2.97	6.54	2.05
6	73.36	6.68	2.72	6.57	2.37	6.30	2.01
7	73.29	6.66	2.18	6.75	2.72	6.43	1.96
8	74.61	6.45	2.45	6.34	2.19	6.09	1.87
9	79.23	4.75	3.00	4.48	2.42	4.10	2.03
10	81.07	4.77	1.77	4.75	1.85	4.23	1.55
11	80.95	4.91	2.43	4.31	1.53	4.01	1.86
12	80.72	4.21	2.26	4.54	2.69	3.98	1.60
13	80.70	4.17	2.29	4.40	2.51	3.93	2.00
14	79.30	4.92	2.63	4.78	2.19	4.25	1.92
15	85.94	3.60	1.00	3.88	1.08	3.37	1.14
16	73.38	6.61	2.19	6.80	2.62	6.45	1.97
17	78.39	5.21	2.21	5.29	2.23	5.12	1.56
18	78.57	5.23	2.45	5.26	1.78	5.17	1.54
19	79.78	4.87	2.50	4.88	1.81	4.70	1.47
20	63.57	9.07	2.98	9.54	3.52	8.66	2.65

Table 6 value of approximate and detail coefficient for 0.2 noises

dataset	Ea	Eh max	Eh min	Ev max	Ev min	Ed max	Ed min
1	74.72	6.07	2.65	6.22	2.55	5.79	1.99
2	77.52	5.50	2.54	5.31	2.13	5.31	1.69
3	78.57	5.40	1.96	5.38	2.20	4.92	1.57
4	79.86	4.92	1.84	5.03	2.07	4.77	1.50
5	71.61	6.96	2.81	7.06	2.97	6.54	2.05
6	73.36	6.68	2.72	6.57	2.37	6.30	2.01
7	73.29	6.66	2.18	6.75	2.72	6.43	1.96
8	74.61	6.45	2.45	6.34	2.19	6.09	1.87
9	79.23	4.75	3.00	4.48	2.42	4.10	2.03
10	81.07	4.77	1.77	4.75	1.85	4.23	1.55
11	80.95	4.91	2.43	4.31	1.53	4.01	1.86
12	80.72	4.21	2.26	4.54	2.69	3.98	1.60
13	80.70	4.17	2.29	4.40	2.51	3.93	2.00
14	79.30	4.92	2.63	4.78	2.19	4.25	1.92
15	85.94	3.60	1.00	3.88	1.08	3.37	1.14
16	73.38	6.61	2.19	6.80	2.62	6.45	1.97
17	78.39	5.21	2.21	5.29	2.23	5.12	1.56
18	78.57	5.23	2.45	5.26	1.78	5.17	1.54
19	79.78	4.87	2.50	4.88	1.81	4.70	1.47
20	63.57	9.07	2.98	9.54	3.52	8.66	2.65

Table 7 value of approximate and detail coefficient for 0.3 noises

dataset	Ea	Eh max	Eh min	Ev max	Ev min	Ed max	Ed min
1	74.72	6.07	2.65	6.22	2.55	5.79	1.99
2	77.52	5.50	2.54	5.31	2.13	5.31	1.69
3	78.57	5.40	1.96	5.38	2.20	4.92	1.57
4	79.86	4.92	1.84	5.03	2.07	4.77	1.50
5	71.61	6.96	2.81	7.06	2.97	6.54	2.05
6	73.36	6.68	2.72	6.57	2.37	6.30	2.01
7	73.29	6.66	2.18	6.75	2.72	6.43	1.96
8	74.61	6.45	2.45	6.34	2.19	6.09	1.87
9	79.23	4.75	3.00	4.48	2.42	4.10	2.03
10	81.07	4.77	1.77	4.75	1.85	4.23	1.55
11	80.95	4.91	2.43	4.31	1.53	4.01	1.86
12	80.72	4.21	2.26	4.54	2.69	3.98	1.60
13	80.70	4.17	2.29	4.40	2.51	3.93	2.00
14	79.30	4.92	2.63	4.78	2.19	4.25	1.92
15	85.94	3.60	1.00	3.88	1.08	3.37	1.14
16	73.38	6.61	2.19	6.80	2.62	6.45	1.97
17	78.39	5.21	2.21	5.29	2.23	5.12	1.56
18	78.57	5.23	2.45	5.26	1.78	5.17	1.54
19	79.78	4.87	2.50	4.88	1.81	4.70	1.47
20	63.57	9.07	2.98	9.54	3.52	8.66	2.65

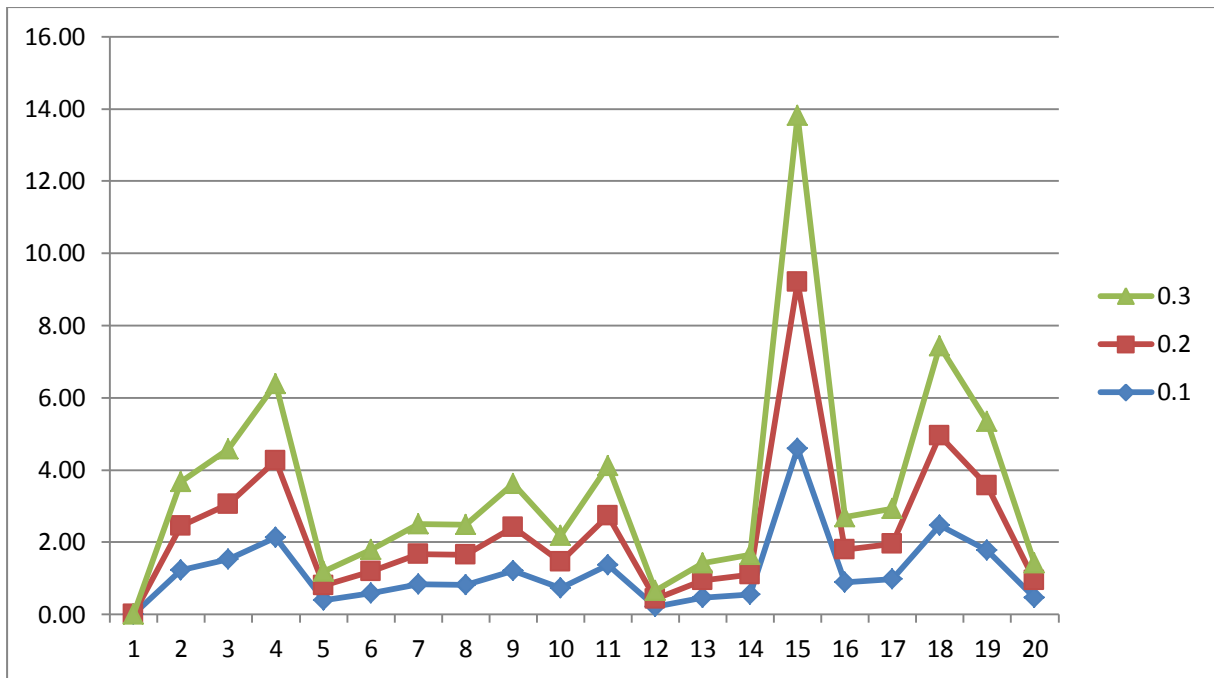


Figure 5 Comparison of Dissimilarity of DWT Technique with 0.1, 0.2, 0.3 noise

Figure 5 above shows a comparison dataset of 0.1, 0.2 and 0.3 dataset of DWT technique comparison. This shows that the fingerprints are very dissimilar between each other. Nevertheless, it show that fingerprint between dataset number 13 and dataset number 20 has the highest dissimilarity. This shows that the fingerprints are very dissimilar between each other. Compare to the GLCM technique, DWT is more sensitive and can detect higher dissimilarity among the dataset. Compare to experiment 1 and experiment 2, this experiment 2 give the most dissimilarity due to higher noise is implied. But, the value of dissimilarity in experiment 3 and experiment 2 are almost the same and need to be looked up until 4 decimal places.

4.2 Future Works

For the future sake of this project, author highly recommended that this project is included with the hardware device for the application purpose. There are also various other technique that can be used for the fingerprint recognition. Nevertheless, the other technique is not known yet regarding their effectiveness and efficiency. The GLCM also has many other techniques that can be used for the fingerprint recognition area. Moreover, GLCM technique can also be used for other recognition such as face recognition, iris of eye recognition and lung clamped detection. Furthermore, the combined of the GLCM and DWT technique will be conducted also in this project, in order to compare the best technique. Furthermore, the dataset database will be increased also in order to achieve higher accuracy and precision value.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

This project title was initially proposed in order to research regarding the fastest method for fingerprint recognition system. This is very essential to be developed as the fingerprint recognition is well-known and used widely throughout the world. Thus, method of GLCM and DWT technique are proposed for this project. The reason this techniques were chose initially is due to the effectiveness and achievable. These techniques also can be done within the required time frame.

CHAPTER 6: REFERENCES

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APPENDICES

GLCM Appendices

Table 8 Dissimilarity of GLCM technique comparison of fingerprint dataset with 0.1 noises

dataset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.00	0.07	0.07	0.19	0.01	0.07	0.11	0.17	0.41	0.16	0.37	0.72	0.80	0.48	1.43	0.09	0.13	0.18	0.26	0.20
2	0.07	0.00	0.01	0.04	0.11	0.01	0.01	0.02	0.20	0.07	0.14	0.38	0.47	0.21	1.03	0.01	0.02	0.03	0.07	0.39
3	0.07	0.01	0.00	0.03	0.11	0.01	0.01	0.03	0.19	0.05	0.13	0.35	0.45	0.20	0.95	0.01	0.01	0.03	0.06	0.37
4	0.19	0.04	0.03	0.00	0.25	0.05	0.02	0.02	0.12	0.05	0.06	0.20	0.29	0.11	0.70	0.03	0.01	0.00	0.01	0.55
5	0.01	0.11	0.11	0.25	0.00	0.11	0.15	0.23	0.53	0.21	0.45	0.84	0.95	0.57	1.53	0.13	0.17	0.24	0.33	0.15
6	0.07	0.01	0.01	0.05	0.11	0.00	0.01	0.03	0.22	0.10	0.16	0.38	0.50	0.21	1.11	0.01	0.02	0.04	0.09	0.41
7	0.11	0.01	0.01	0.02	0.15	0.01	0.00	0.01	0.19	0.08	0.14	0.31	0.42	0.17	0.98	0.00	0.01	0.02	0.06	0.45
8	0.17	0.02	0.03	0.02	0.23	0.03	0.01	0.00	0.13	0.10	0.09	0.24	0.33	0.12	0.91	0.02	0.02	0.01	0.04	0.57
9	0.41	0.20	0.19	0.12	0.53	0.22	0.19	0.13	0.00	0.15	0.07	0.11	0.08	0.08	0.66	0.21	0.18	0.12	0.11	0.92
10	0.16	0.07	0.05	0.05	0.21	0.10	0.08	0.10	0.15	0.00	0.11	0.32	0.35	0.21	0.65	0.09	0.07	0.07	0.07	0.40
11	0.37	0.14	0.13	0.06	0.45	0.16	0.14	0.09	0.07	0.11	0.00	0.12	0.21	0.04	0.57	0.15	0.10	0.07	0.04	0.80
12	0.72	0.38	0.35	0.20	0.84	0.38	0.31	0.24	0.11	0.32	0.12	0.00	0.09	0.05	0.51	0.34	0.27	0.22	0.16	1.29
13	0.80	0.47	0.45	0.29	0.95	0.50	0.42	0.33	0.08	0.35	0.21	0.09	0.00	0.17	0.49	0.46	0.41	0.31	0.26	1.38
14	0.48	0.21	0.20	0.11	0.57	0.21	0.17	0.12	0.08	0.21	0.04	0.05	0.17	0.00	0.67	0.18	0.14	0.11	0.08	1.00
15	1.43	1.03	0.95	0.70	1.53	1.11	0.98	0.91	0.66	0.65	0.57	0.51	0.49	0.67	0.00	1.02	0.87	0.77	0.61	1.68
16	0.09	0.01	0.01	0.03	0.13	0.01	0.00	0.02	0.21	0.09	0.15	0.34	0.46	0.18	1.02	0.00	0.01	0.03	0.07	0.43
17	0.13	0.02	0.01	0.01	0.17	0.02	0.01	0.02	0.18	0.07	0.10	0.27	0.41	0.14	0.87	0.01	0.00	0.01	0.03	0.47
18	0.18	0.03	0.03	0.00	0.24	0.04	0.02	0.01	0.12	0.07	0.07	0.22	0.31	0.11	0.77	0.03	0.01	0.00	0.01	0.55
19	0.26	0.07	0.06	0.01	0.33	0.09	0.06	0.04	0.11	0.07	0.04	0.16	0.26	0.08	0.61	0.07	0.03	0.01	0.00	0.63
20	0.20	0.39	0.37	0.55	0.15	0.41	0.45	0.57	0.92	0.40	0.80	1.29	1.38	1.00	1.68	0.43	0.47	0.55	0.63	0.00

Table 9 Dissimilarity of GLCM technique comparison of fingerprint dataset with 0.2 noises

dataset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.00	0.07	0.07	0.19	0.01	0.07	0.11	0.17	0.41	0.16	0.37	0.72	0.80	0.48	1.43	0.09	0.13	0.18	0.26	0.20
2	0.07	0.00	0.01	0.04	0.11	0.01	0.01	0.02	0.20	0.07	0.14	0.38	0.47	0.21	1.03	0.01	0.02	0.03	0.07	0.39
3	0.07	0.01	0.00	0.03	0.11	0.01	0.01	0.03	0.19	0.05	0.13	0.35	0.45	0.20	0.95	0.01	0.01	0.03	0.06	0.37
4	0.19	0.04	0.03	0.00	0.25	0.05	0.02	0.02	0.12	0.05	0.06	0.20	0.29	0.11	0.70	0.03	0.01	0.00	0.01	0.55
5	0.01	0.11	0.11	0.25	0.00	0.11	0.15	0.23	0.53	0.21	0.45	0.84	0.95	0.57	1.53	0.13	0.17	0.24	0.33	0.15
6	0.07	0.01	0.01	0.05	0.11	0.00	0.01	0.03	0.22	0.10	0.16	0.38	0.50	0.21	1.11	0.01	0.02	0.04	0.09	0.41
7	0.11	0.01	0.01	0.02	0.15	0.01	0.00	0.01	0.19	0.08	0.14	0.31	0.42	0.17	0.98	0.00	0.01	0.02	0.06	0.45
8	0.17	0.02	0.03	0.02	0.23	0.03	0.01	0.00	0.13	0.10	0.09	0.24	0.33	0.12	0.91	0.02	0.02	0.01	0.04	0.57
9	0.41	0.20	0.19	0.12	0.53	0.22	0.19	0.13	0.00	0.15	0.07	0.11	0.08	0.08	0.66	0.21	0.18	0.12	0.11	0.92
10	0.16	0.07	0.05	0.05	0.21	0.10	0.08	0.10	0.15	0.00	0.11	0.32	0.35	0.21	0.65	0.09	0.07	0.07	0.07	0.40
11	0.37	0.14	0.13	0.06	0.45	0.16	0.14	0.09	0.07	0.11	0.00	0.12	0.21	0.04	0.57	0.15	0.10	0.07	0.04	0.80
12	0.72	0.38	0.35	0.20	0.84	0.38	0.31	0.24	0.11	0.32	0.12	0.00	0.09	0.05	0.51	0.34	0.27	0.22	0.16	1.29
13	0.80	0.47	0.45	0.29	0.95	0.50	0.42	0.33	0.08	0.35	0.21	0.09	0.00	0.17	0.49	0.46	0.41	0.31	0.26	1.38
14	0.48	0.21	0.20	0.11	0.57	0.21	0.17	0.12	0.08	0.21	0.04	0.05	0.17	0.00	0.67	0.18	0.14	0.11	0.08	1.00
15	1.43	1.03	0.95	0.70	1.53	1.11	0.98	0.91	0.66	0.65	0.57	0.51	0.49	0.67	0.00	1.02	0.87	0.77	0.61	1.68
16	0.09	0.01	0.01	0.03	0.13	0.01	0.00	0.02	0.21	0.09	0.15	0.34	0.46	0.18	1.02	0.00	0.01	0.03	0.07	0.43
17	0.13	0.02	0.01	0.01	0.17	0.02	0.01	0.02	0.18	0.07	0.10	0.27	0.41	0.14	0.87	0.01	0.00	0.01	0.03	0.47
18	0.18	0.03	0.03	0.00	0.24	0.04	0.02	0.01	0.12	0.07	0.07	0.22	0.31	0.11	0.77	0.03	0.01	0.00	0.01	0.55
19	0.26	0.07	0.06	0.01	0.33	0.09	0.06	0.04	0.11	0.07	0.04	0.16	0.26	0.08	0.61	0.07	0.03	0.01	0.00	0.63
20	0.20	0.39	0.37	0.55	0.15	0.41	0.45	0.57	0.92	0.40	0.80	1.29	1.38	1.00	1.68	0.43	0.47	0.55	0.63	0.00

Table 10 Dissimilarity of GLCM technique comparison of fingerprint dataset with 0.3 noises

dataset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.00	0.07	0.07	0.19	0.01	0.07	0.11	0.17	0.41	0.16	0.37	0.72	0.80	0.48	1.43	0.09	0.13	0.18	0.26	0.20
2	0.07	0.00	0.01	0.04	0.11	0.01	0.01	0.02	0.20	0.07	0.14	0.38	0.47	0.21	1.03	0.01	0.02	0.03	0.07	0.39

3	0.07	0.01	0.00	0.03	0.11	0.01	0.01	0.03	0.19	0.05	0.13	0.35	0.45	0.20	0.95	0.01	0.01	0.03	0.06	0.37
4	0.19	0.04	0.03	0.00	0.25	0.05	0.02	0.02	0.12	0.05	0.06	0.20	0.29	0.11	0.70	0.03	0.01	0.00	0.01	0.55
5	0.01	0.11	0.11	0.25	0.00	0.11	0.15	0.23	0.53	0.21	0.45	0.84	0.95	0.57	1.53	0.13	0.17	0.24	0.33	0.15
6	0.07	0.01	0.01	0.05	0.11	0.00	0.01	0.03	0.22	0.10	0.16	0.38	0.50	0.21	1.11	0.01	0.02	0.04	0.09	0.41
7	0.11	0.01	0.01	0.02	0.15	0.01	0.00	0.01	0.19	0.08	0.14	0.31	0.42	0.17	0.98	0.00	0.01	0.02	0.06	0.45
8	0.17	0.02	0.03	0.02	0.23	0.03	0.01	0.00	0.13	0.10	0.09	0.24	0.33	0.12	0.91	0.02	0.02	0.01	0.04	0.57
9	0.41	0.20	0.19	0.12	0.53	0.22	0.19	0.13	0.00	0.15	0.07	0.11	0.08	0.08	0.66	0.21	0.18	0.12	0.11	0.92
10	0.16	0.07	0.05	0.05	0.21	0.10	0.08	0.10	0.15	0.00	0.11	0.32	0.35	0.21	0.65	0.09	0.07	0.07	0.07	0.40
11	0.37	0.14	0.13	0.06	0.45	0.16	0.14	0.09	0.07	0.11	0.00	0.12	0.21	0.04	0.57	0.15	0.10	0.07	0.04	0.80
12	0.72	0.38	0.35	0.20	0.84	0.38	0.31	0.24	0.11	0.32	0.12	0.00	0.09	0.05	0.51	0.34	0.27	0.22	0.16	1.29
13	0.80	0.47	0.45	0.29	0.95	0.50	0.42	0.33	0.08	0.35	0.21	0.09	0.00	0.17	0.49	0.46	0.41	0.31	0.26	1.38
14	0.48	0.21	0.20	0.11	0.57	0.21	0.17	0.12	0.08	0.21	0.04	0.05	0.17	0.00	0.67	0.18	0.14	0.11	0.08	1.00
15	1.43	1.03	0.95	0.70	1.53	1.11	0.98	0.91	0.66	0.65	0.57	0.51	0.49	0.67	0.00	1.02	0.87	0.77	0.61	1.68
16	0.09	0.01	0.01	0.03	0.13	0.01	0.00	0.02	0.21	0.09	0.15	0.34	0.46	0.18	1.02	0.00	0.01	0.03	0.07	0.43
17	0.13	0.02	0.01	0.01	0.17	0.02	0.01	0.02	0.18	0.07	0.10	0.27	0.41	0.14	0.87	0.01	0.00	0.01	0.03	0.47
18	0.18	0.03	0.03	0.00	0.24	0.04	0.02	0.01	0.12	0.07	0.07	0.22	0.31	0.11	0.77	0.03	0.01	0.00	0.01	0.55
19	0.26	0.07	0.06	0.01	0.33	0.09	0.06	0.04	0.11	0.07	0.04	0.16	0.26	0.08	0.61	0.07	0.03	0.01	0.00	0.63
20	0.20	0.39	0.37	0.55	0.15	0.41	0.45	0.57	0.92	0.40	0.80	1.29	1.38	1.00	1.68	0.43	0.47	0.55	0.63	0.00

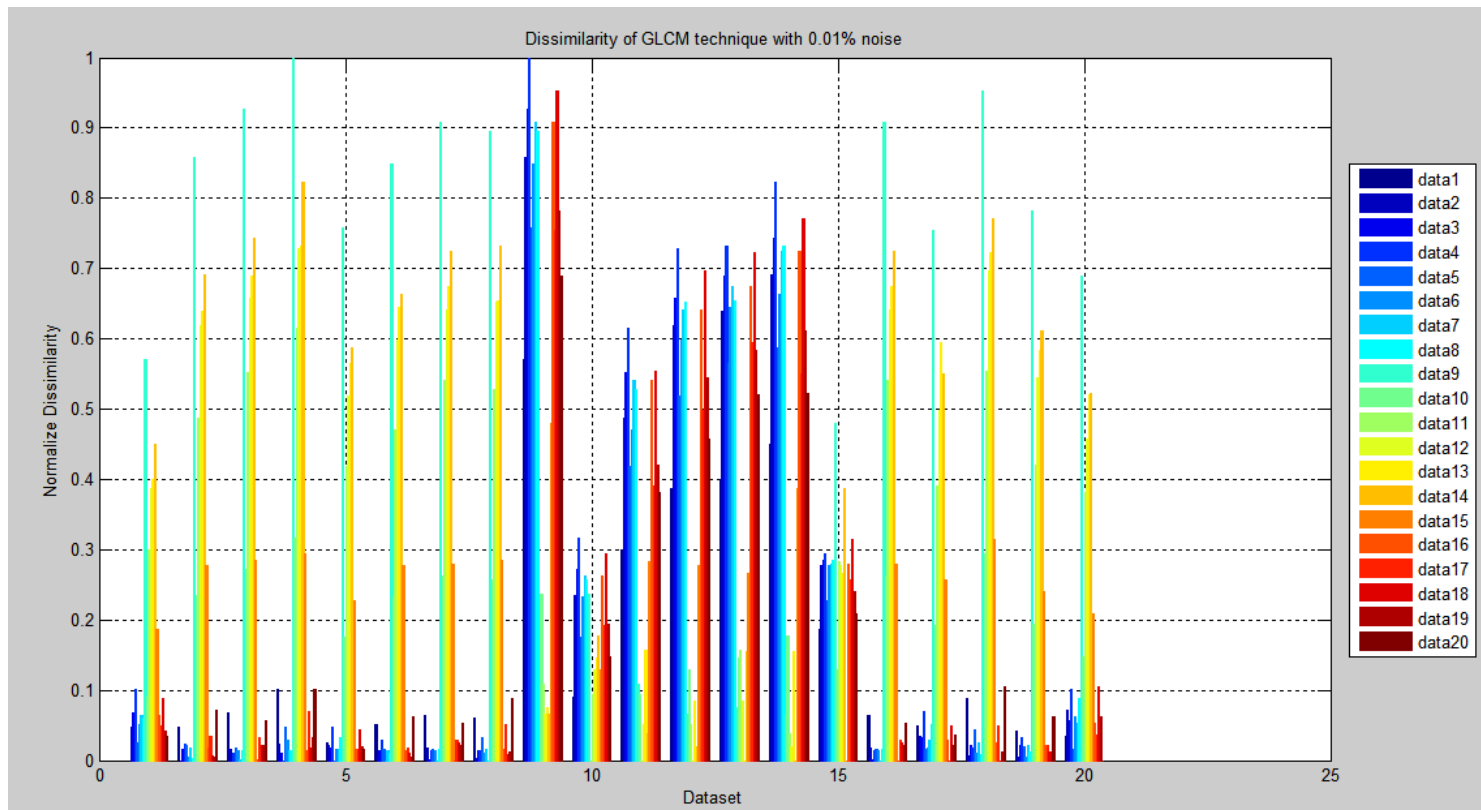


Figure 6 Normalize dissimilarity of GLCM technique with 0.1 noise between datasets

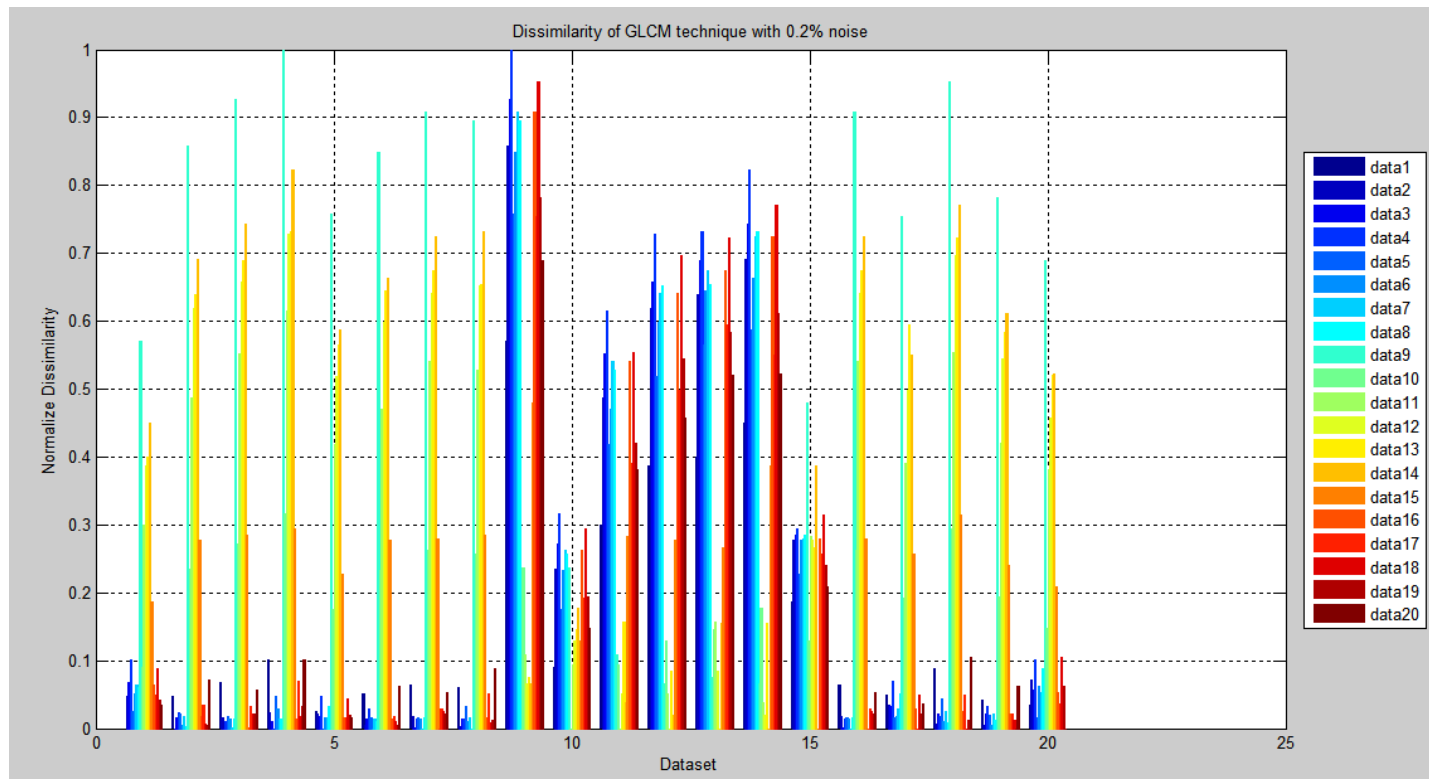


Figure 7 Normalize dissimilarity of GLCM technique with 0.2 noises between datasets

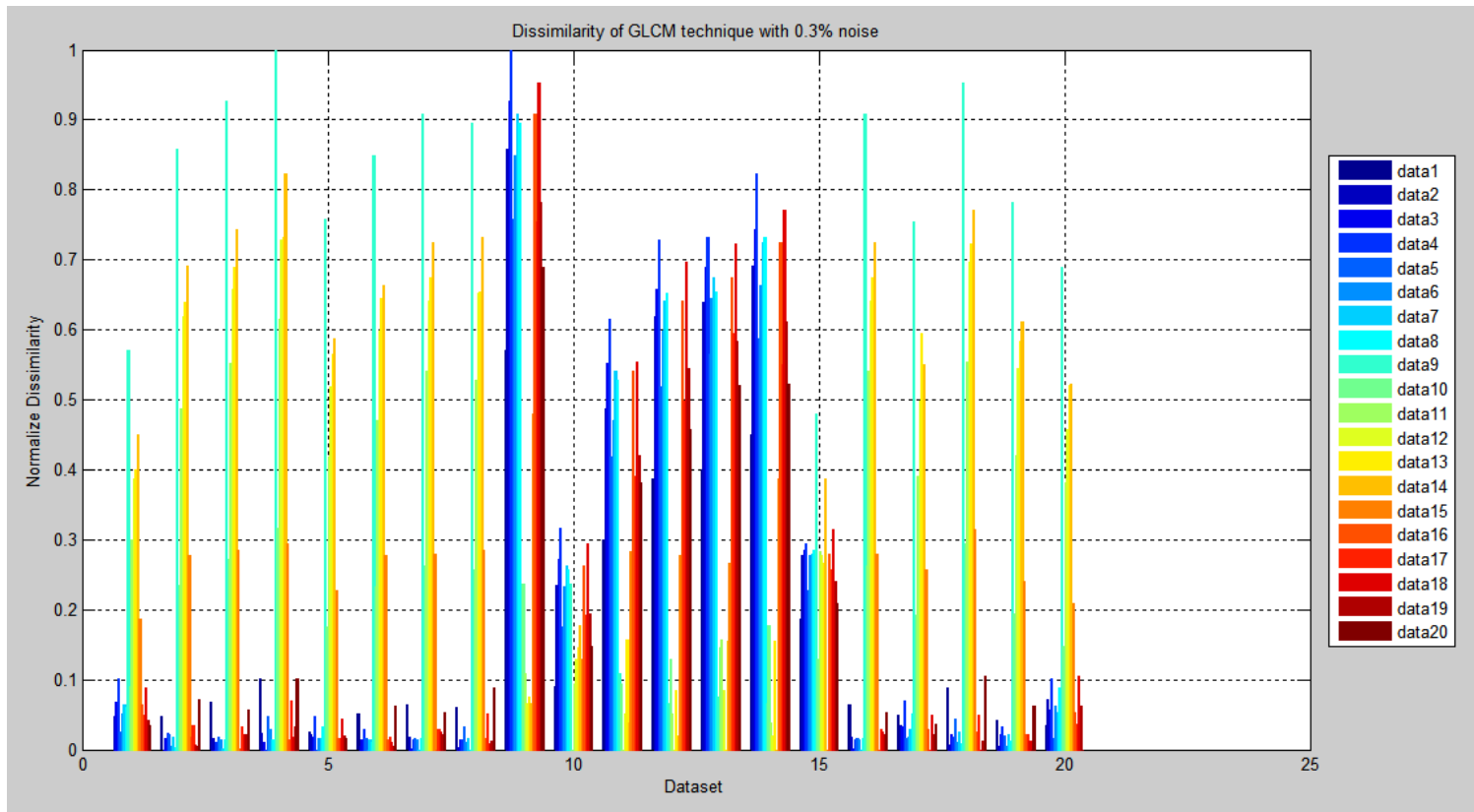


Figure 8 Normalize dissimilarity of GLCM technique with 0.3 noises between datasets

DWT Appendices

Table 11 Dissimilarity of DWT technique comparison of fingerprint dataset with 0.1 noises

dataset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.00	1.22	1.52	2.13	0.40	0.60	0.84	0.83	1.21	0.73	1.37	0.22	0.47	0.55	4.60	0.90	0.97	2.48	1.78	0.47
2	1.22	0.00	0.72	0.67	1.75	0.37	1.11	0.29	3.63	0.88	1.60	2.19	2.36	2.45	3.21	1.09	0.23	0.34	0.10	1.88
3	1.52	0.72	0.00	0.11	1.66	1.23	0.38	0.79	4.88	0.98	3.08	2.33	2.57	3.44	2.47	0.37	0.28	1.34	0.85	1.13
4	2.13	0.67	0.11	0.00	2.30	1.36	0.72	0.86	5.71	1.25	3.29	3.11	3.37	4.12	2.20	0.68	0.37	0.97	0.65	1.82
5	0.40	1.75	1.66	2.30	0.00	1.14	1.13	1.51	1.95	1.59	2.75	0.44	1.08	1.42	5.51	1.21	1.14	2.98	2.24	0.64
6	0.60	0.37	1.23	1.36	1.14	0.00	0.95	0.16	2.29	0.53	0.86	1.30	1.74	1.24	3.38	0.96	0.53	0.96	0.63	1.42
7	0.84	1.11	0.38	0.72	1.13	0.95	0.00	0.59	3.63	0.41	2.30	1.36	1.76	2.21	2.27	0.00	0.61	2.09	1.46	0.41
8	0.83	0.29	0.79	0.86	1.51	0.16	0.59	0.00	3.03	0.25	0.97	1.61	1.92	1.71	2.46	0.58	0.43	0.87	0.54	1.31
9	1.21	3.63	4.88	5.71	1.95	2.29	3.63	3.03	0.00	2.80	1.78	0.89	0.88	0.31	8.32	3.74	3.71	5.24	4.48	2.64
10	0.73	0.88	0.98	1.25	1.59	0.53	0.41	0.25	2.80	0.00	0.91	1.39	1.64	1.44	2.36	0.40	0.91	1.83	1.34	0.84
11	1.37	1.60	3.08	3.29	2.75	0.86	2.30	0.97	1.78	0.91	0.00	1.97	2.03	0.93	4.20	2.31	2.28	2.40	2.12	2.60
12	0.22	2.19	2.33	3.11	0.44	1.30	1.36	1.61	0.89	1.39	1.97	0.00	0.29	0.52	5.69	1.45	1.76	3.72	2.88	0.68
13	0.47	2.36	2.57	3.37	1.08	1.74	1.76	1.92	0.88	1.64	2.03	0.29	0.00	0.68	6.05	1.85	2.03	3.93	3.07	1.01
14	0.55	2.45	3.44	4.12	1.42	1.24	2.21	1.71	0.31	1.44	0.93	0.52	0.68	0.00	6.03	2.29	2.53	3.85	3.18	1.60
15	4.60	3.21	2.47	2.20	5.51	3.38	2.27	2.46	8.32	2.36	4.20	5.69	6.05	6.03	0.00	2.16	3.18	3.13	3.12	3.87
16	0.90	1.09	0.37	0.68	1.21	0.96	0.00	0.58	3.74	0.40	2.31	1.45	1.85	2.29	2.16	0.00	0.61	2.04	1.44	0.46
17	0.97	0.23	0.28	0.37	1.14	0.53	0.61	0.43	3.71	0.91	2.28	1.76	2.03	2.53	3.18	0.61	0.00	0.72	0.32	1.21
18	2.48	0.34	1.34	0.97	2.98	0.96	2.09	0.87	5.24	1.83	2.40	3.72	3.93	3.85	3.13	2.04	0.72	0.00	0.10	3.25
19	1.78	0.10	0.85	0.65	2.24	0.63	1.46	0.54	4.48	1.34	2.12	2.88	3.07	3.18	3.12	1.44	0.32	0.10	0.00	2.43
20	0.47	1.88	1.13	1.82	0.64	1.42	0.41	1.31	2.64	0.84	2.60	0.68	1.01	1.60	3.87	0.46	1.21	3.25	2.43	0.00

Table 12 Dissimilarity of DWT technique comparison of fingerprint dataset with 0.2 noises

dataset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.00	0.07	0.07	0.19	0.01	0.07	0.11	0.17	0.41	0.16	0.37	0.72	0.80	0.48	1.43	0.09	0.13	0.18	0.26	0.20
2	0.07	0.00	0.01	0.04	0.11	0.01	0.01	0.02	0.20	0.07	0.14	0.38	0.47	0.21	1.03	0.01	0.02	0.03	0.07	0.39
3	0.07	0.01	0.00	0.03	0.11	0.01	0.01	0.03	0.19	0.05	0.13	0.35	0.45	0.20	0.95	0.01	0.01	0.03	0.06	0.37
4	0.19	0.04	0.03	0.00	0.25	0.05	0.02	0.02	0.12	0.05	0.06	0.20	0.29	0.11	0.70	0.03	0.01	0.00	0.01	0.55
5	0.01	0.11	0.11	0.25	0.00	0.11	0.15	0.23	0.53	0.21	0.45	0.84	0.95	0.57	1.53	0.13	0.17	0.24	0.33	0.15
6	0.07	0.01	0.01	0.05	0.11	0.00	0.01	0.03	0.22	0.10	0.16	0.38	0.50	0.21	1.11	0.01	0.02	0.04	0.09	0.41
7	0.11	0.01	0.01	0.02	0.15	0.01	0.00	0.01	0.19	0.08	0.14	0.31	0.42	0.17	0.98	0.00	0.01	0.02	0.06	0.45
8	0.17	0.02	0.03	0.02	0.23	0.03	0.01	0.00	0.13	0.10	0.09	0.24	0.33	0.12	0.91	0.02	0.02	0.01	0.04	0.57
9	0.41	0.20	0.19	0.12	0.53	0.22	0.19	0.13	0.00	0.15	0.07	0.11	0.08	0.08	0.66	0.21	0.18	0.12	0.11	0.92
10	0.16	0.07	0.05	0.05	0.21	0.10	0.08	0.10	0.15	0.00	0.11	0.32	0.35	0.21	0.65	0.09	0.07	0.07	0.07	0.40
11	0.37	0.14	0.13	0.06	0.45	0.16	0.14	0.09	0.07	0.11	0.00	0.12	0.21	0.04	0.57	0.15	0.10	0.07	0.04	0.80
12	0.72	0.38	0.35	0.20	0.84	0.38	0.31	0.24	0.11	0.32	0.12	0.00	0.09	0.05	0.51	0.34	0.27	0.22	0.16	1.29
13	0.80	0.47	0.45	0.29	0.95	0.50	0.42	0.33	0.08	0.35	0.21	0.09	0.00	0.17	0.49	0.46	0.41	0.31	0.26	1.38
14	0.48	0.21	0.20	0.11	0.57	0.21	0.17	0.12	0.08	0.21	0.04	0.05	0.17	0.00	0.67	0.18	0.14	0.11	0.08	1.00
15	1.43	1.03	0.95	0.70	1.53	1.11	0.98	0.91	0.66	0.65	0.57	0.51	0.49	0.67	0.00	1.02	0.87	0.77	0.61	1.68
16	0.09	0.01	0.01	0.03	0.13	0.01	0.00	0.02	0.21	0.09	0.15	0.34	0.46	0.18	1.02	0.00	0.01	0.03	0.07	0.43
17	0.13	0.02	0.01	0.01	0.17	0.02	0.01	0.02	0.18	0.07	0.10	0.27	0.41	0.14	0.87	0.01	0.00	0.01	0.03	0.47
18	0.18	0.03	0.03	0.00	0.24	0.04	0.02	0.01	0.12	0.07	0.07	0.22	0.31	0.11	0.77	0.03	0.01	0.00	0.01	0.55
19	0.26	0.07	0.06	0.01	0.33	0.09	0.06	0.04	0.11	0.07	0.04	0.16	0.26	0.08	0.61	0.07	0.03	0.01	0.00	0.63
20	0.20	0.39	0.37	0.55	0.15	0.41	0.45	0.57	0.92	0.40	0.80	1.29	1.38	1.00	1.68	0.43	0.47	0.55	0.63	0.00

Table 13 Dissimilarity of DWT technique comparison of fingerprint dataset with 0.3 noises

dataset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.00	1.22	1.52	2.13	0.40	0.60	0.84	0.83	1.21	0.73	1.37	0.22	0.47	0.55	4.60	0.90	0.97	2.48	1.78	0.47
2	1.22	0.00	0.72	0.67	1.75	0.37	1.11	0.29	3.63	0.88	1.60	2.19	2.36	2.45	3.21	1.09	0.23	0.34	0.10	1.88
3	1.52	0.72	0.00	0.11	1.66	1.23	0.38	0.79	4.88	0.98	3.08	2.33	2.57	3.44	2.47	0.37	0.28	1.34	0.85	1.13
4	2.13	0.67	0.11	0.00	2.30	1.36	0.72	0.86	5.71	1.25	3.29	3.11	3.37	4.12	2.20	0.68	0.37	0.97	0.65	1.82
5	0.40	1.75	1.66	2.30	0.00	1.14	1.13	1.51	1.95	1.59	2.75	0.44	1.08	1.42	5.51	1.21	1.14	2.98	2.24	0.64
6	0.60	0.37	1.23	1.36	1.14	0.00	0.95	0.16	2.29	0.53	0.86	1.30	1.74	1.24	3.38	0.96	0.53	0.96	0.63	1.42
7	0.84	1.11	0.38	0.72	1.13	0.95	0.00	0.59	3.63	0.41	2.30	1.36	1.76	2.21	2.27	0.00	0.61	2.09	1.46	0.41
8	0.83	0.29	0.79	0.86	1.51	0.16	0.59	0.00	3.03	0.25	0.97	1.61	1.92	1.71	2.46	0.58	0.43	0.87	0.54	1.31
9	1.21	3.63	4.88	5.71	1.95	2.29	3.63	3.03	0.00	2.80	1.78	0.89	0.88	0.31	8.32	3.74	3.71	5.24	4.48	2.64
10	0.73	0.88	0.98	1.25	1.59	0.53	0.41	0.25	2.80	0.00	0.91	1.39	1.64	1.44	2.36	0.40	0.91	1.83	1.34	0.84
11	1.37	1.60	3.08	3.29	2.75	0.86	2.30	0.97	1.78	0.91	0.00	1.97	2.03	0.93	4.20	2.31	2.28	2.40	2.12	2.60
12	0.22	2.19	2.33	3.11	0.44	1.30	1.36	1.61	0.89	1.39	1.97	0.00	0.29	0.52	5.69	1.45	1.76	3.72	2.88	0.68
13	0.47	2.36	2.57	3.37	1.08	1.74	1.76	1.92	0.88	1.64	2.03	0.29	0.00	0.68	6.05	1.85	2.03	3.93	3.07	1.01
14	0.55	2.45	3.44	4.12	1.42	1.24	2.21	1.71	0.31	1.44	0.93	0.52	0.68	0.00	6.03	2.29	2.53	3.85	3.18	1.60
15	4.60	3.21	2.47	2.20	5.51	3.38	2.27	2.46	8.32	2.36	4.20	5.69	6.05	6.03	0.00	2.16	3.18	3.13	3.12	3.87
16	0.90	1.09	0.37	0.68	1.21	0.96	0.00	0.58	3.74	0.40	2.31	1.45	1.85	2.29	2.16	0.00	0.61	2.04	1.44	0.46
17	0.97	0.23	0.28	0.37	1.14	0.53	0.61	0.43	3.71	0.91	2.28	1.76	2.03	2.53	3.18	0.61	0.00	0.72	0.32	1.21
18	2.48	0.34	1.34	0.97	2.98	0.96	2.09	0.87	5.24	1.83	2.40	3.72	3.93	3.85	3.13	2.04	0.72	0.00	0.10	3.25
19	1.78	0.10	0.85	0.65	2.24	0.63	1.46	0.54	4.48	1.34	2.12	2.88	3.07	3.18	3.12	1.44	0.32	0.10	0.00	2.43
20	0.47	1.88	1.13	1.82	0.64	1.42	0.41	1.31	2.64	0.84	2.60	0.68	1.01	1.60	3.87	0.46	1.21	3.25	2.43	0.00

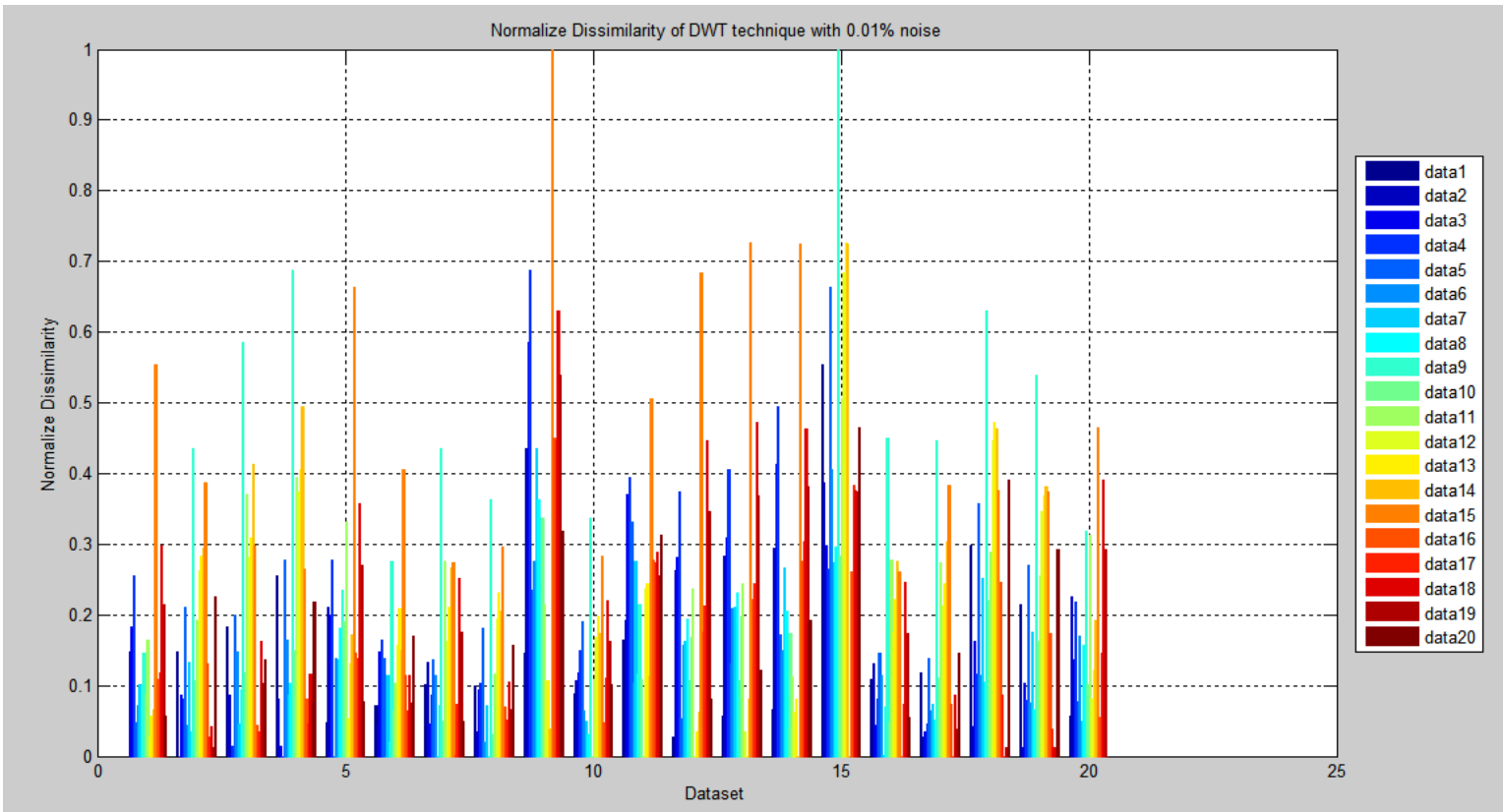


Figure 9 Normalize dissimilarity of DWT technique with 0.1 noises between datasets

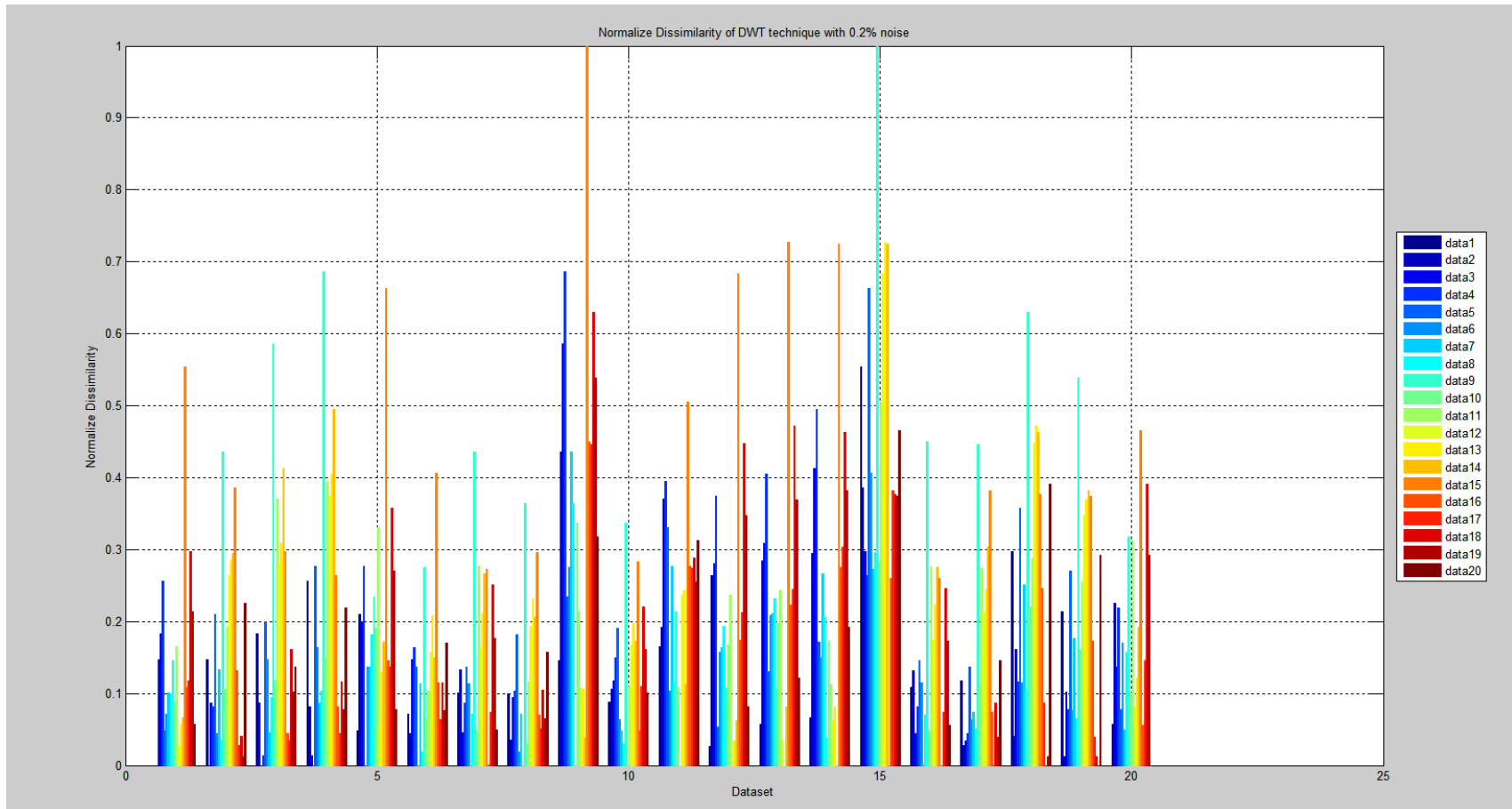


Figure 10 Normalize dissimilarity of DWT technique with 0.2 noises between datasets

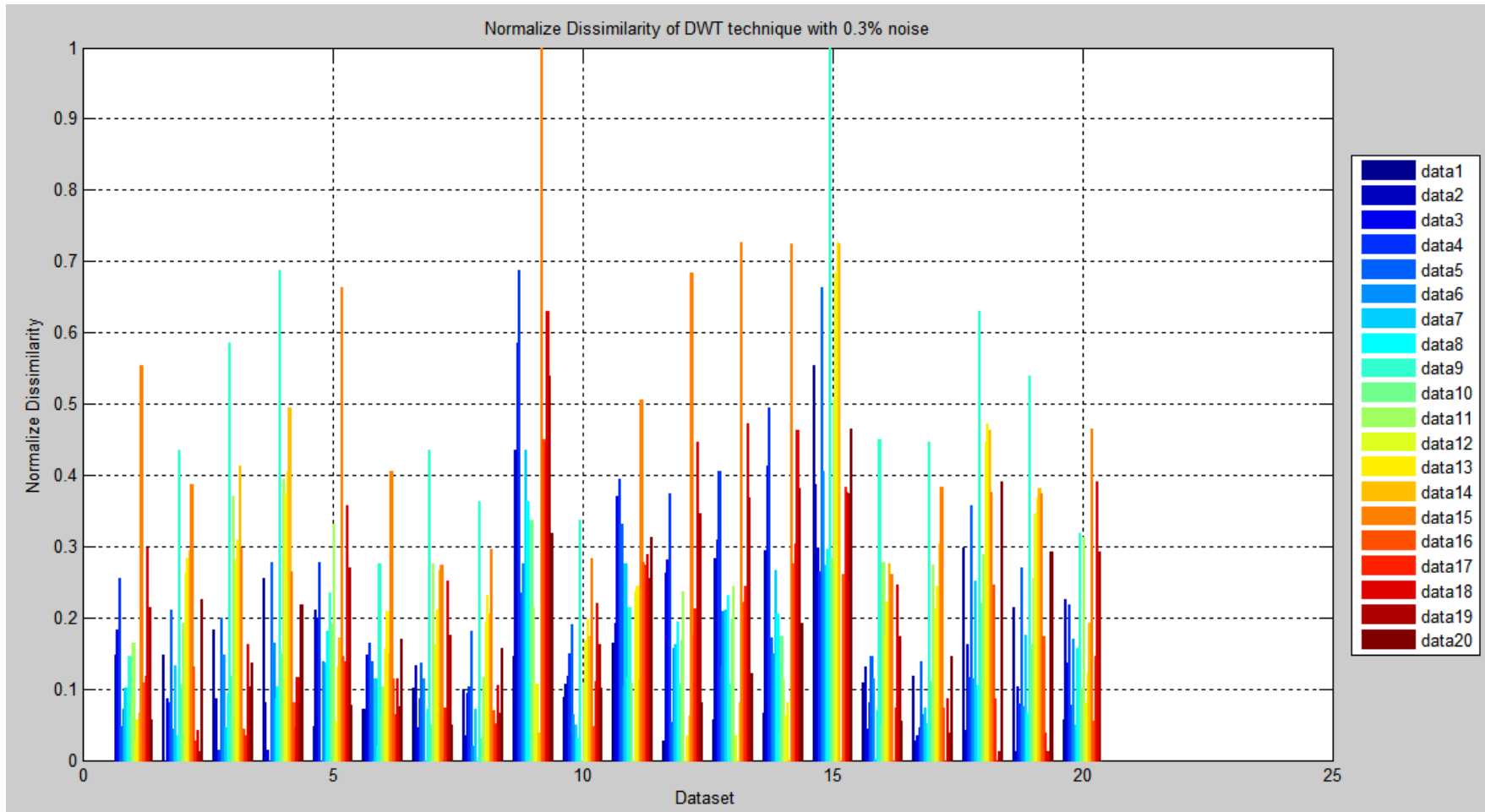


Figure 11 Normalize dissimilarity of DWT technique with 0.3 noises between datasets

Fingerprint Appendices

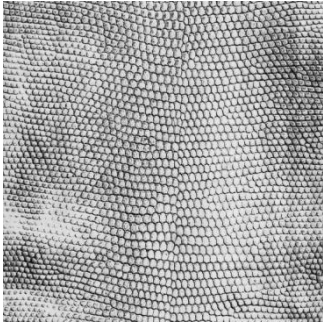


Figure 12 Various Texture File V1

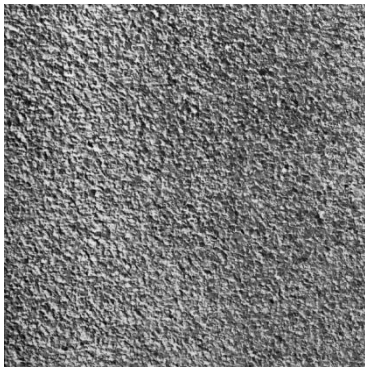


Figure 13 Various Texture File V2

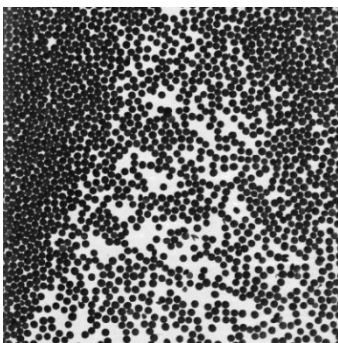


Figure 14 Various Texture File V3



Figure 15 database fingerprint V3



Figure 16 database fingerprint V1



Figure 17 database fingerprint V2



Figure 18 database fingerprint V4

Table 12: Table of project timeline

NO	SUBJECT	ALLOCATION	SEMESTER 1 (FYP I)															SEMESTER 2 (FYP II)																		
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15				
1	FYP Topic Selection	1 week	■																																	
2	Project Introduction	1 week		■																																
3	Extended Proposal	4 weeks			■	■	■	■																												
4	Extended Proposal Submission	30-Oct-14							■																											
5	Proposal Defense Preparation	3 weeks							■	■																										
6	Introduction to MATLAB	3 weeks									■	■																								
7	Proposal Defense Evaluation	2 weeks									■	■																								
8	Hands-on use with MATLAB	3 weeks										■	■	■																						
9	Submission of Interim Draft Report	1 week																																		
10	Submission of Interim Report	1 week																																		
11	Preparation of MATLAB experiment	1 week																																		
12	MATLAB experiment	1 week																																		
13	Data Validation of GLCM and SVD technique	5 weeks																																		
14	Progress Report Preparation	5 weeks																																		
15	Progress Report Submission	1 week																																		
16	Finalized the GLCM and SVD technique	3 weeks																																		
17	Pre-SEDEX	1 week																																		
18	Investigating the Integrity and Reliability of the Technique	3 weeks																																		
19	Preparation of Final Report	3 weeks																																		
20	Submission of Draft Final Report	1 week																																		
21	Submission of Dissertation (Soft Bound)	1 week																																		
22	Submission of Technical Paper	1 week																																		
23	Viva	1 week																																		
24	Submission of Dissertation (Hard Bound)	1 week																																		

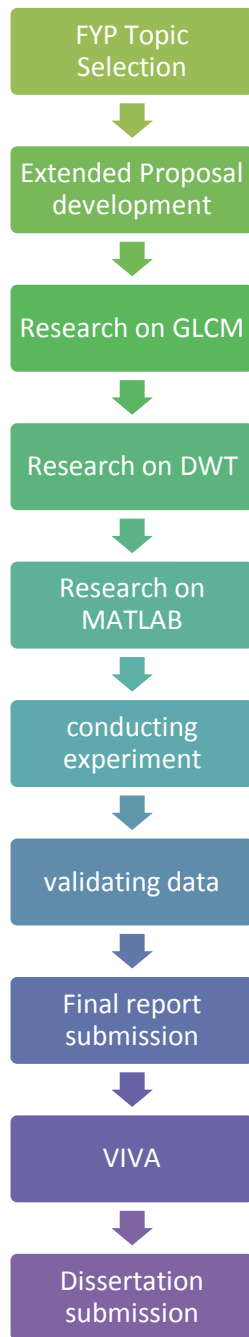


Figure 19 Flow chart of project key-milestone

Coding

Dissimilarity Matching Square Matrix Computation

```
% distMATChiSquare computes the dissimilarity between training samples and a test sample
% DV = distMATChiSquare(train, test) returns the distance vector between training samples and a test sample.
% The input "train" is a n*d matrix, and each row of it represent one
% training sample. The "test" is a 1*d vector.

% Examples
% -----
%     I1=imread('rice1.png');
%     I2=imread('rice2.png');
%     I3=imread('rice3.png');
%     mapping=getmapping(8,'u2');
%     M(1,:)=LBPV(I1,1,8,mapping); % LBPV histogram in (8,1) neighborhood using uniform patterns
%     M(2,:)=LBPV(I2,1,8,mapping);
%     S=LBPV(I3,1,8,mapping);
%     DV = distMATChiSquare(M,S);

function DV = distMATChiSquare(trains, test)
% Version 1.0
% Authors: Zhenhua Guo, Lei Zhang and David Zhang
% Copyright © Biometrics Research Centre, the Hong Kong Polytechnic University
% trains=M;
% test=S;DistMat = subMatrix2./addMatrix;
[train_row, train_col] = size(trains);
[test_row, test_col] = size(test);

testExtend = repmat(test, train_row, 1);
subMatrix = trains-testExtend;
subMatrix2 = subMatrix.^2;
addMatrix = trains+testExtend;
DistMat = subMatrix2./addMatrix;
DV = sum(DistMat,2);
idxZero = find(addMatrix==0);
addMatrix(idxZero)=1;
```

Proposing noise on Fingerprint Database Computation

```
clc;clear all;close all;

m=0
v = 0.3;

I = imread('original\1.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1); imshow(I,[])
save('noisvim\1.mat','I');

I = imread('original\2.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\2.mat','I');

I = imread('original\3.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\3.mat','I');

I = imread('original\4.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\4.mat','I');

I = imread('original\5.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\5.mat','I');

I = imread('original\6.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\6.mat','I');

I = imread('original\7.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\7.mat','I');

I = imread('original\8.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\8.mat','I');

I = imread('original\9.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\9.mat','I');

I = imread('original\10.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\10.mat','I');

I = imread('original\11.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\11.mat','I');

I = imread('original\12.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\12.mat','I');

I = imread('original\13.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisvim\13.mat','I');
```

```

I = imread('original\14.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisyim\14.mat','I');

I = imread('original\15.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisyim\15.mat','I');

I = imread('original\16.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisyim\16.mat','I');

I = imread('original\17.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisyim\17.mat','I');

I = imread('original\18.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisyim\18.mat','I');

I = imread('original\19.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisyim\19.mat','I');

I = imread('original\20.jpg');
I = double(imnoise(I,'gaussian',m,v));
I = I(:,:,1);
save('noisyim\20.mat','I');

```

GLCM Technique Computation

```
clear all; close all; clc
fet1= zeros(1,16);
% fet2= zeros(1,16);
% fet3= zeros(1,16);
% fet4= zeros(1,16);
fet5= zeros(1,16);

lim1= 20;
for images=1:lim1
str = strcat(int2str(images),'.mat'); %% In this case image files should be in same Folder
%eval('I=imread(str);');
eval('load(str);');
%I = rgb2gray(I);
offsets0=[0,1;-1,1;-1,0;-1,-1]; % [0,1]=0, [-1,1]=45, [-1,0]=90, [-1,-1]=135.
glcm = graycomatrix(I,'GrayLimits', [min(I(:)) max(I(:))],'Offset',offsets0,'Symmetric', true);
stats1= graycoprops(glcm, {'Contrast','Correlation','Energy','Homogeneity'});
Cont1=stats1.Contrast; % contrast
Cont2= mean(Cont1); % get the mean value

corr1=stats1.Correlation; % correlation
corr2=mean(corr1); % get the mean value

eng1=stats1.Energy; % energy
eng2=mean(eng1); % get the mean value

Hom1=stats1.Homogeneity; % homogeneity
Hom2=mean(Hom1); % get the mean value

j=[Cont2 corr2 eng2 Hom2];
tf=[Cont1 corr1 eng1 Hom1]; % all feature concatenated
% fet1=cat(1,fet1,tf);
fet5=cat(1,fet5,tf);
end
```

DWT Technique Computation

```
clear all; close all; clc;

fet5= zeros(1,7);
lim1= 20;
for images=1:lim1
str = strcat(int2str(images),'.mat'); %% In this case image files should be in same Folder
%eval('I=imread(str);');
eval('load(str);');
I = double(I);
% figure(images); imshow(I,[]);
[C,S] = wavedec2(I,2,'sym4');
[Ea,Eh,Ev,Ed] = wenergy2(C,S);
H = [Ea,Eh,Ev,Ed];
fet5=cat(1,fet5,H);

g = [Ea,Eh,Ev,Ed]
end

fet2= zeros(1,7);
lim2 = 20;
for images=1:lim2
str = strcat(int2str(images),'.jpg'); %% In this case image files should be in same Folder
%eval('I=imread(str);');
%eval('load(str);');
I = double(I);
% figure(images); imshow(I,[]);
[C,S] = wavedec2(I,2,'sym4');
[Ea,Eh,Ev,Ed] = wenergy2(C,S);
H = [Ea,Eh,Ev,Ed];
fet2=cat(1,fet2,H);
end
```


Obtaining Comparison between dataset Normalized Graph for GLCM technique Computation

```
clc;clear all;close all
% I1 = imread('7.jpg');
% figure;imshow(I1,[]);
% I2 = imread('original\16.jpg');
% figure;imshow(I2,[]);
load train.mat
load test.mat
load noiseqlcm2.mat

lim1 = 20;
tdv = RUNDIS(fet1(2:lim1+1,:),fet4(2:lim1+1,:));

%-----normalization-----%
maxv = max(tdv(:));
ntdv = tdv./maxv;
minv = min(ntdv);

%-----normalize dy graph-----%
figure(1); grid; bar(1:lim1,ntdv)
title ('Dissimilarity of GLCM technique with 0.2% noise')
xlabel('Dataset')
ylabel('Normalize Dissimilarity')
legend(lim1,'Location','eastoutside','Orientation','vertical')
grid;
```

Obtaining Comparison between dataset Normalized Graph for DWT technique Computation

```
clc;clear all;close all
% I1 = imread('7.jpg');
% figure;imshow(I1,[]);
% I2 = imread('original\16.jpg');
% figure;imshow(I2,[]);

load traindw.mat
load testdw.mat
load noisedwt1.mat

lim1 = 20;
lim2 = 20;
tdv = RUNDIS(fet1(2:lim1+1,:),fet3(2:lim2+1,:));

%-----normalization-----%
maxv = max(tdv(:));
ntdv = tdv./maxv;
minv = min(ntdv);

%-----normalize dy graph-----%
figure(2); grid; bar(1:lim1,ntdv)
title ('Normalize Dissimilarity of DWT technique with 0.3% noise')
xlabel('Dataset')
ylabel('Normalize Dissimilarity')
legend(lim1,'Location','eastoutside','Orientation','vertical')
grid;
```