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IMPLEMENTATION OF IMAGE TEXTURE ANALYSIS USING GRAY LEVEL RUN LENGTH APPROACH

By

SITI HAJAR MOHD YAKOP

FINAL PROJECT REPORT

Submitted to the Electrical & Electronics Engineering Programme
in Partial Fulfillment of the Requirements
for the Degree
Bachelor of Engineering (Hons)
(Electrical & Electronics Engineering)

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CERTIFICATION OF APPROVAL

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Approved:

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Project Supervisor

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK

June 2006

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

Siti Hajar Mohd Yakop

ABSTRACT

With the dramatic increase of imaging techniques, there is a great demand for new approaches in texture analysis. This paper presents a new approach for texture analysis using statistical method and gray level run length matrix (GLRLM) approach as the second order statistics approach. The objective of this project is to develop algorithms in MATLAB and be able to implement image texture analysis by using the developed algorithms. This project is taken to apply statistical approach in image analysis and classification. The method used is statistical method which is divided into first order statistics and second order statistics. The scope of this project is concentrated in three parts which are algorithm development and verification, image analysis and image classification. MATLAB software is used as the main tools in this project to develop both the first and second order algorithms. From this project it is learned that statistical approach is capable in discriminating images. For future recommendations, this approach can be tested on a medical image to widen the scope of practiced for statistical implementation in texture analysis.

ACKNOWLEDGEMENTS

Alhamdulillah, with blessings from Allah S.W.T., this project has been completed successfully according to the targeted time frame. I would like to sincerely thank University of Technology PETRONAS in particular for giving me a wonderful opportunity to carry out this meaningful project.

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Finally, my appreciation goes to my partner for this project, Miss Norhidayah Jamaludin, my fellow friends and my family who have helped me in various tasks and being a good team player as well as supplying me with undivided support in completing this project.

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LIST OF ABBREVIATIONS

MRI	Magnetic Resonance Imaging
MATLAB	Mathematical Laboratory Software
TIFF	Tagged Image File Format
CG	Computer Graphic
FOS	First Order Statistics
SOS	Second Order Statistics
GLRLM	Gray Level Run Length Method
GLRLM's	Gray Level Run Length Matrices
SRE	Short Run Emphasis
LRE	Long Run Emphasis
GLN	Gray Level Distribution
RLN	Run Length Distribution
RP	Run Percentage

CHAPTER 1
INTRODUCTION

This chapter describes four subsections which are the background of study, the problem statement, the objectives of the project and the scope of study. Background of study describes the project generally and how it narrows down to the project's implementation. The problem statement will focus on the situation of the problem and research questions which lead to the objectives of the project. Lastly, the scope of study will clarify specifically the project frame and the project work boundary to ensure the feasibility within the given time frame.

1.1 Background of Study

"MRI", which stands for "magnetic resonance imaging," is a method used in medical industry to diagnose a disease. MRI uses a powerful magnet and precisely programmed radio signals to "see" inside the body. MRI images are interpreted and analyzed by the doctors manually. In some cases, the cause or defects shown in the MRI images are overlooked. This will cause a delay in the diagnosing process. Patients with critical issues cannot be hold up in treatment. Considering this fact, instead of using traditional diagnosing method, texture analysis approach can be implemented as an alternative for a faster diagnosing result. By texture analysis method, image can be processed in less time duration. This can help in acquiring more accurate diagnosing results by using a more efficient method. This approach can be further studied for implementation in the image processing industry [1]. Thus, the objective of this project is to be able to used image texture analysis to improve currently used technique in medical image processing industry [2].

Texture analysis approach consists of two techniques namely structural method and statistical method. Texture can be defined formally in a structural manner where texture is defined formally as a field of a set of basic patterns arranged according to some placement rules. This type of texture is generated by one or more basic local patterns that are repeated in a periodic manner over some image region. This definition is most applicable to deterministic types of textures such as line arrays, checkerboards and hexagonal tilings. Otherwise, a texture can be defined in a statistic manner as a stochastic field of homogenous intensity variations. This type of image texture such as aerial photograph of the earth does not seem to possess an isolated basic pattern nor a dominant repetition frequency and instead they seem to possess some random structure. Figure 1 and Figure 2 are examples of the deterministic and stochastic types of image texture accordingly [3].

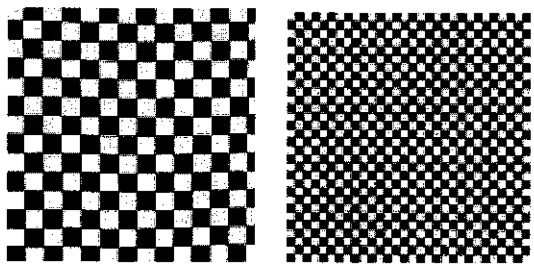


Figure 1 Illustration of deterministic type of images [4].

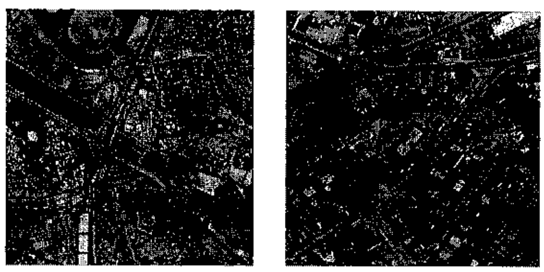


Figure 2 Illustration of stochastic type of images [4].

For this project, statistical method is chosen instead of structural method and the gray level run length method (GLRLM) will be used to perform the second order statistics. Statistical method is chosen because of the advantages offered by it which are first; this type of analysis is good in 'micro textures' (small scale texture) and poor performer in 'macro textures' (large scale texture) and secondly; this method is the more common and less complicated compared to structural method. Furthermore, since structural method is rarely used, the method is not highly developed. For the second order statistic, GLRLM is used for three main reasons. The major reason for the use of the GLRLM is that the length of the runs reflects the size of the texture elements. Furthermore, the GLRLM matrices also contain the information about the alignment of the texture. Finally, the surface slant and the surface tilt of a textured surface are also reflected in the GLRLM matrices. This shows that the GLRM matrices respond to the range and orientation of a textured surface in a direct and meaningful way [4].

Improvements can be done in various ways for image processing technology. A solution to the texture analysis problem will greatly advance the image processing and pattern recognition fields and it will also bring much benefit to many possible applications in the areas of biomedical image processing (cell analysis), industrial automation (quality control) and remote sensing (crop estimation, ecology studies, etc.) [3].

1.2 Problem Statement

Image texture analysis has been widely used in image processing field to analyze any type of digital image to provide information on characteristics of the image. Features relating to the image properties produced by texture measures are extracted, calculated and classified. Different types of images show different texture and pixel distribution pattern in an image. These differences will then be used to classify the properties of the image and identify the type of the image.

1.3 Objectives

For this project, the objectives to be met are as follows:

1. To design the algorithms of texture analysis by using MATLAB for both first order and second order analysis.
2. To verify the algorithms written by simulation and calculation.
3. To be able to analyze the image by using the algorithm developed.
4. To classify the images analyzed by statistical method.
5. To perform an effective implementation of the algorithms and enhance the existing technology in image processing field.

1.4 Scope of study

Figure 3 indicates the scope of study of the project. The main section involves four essential procedures. Specifically, this project is focused on developing the algorithm of first order and second order statistics, verification process, implementing the algorithm and classifying the images. The algorithm is developed by using MATLAB software. In order to prove that the algorithm is accurate, verification is made by calculation and array simulation. Afterwards, the sample image is fed into the system to be simulated. The output represents the characteristics of the image fed. From the features extracted, the image is then classified according to their types.

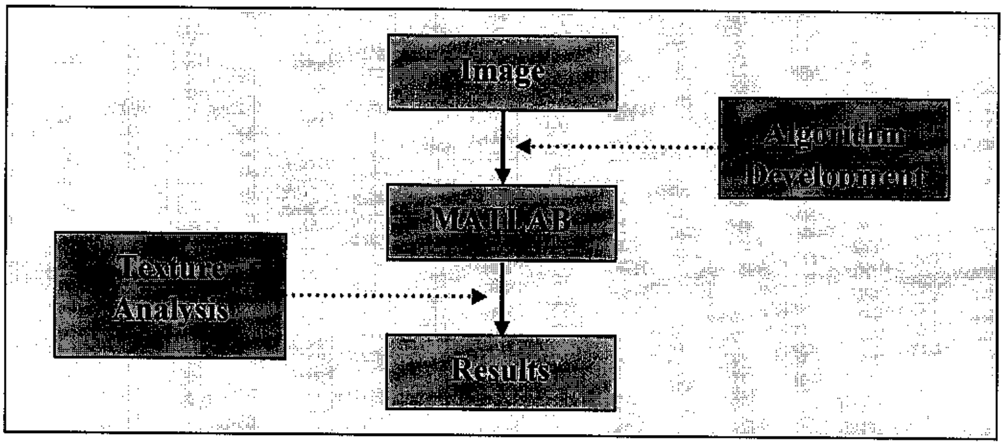


Figure 3 The scope of study of the project.

The project is given a one year time duration to be completed. To organize the project flow, the tasks are divided into two main categories which are:

1. Software development
    i. Part I: Developing and verifying the first order statistic's algorithm by using MATLAB.
    ii. Part II: Developing and verifying the second order statistic's algorithm by using MATLAB.
2. Analyzing and classifying images.

CHAPTER 2
LITERATURE REVIEW

This chapter describes the analytical, critical and objective review of written materials on the project. It provides the background information on the research area and to identify the existing discovery about image texture analysis. This section contains all the relevant theories, hypotheses, facts and data which are relevant to the objective and the findings of the project.

2.1 Introduction to Texture Analysis

Texture is an important characteristic for the analysis of many types of images. It can be seen in all images from multispectral scanner images obtained from aircraft or satellite platforms (which the remote sensing community analyzes) to microscopic images of cell cultures or tissue samples (which the biomedical community analyzes)[5].

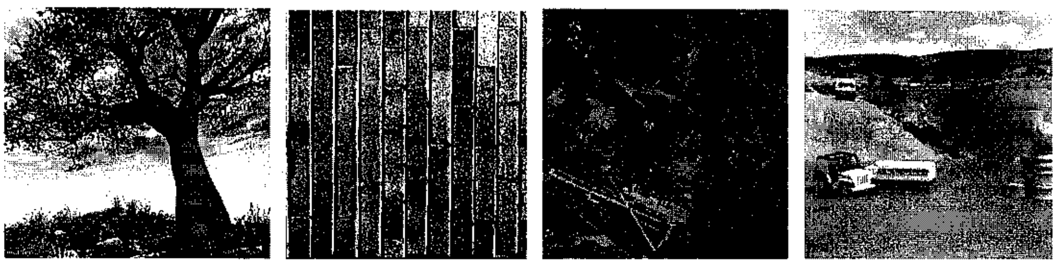


Figure 4 Illustration of various types of image textures [4]

Figure 4 shows various types of textures. Nature gives us so many different types of image texture which varies in many ways. Visual textures are spatially extended visual patterns of more or less accurate repetitions of some basic texture elements, called texels. Each texel usually contains several pixels. Its characteristics and placement can be periodic, quasi-periodic or random. Thus, textures may have statistical or structural properties, or both. Texture features characterize the statistical or structural relationship between pixels (or texels), and provide measures of properties such as contrast, smoothness, coarseness, randomness, regularity, linearity, directionality, periodicity, and structural complexity [6].

In digital image, texture is depicted by spatial interrelationships or spatial arrangement of the image pixels. Visually, these spatial interrelationship or arrangements of image pixels are seen as changes in intensity patterns or grey tones. Thus in automatic analysis, information about texture has to be derived from gray tones of the image pixels. Because of various textures available, several types of texture analysis approach evolved [7].

2.2 Texture analysis Approach

A number of texture analysis methods have been proposed some of which are frequently referred to in the correspondence. Haralick [8] categorized the various proposals into three groups: the statistical techniques, the structural methods and the statistical-structural approaches.

Statistical methods are often based on accumulating second or higher order statistics (matrices), and using feature vectors that describe these probability distributions directly, and therefore describe the image texture only indirectly. Structural methods are based upon an assumption that textures are composed of texels (structural relationship between pixels) which are regular and repetitive. Both texels and placement rules have to be described. Structural-statistical methods characterize the texel by a feature vector and describe the probability distribution of these features statistically [6].

A major disadvantage of almost all of these approaches is that they do not have general applicability which means they cannot be applied to different classes of textures with reasonable success. For instance while the statistical techniques are generally good for micro textures (small scale texture) and are poor performers on macro textures (large scale texture), the reverse is the case for structural techniques. Another disadvantage of some of the existing methods is the computational cost involved, either in terms of memory requirement, computation time or implementation complexity [6].

2.3 Structural Method

The structural approach assumes that a set of primitive units ("pattern") can be easily identified. It then defines the texture as a combination of such primitives according to different placement rules. There are two major problems with this approach. First, it is not so easy to identify the primitives unless the texture is artificial or not too complex. Secondly, the definition that the patterns are repeated according to some pre-specified rules should allow for a random change in the replication process and the same should apply for the patterns themselves [3].

Haralick [8] remarks that tone (primitives) and texture are not independent concepts; when there is little variation of tonal primitives, the dominant property of the image is tone and when there is a wide variation of tonal primitives, the dominant property of that image is texture. Structural method is cognitive rather than a perceptual approach and it would usually rely on a prior knowledge. All taken into consideration, the structural approach is not yet widely used and therefore, this approach is not very highly developed. Hence, for this project statistical approach is chosen for the analysis [3].

2.4 Statistical Method

The statistical ("impressionistic") approach extracts a set of parameters ("features") from a given image. The parameters are then used as the input features for classification using the well known techniques of statistical pattern recognition. The parameters are derived over the space or frequency domain. Some of the main statistical methods are mentioned next. The gray level difference method estimates the probability density function for difference taken between picture function values. The spatial gray level dependence method estimates the joint gray levels located at a distance "d" and an angle "α". The gray level difference and the joint gray level distributions are also known as the first and second order statistics respectively. The second order statistics are usually tabulated as co-occurrence matrices [3].

Furthermore, the first order statistics are embedded in second order statistics as marginal density functions. Thus we cannot find two pictures with identical second order statistics and different first order statistics. Usually a reduction in the number of gray levels via histogram equalization techniques is a necessary processing step for computational efficiency. Common features extracted from above statistics are the mean, variance (spread of distribution), coarseness, skewness (tiltness of distribution) and Kurtosis (Sharpness of distribution). The gray level run length method estimates the length of identical runs, where an identical run is defined as a set of connected pixels having the same gray level [3].

The first and second order statistics are by far the most used statistical methods for texture discrimination. One problem with these methods is defining the distance "d" and the angle "α" which would fully specify the method. Davis [9] pointed out that a statistical method relates both the partition of an image into cells and subsequently with the assignment of gray levels to the cells. The first and second order statistics as defined by Haralick [8] mainly related with the assignment aspect.

2.4.1 First Order Statistics

First order statistic is not a great value in providing texture information but they are conceptually simple and may be used to pre-process the signal before applying second order statistics. The properties frequently used are the first four moments of the image. These are obtained from the histogram of the image [8].

Let b be a random variable representing the pixel intensity, $0 \leq b \leq L-1$, where L is the number of distinct grey level; and let $P(b)$ be the corresponding histogram of the image defined such that if $N(b)$ is the number of pixels of intensity b in the image and M is the total number of pixels in the image then [7]:

$$P(b) = \frac{N(b)}{M} \tag{2.1}$$

The first four moments are then defined as:

1. Mean $$m = \sum_{b=0}^{L-1} bP(b) \tag{2.2}$$

The mean gives the average grey level of the image.

2. Variance $$\sigma^2 = \sum_{b=0}^{L-1} (b-m)^2 P(b) \tag{2.3}$$

The variance is of the significance in texture description. A texture with a small variance represents one in which the image tends to be relatively smooth. A measure of the coarseness of a texture may be defined in terms of the variance as:

$$Coarseness = 1 - \frac{1}{1+\sigma^2} \tag{2.4}$$

3. Skew $$skew = \frac{1}{\sigma^3} \sum_{b=0}^{L-1} (b-m)^3 P(b) \tag{2.5}$$

Skewness is a measure of the symmetry of the histogram.

4. Kurtosis $$Kur = \frac{1}{\sigma^4} \sum_{b=0}^{L-1} (b-m)^4 P(b) \tag{2.6}$$

Kurtosis indicates the flatness of the histogram.

Other first order statistics are:

5. Energy $$eng = \sum_{b=0}^{L-1} \left[P(b)^2\right] \tag{2.7}$$

Large values of energy correspond to homogenous regions.

6. Entropy $$etp = \sum_{b=0}^{L-1} P(b) \log\left[P(b)\right] \tag{2.8}$$

Large values of entropy imply a more uniform distribution of grey levels.

7. Median $$med = k \text{ when } \sum_{b=0}^{k-1} P(b) = \sum_{b=k}^{L-1} P(b) = \frac{1}{2} \tag{2.9}$$

The median gives the value of the middle grey level.

8. Mode $mod = k$ when $P(k) \geq P(b)$ for $0 \leq b \leq L-1$ (2.10)

The mode gives the most frequently occurring grey level and is most useful when there is a single sharp maximum in the histogram.

Texture measures using the histogram only do not take the neighborhood relations between pixels into consideration. To do this, second order statistics need to be used [7].

2.4.2 Second Order Statistics

In this project, the gray level run length method (GLRLM) is used for second order statistic. This approach is based on computing the number of gray level runs of various lengths. It characterizes coarse textures as having many pixels in a constant gray tone run and fine textures as having few pixels in a constant gray tone run. A gray level run is actually a set of linearly adjacent picture points having the same grey level value. The length of the run is the number of picture points within the run [10].

GLRLM is actually the probability of several connected co linear pixels so close in gray level that they form "gray level runs". A gray level run is a set of consecutive, collinear picture points having the same gray level value. The length of the run is the number of pixels in a run. All the features of GLRLM contain run length or gray level and never have both of them at the same time. Stated below are some of the properties of GLRLM.

1. It does not capture the true shape aspects of texels.
2. Discard information on contrast between gray levels.

The element $r'(i,j|\theta)$ of the gray level run length matrix

$$R(\theta) = [r'(i,j|\theta)] \tag{2.11}$$

specifies the estimated number of times a picture contains a run length j for gray level i in the angle θ direction. For a given picture, a set of the gray level run length matrices is computed for runs with any given direction. However, only four gray level run length matrices $R(\theta), \theta = 0^{\circ}, 45^{\circ}, 90^{\circ}, 135^{\circ}$, are computed for each picture. From each of these matrices, five features are computed. They are as follows:

1. Short Run Emphasis $$RF(R(\theta)) = \frac{1}{T_R} \sum_{i=0}^{N_G-1} \sum_{j-1}^{N_R} \frac{r'(i,j|\theta)}{j^2} \qquad (2.12)$$

2. Long Run Emphasis $$RF_2(R(\theta)) = \frac{1}{T_R} \sum_{i=0}^{N_G-1} \sum_{j=1}^{N_R} j^2 r'(i,j|\theta) \qquad (2.13)$$

3. Gray Level Distribution $$RF_3(R(\theta)) = \frac{1}{T_R} \sum_{i=0}^{N_G-1} \left[\sum_{j=1}^{N_R} r'(i,j|\theta) \right]^2 \qquad (2.14)$$

4. Run Length Distribution $$RF_4(R(\theta)) = \frac{1}{T_R} \sum_{j=1}^{N_R} \left[\sum_{i=0}^{N_G-1} r'(i,j|\theta) \right]^2 \qquad (2.15)$$

5. Run Percentages $$RF_5(R(\theta)) = \frac{1}{T_P} \sum_{i=0}^{N_G-1} \sum_{j=1}^{N_R} r'(i,j|\theta) \qquad (2.16)$$

where N_G is the number of gray levels, and N_R is the number of run length in the matrix

$$T_R = \sum_{i=0}^{N_G-1} \sum_{j=1}^{N_R} r'(i,j|\theta) \qquad (2.17)$$

and T_P is the number of points in the picture.

Each of the features is actually a distinguished primitive characteristic or attribute of an image field. After normalizing the gray level run length matrices, numerical measures are then extracted. They can be used to characterize the image texture statistically.

CHAPTER 3
METHODOLOGY/PROJECT WORK

Methodology of the project is the branch of philosophy that analyzes the principle and procedures of this project. This chapter outlines the project stages individually by each stage, the project flow generally, the implementation of the statistical analysis method in particular, the sample of images used in the analysis and tools which are relevant to this project.

3.1 Project Design Stage

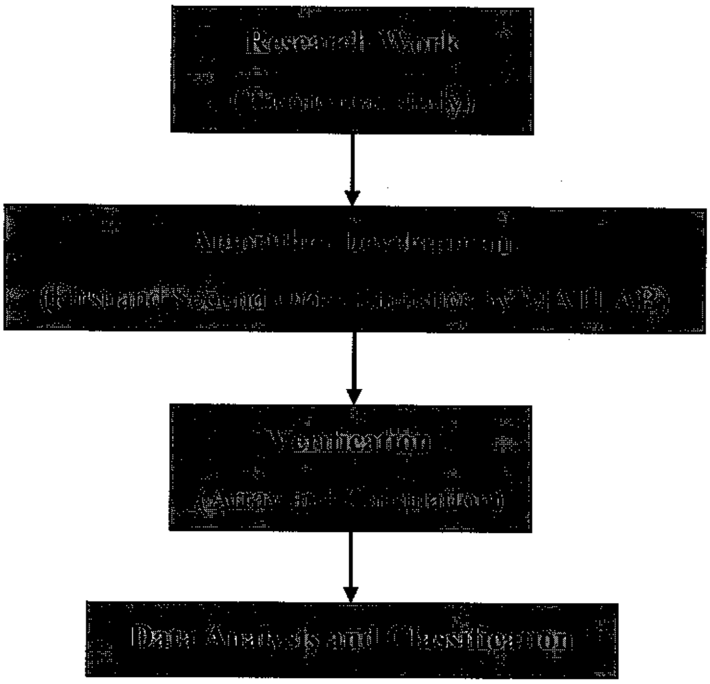


Figure 5 Block diagram of the project stages.

Figure 5 illustrates that the project stage is broken down to four sub stages which are first; research, where all data and information supporting the project scope is compiled and studied. The second stage is the development of the algorithm, where the first order and the second order statistics are developed. After being developed, all algorithms are being verified through calculation and array simulation and lastly followed by data analysis and classification.

3.2 Implementation of Statistical Analysis Method

Figure 6 indicates the process flow of the statistical analysis implementation. Image will be fed into MATLAB program to be converted into a set of data which contains a set of numbers in matrix form. This data represent the histogram of the image plotted by using MATLAB program. From this histogram, properties such as total number of pixels distributed can be obtained and used in both first order and second order statistics to analyze the image. The features of each image will be extracted, analyzed and classified. Lastly before analyzing the images, the results of the first order and the second order statistics are represented in graphical forms to be concluded.

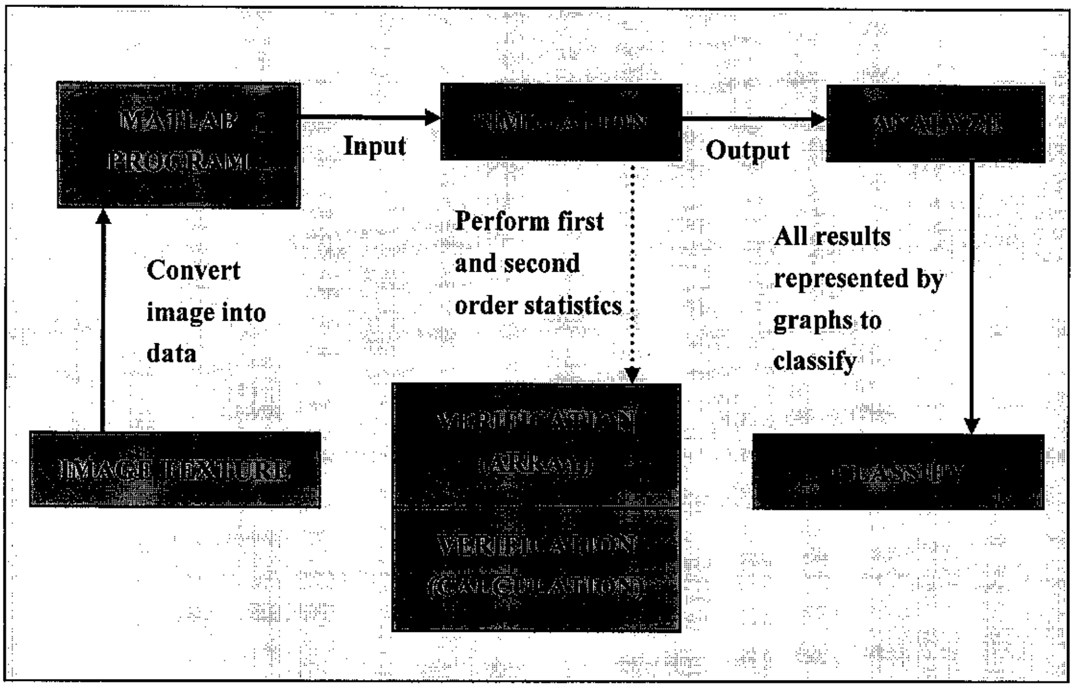


Figure 6 Block diagram of image texture analysis implementation

3.2.1 First Order Statistics

In the first order statistics, the first step taken is to identify the characteristics involved to analyze the images. The characteristics are represented by a set of equations as stated in Chapter 2. These equations carry the meanings of each image.

From the mathematical equation, the first order algorithm is developed and verified before image analysis is applied.

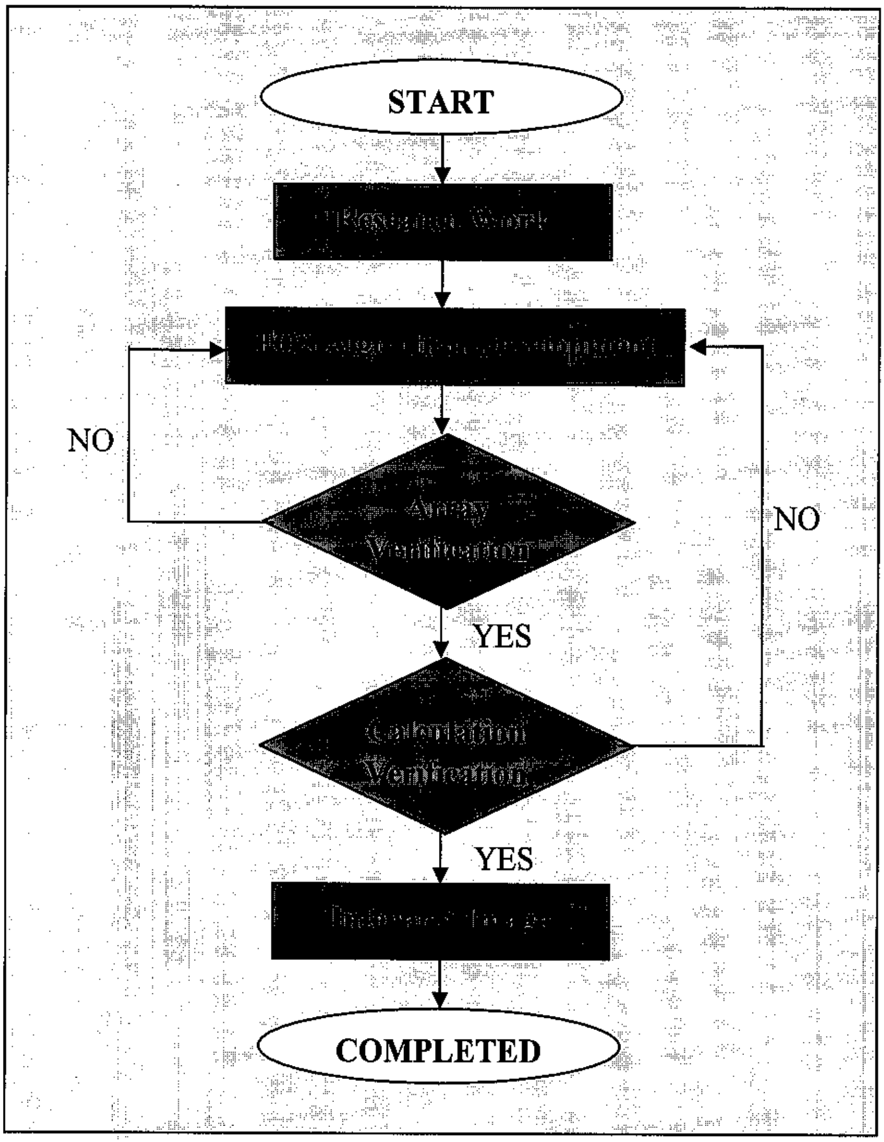


Figure 7 Block diagram of the first order statistics implementation

Figure 7 explains the flow of the first order statistics implementation process from research up until the compilation of the results.

3.2.1.1 Algorithm Development

The identified problem is analyzed at this stage. Figure 7 illustrates a captured image of MATLAB M-file Editor implementation. A strong basis in MATLAB familiarization is needed to proceed from this stage. For the first order statistic, the algorithm is developed by using MATLAB M-file Editor.

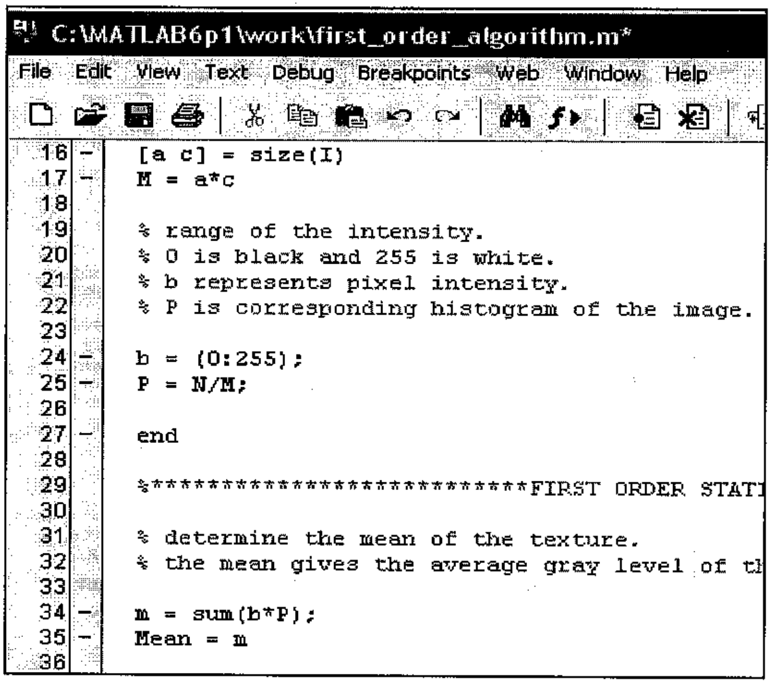


Figure 8 Captured image of MATLAB M-file Editor

3.2.1.2 Verification

Verification of the algorithms comes after the algorithm development. During this stage, the algorithm written by using MATLAB is verified by using two different methods. The first method is where the verification process uses different sets of array that will be fed into the algorithms and produce a set of answers. These answers of each property will be verified again theoretically, which is the second method. Manual mathematics calculation is done to prove the array output to be correct. The results from each simulation are then tabulated and the percentage of error is calculated.

3.2.1.3 Data Analysis and Classification

By the end of the project, the simulation results will be analyzed and a comparison study will be conducted between the results obtained by algorithm written by MATLAB and the verification results. In this last stage, the features obtained for the image is studied and analyzed. These features will tell the characteristics of each image. When the classification stage is done, the project proceeds to the second order statistics.

3.2.2 Second Order Statistics

For the second order statistics, the method used is GLRLM approach. This method is mainly based on the run length approach, which means it uses the same statistical method as the first order to extract the textural features from a set of gray level run length matrices (GLRLM's) of the images. For a given image, GLRLM's is computed for runs with any given direction. However, only four commonly used directions which are 0°, 45°, 90° and 135° are selected in computing the run lengths. The matrix element (i.j) specifies the number of times that the image contains a run length j as well as having gray level i in the given direction [11].

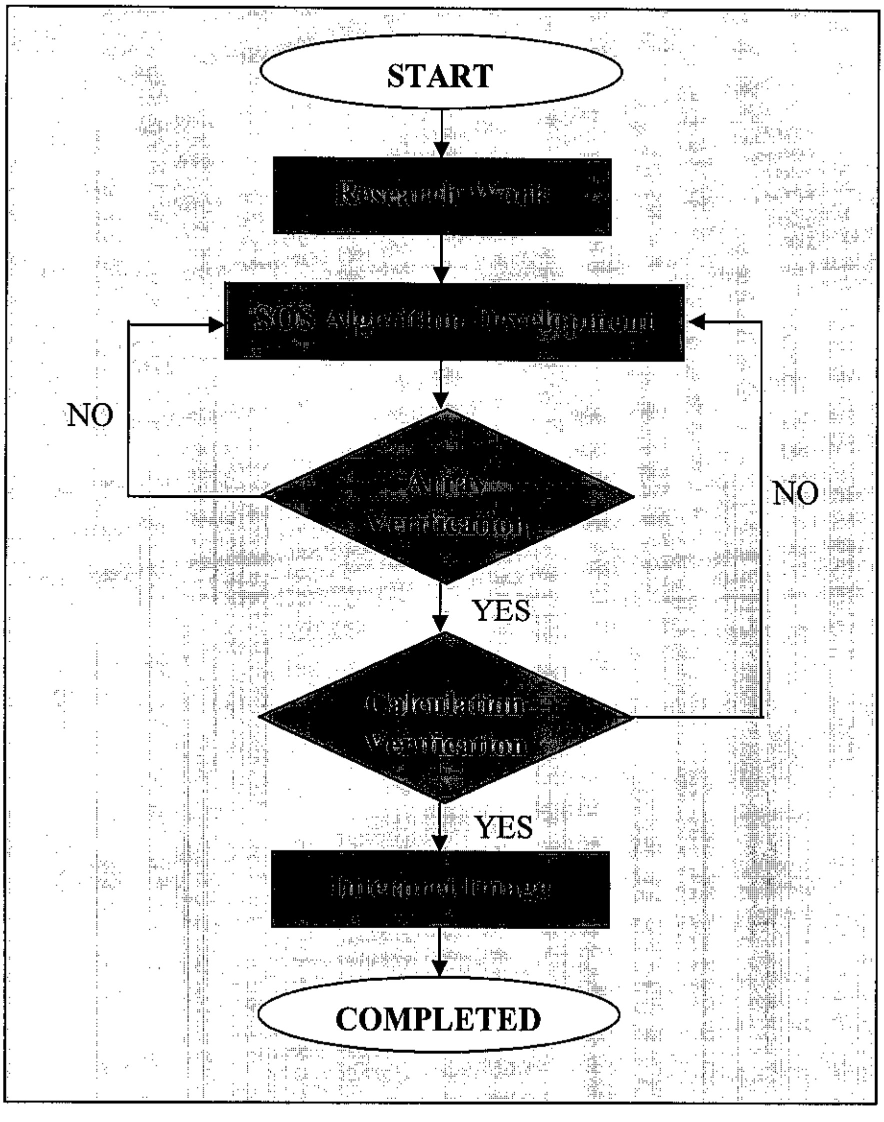


Figure 9 Block diagram of the second order statistic implementation

Figure 9 exhibits how the second order statistics is being carried out. From the diagram, the first step is to develop the algorithms; then followed by algorithm verification and the last step is to analyze and to classify the image.

3.2.2.1 Algorithm Development

The algorithm is developed by computing the GLRLM's based on the equations in Chapter 2. The algorithm is written by using MATLAB software. M-file Editor provides a tool in developing the algorithm as well as to simulate the algorithm written. Since GLRLM approach involves relationships between neighboring pixels, the algorithm is needed to run in a loop to ensure all pixels are analyzed. Verification is then made to verify the results of the image analysis.

3.2.2.2 Verification

Same as the first order algorithm, the verification is done by using array as image and calculation. The percentage of error for both results is calculated and compared.

3.2.2.3 Data Analysis and Classification

All results are tabulated and studied to classify the image. From the features extracted, the type of each image analyzed is obtained.

3.3 Sample Images

Images chosen are based on three types of images which are Brodatz textures, aerial images and computer graphics images. For this simulation, thirty different images for every image type will be fed as the input for the algorithm and all thirty images are having the same image size which is chosen to be 8 bits/pixels (black and white images or monochrome) and 512 x 512 pixels in size.

3.3.1 Brodatz Textures

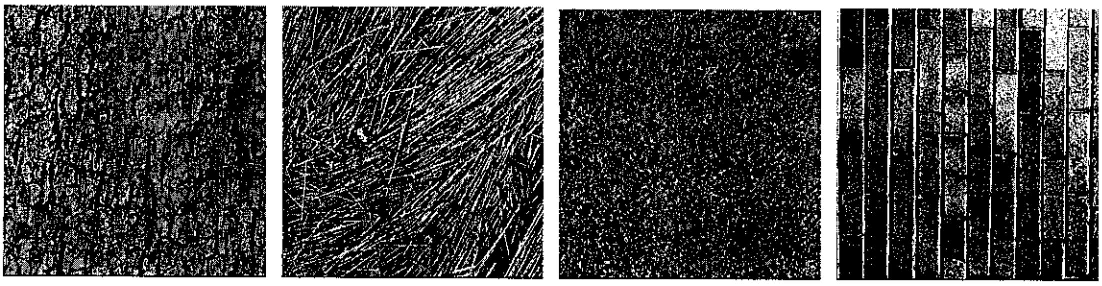


Figure 10 Example of Brodatz textures [20]

The first type is Brodatz texture. Figure 10 shows some examples of Brodatz textures. These images are obtained from *The USC-SIPI Image Database.* The USC-SIPI image database is a collection of digitized images. It is maintained primarily to support research in image processing, image analysis, and machine vision. The images are in TIFF file format as supported by MATLAB. TIFF stands for 'Tagged Image File Format', one of the most common graphic file formats for line-art and photographic images. A TIFF file always consists of pixels; it can store information at any resolution the user requests and can include color or black and white data. Brodatz textures often are based on natures and surroundings such as grass, brick wall, blood cells and skin of the trees.

3.3.2 Aerial Images

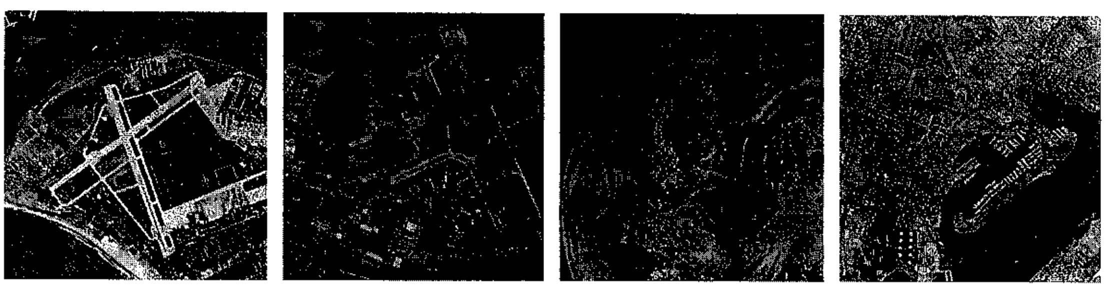


Figure 11 Example of Aerial images [20]

Figure 11 illustrates four samples of aerial type images. Aerial can be defined as in or belonging to the air or operating (for or by means of aircraft or elevated cables) in the air; "aerial particles"; "small aerial creatures such as butterflies"; "aerial warfare"; "aerial photography"; "aerial cable cars" [11]. Thus, aerial images are a photograph of part of earth's surface usually taken from an airplane. Thirty images of the same type are analyzed. These images will give a range of values for each features extracted from them. Classification of images is done based on the range value obtained.

3.3.3 Computer Graphic Images

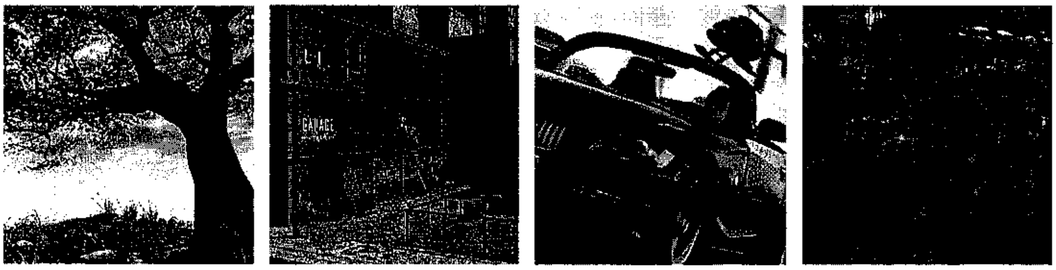


Figure 12 Example of Computer Graphic images [4]

Figure 12 illustrates four examples of computer graphic images. Computer graphic (CG) is the field of visual computing, where one utilizes computers both to generate visual images synthetically and to integrate or alter visual and spatial information sampled from the real world [12]. As other types of images, thirty sample images from computer graphic are analyzed in this project.

3.4 Tools Identification

In this project MATLAB plays a big part to get the results. Firstly, MATLAB is used to read image and convert it into a set of data and simulate the histogram which represents the image. MATLAB is also used in the verification process which goes through two different methods; first by using array simulation and secondly by mathematics calculation. Familiarization with the software helps in terms of saving time and producing good results.

Besides MATLAB, Microsoft Office Picture Manager is used to edit the image into selected size. Another tools used in preparing the images is IrfanView Software. This software is used to change any colored image into monochrome image.

3.5 Tasks Accomplished

For the first order statistics, all the tasks have been accomplished accordingly. This includes the algorithm development, algorithm verification, image analysis implementation and lastly data analysis and classification. All results and data are compiled in Chapter 4 and all discussions are also provided in detail in the same chapter.

As for the second order statistic, the algorithm is developed but is having some unresolved errors which prevents the project to proceed. However, the approach implementation is discussed in this paper and the expected results are mentioned in Chapter 4. This project should run smoothly when the errors of the second order statistics algorithm are solved.

CHAPTER 4
RESULTS AND DISCUSSION

This chapter presents the findings and outcome of the project work. All the gathered data of the project work is presented and tabulated in this chapter. All findings are then discussed and analyzed through this chapter. The findings will be started with the first order statistics implementation and followed by the second order statistics implementation. Each part is sub divided into verification, results and data classification.

4.1 First Order Statistics Implementation

4.1.1 Algorithm Development

The first order statistics algorithm is successfully developed. For further revision, the algorithm written can be referred in *Appendix E.*

4.1.2 Verification

As mentioned, the algorithm developed needs to be verified before the images can be analyzed by using the same algorithm for precise results. Table 1 and Table 2 show the verification done by using array simulation and mathematical calculation.

Table 1 Tabulated verification results by using array

Array	Mean	Variance	Coarseness	Skewness	Kurtosis	Energy	Entropy
1	12	604	0.9983	-0.4123	0.1711	4	0.6021
2	48	23264	1.0000	-0.2893	0.0838	16	2.4083
3	75	73630	1.0000	-0.2589	0.0671	25	3.4949

Table 2 Tabulated verification results by using calculation

Array	Mean	Variance	Coarseness	Skewness	Kurtosis	Energy	Entropy
1	12	604	0.9983	-0.4123	0.1711	4	0.6021
2	48	23264	1.0000	-0.2893	0.0838	16	2.4083
3	75	73630	1.0000	-0.2589	0.0671	25	3.4949

Table 3 Error percentage between calculation results and array simulation

Array	Percentage of error (%)
1	0.00
2	0.00
3	0.00

Table 3 indicates the differences between the two results are put as the percentage of error. A low percentage of error indicates a higher accuracy of the algorithm. Thus, the algorithm is verified.

4.1.3 First Order Statistics by MATLAB

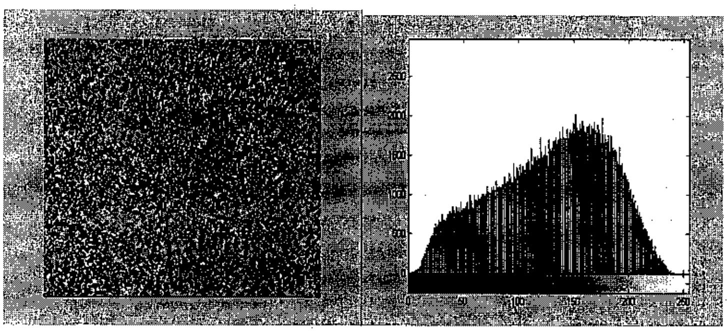


Figure 13 Example of input image and its histogram

As shown in Figure 13, each image is represented by a histogram. Histogram represents the pixel distribution in an image according to the pixel intensity. In this analysis, the range of the histogram is from zero (0) to 255. Zero represents a black and 255 represents white. This range is a default interval for monochrome image or gray scale image. Darker image means the majority of the pixels has a high intensity or vice versa.

Table 4 Tabulated average FOS value for each type of image

Features	Types of Image		
	Brodatz	**Aerial**	**Computer Graphic**
Mean	144.287	151.767	119.7319
Variance	3351.8252	919.1	3727.5219
Coarseness	0.9992	0.9983	0.9996
Skew	-0.6306	0.0857	0.0984
Kurtosis	4.9033	2.84	2.3075
Energy	0.0161	0.0125	0.0086
Entropy	-2.0152	-1.9923	-2.2602
Median	148.3667	152.33	115.2667
Mode	151.0333	153.43	134.9

Table 4 indicates the tabulated average values of first order statistics for three types of image. Values of each features for each image is attached in *Appendix H, Appendix I and Appendix J* for reference. From the complete table, only average values of each feature are extracted to produce the FOS range for all three types of images. Image classification is performed based on the ranged formed in Table 5.

Table 5 Tabulated FOS range for each type of image

Features	Types of Image		
	Brodatz	**Aerial**	**Computer Graphic**
Mean	111.3804 to 212.8173	111.909 to 183.6457	81.2447 to 216.1798
Variance	236.0116 to 9867.8	259.4701 to 1799.4	254.5578 to 8319.5
Coarseness	0.9958 to 0.9999	0.9962 to 0.9996	0.9961 to 0.9999
Skew	-2.5270 to -0.0005	-3.623 to 1.3156	-1.4653 to 1.1308
Kurtosis	1.4366 to 40.6608	1.6496 to 6.516	1.5375 to 6.9079
Energy	0.0053 to 0.1388	0.00126 to 0.0185	0.0043 to 0.0645
Entropy	-2.3090 to -1.7017	-2.2312 to -1.7727	-2.3498 to -1.7377
Median	110 to 219	110 to 187	58 to 219
Mode	0 – 255	55 to 215	0 - 255

Figure 14 until Figure 22 shows the values of each features represented in graph form. The values represent each characteristics of all thirty image selected for all three types of images.

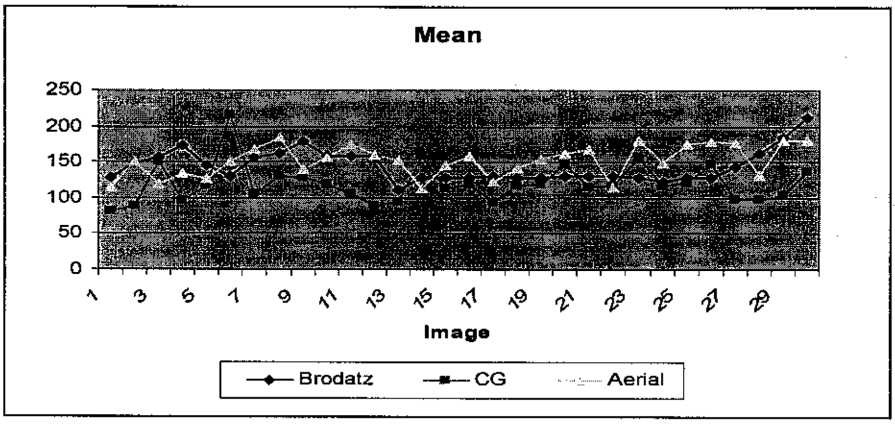


Figure 14 Graph representation of Mean value

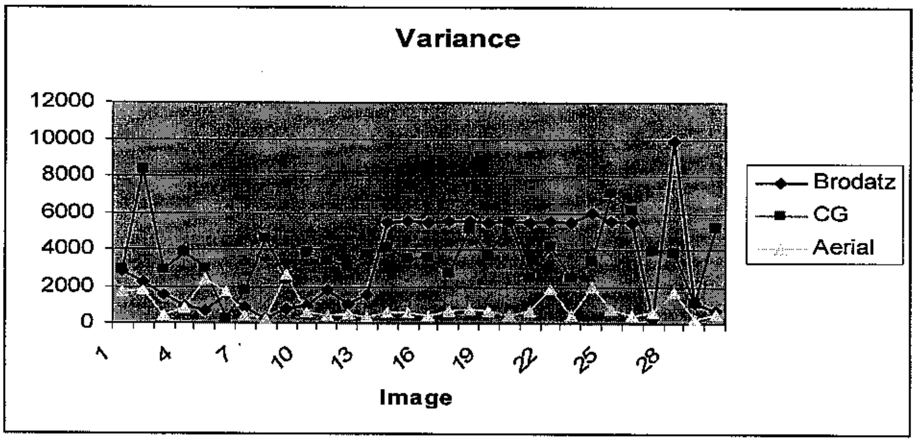


Figure 15 Graph representation of Variance value

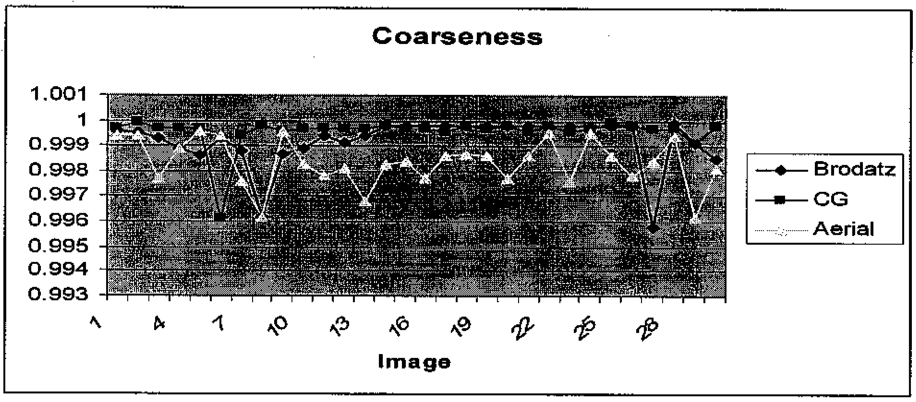


Figure 16 Graph representation of Coarseness value

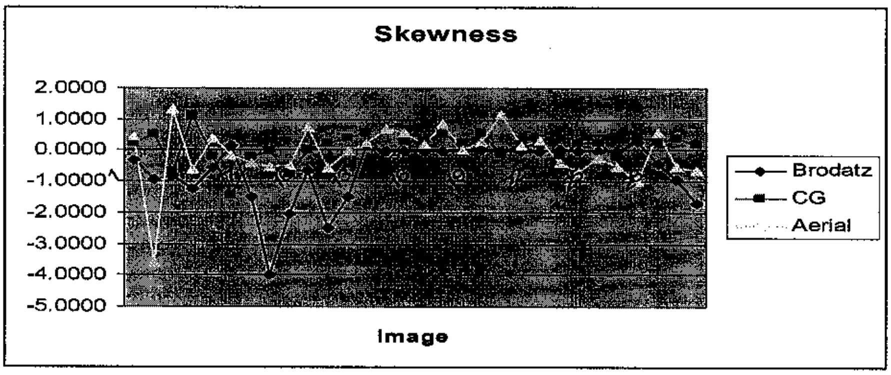


Figure 17 Graph representation of Skewness value

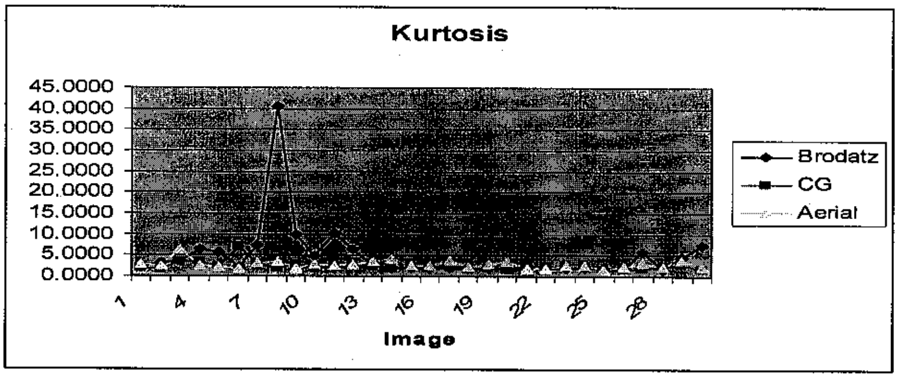


Figure 18 Graph representation of Kurtosis value

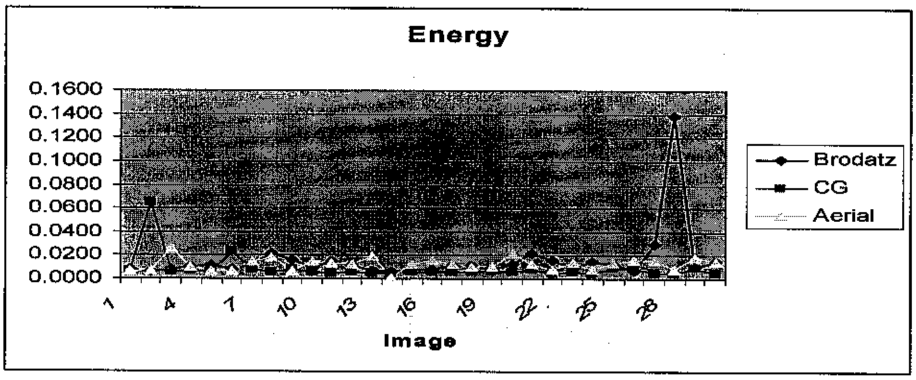


Figure 19 Graph representation of Entropy value

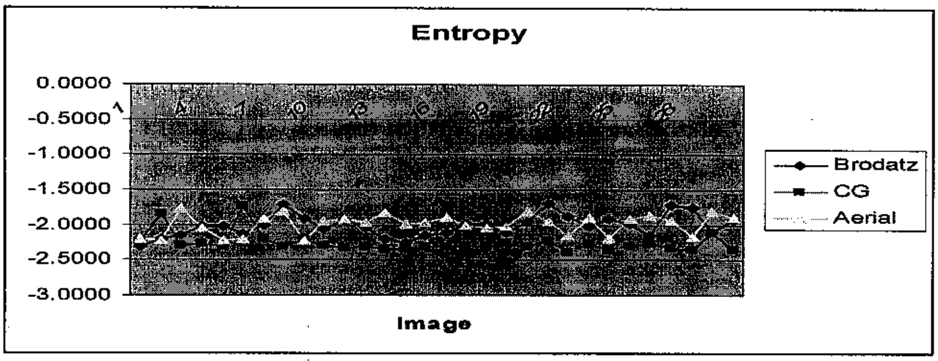


Figure 20 Graph representation of Energy value

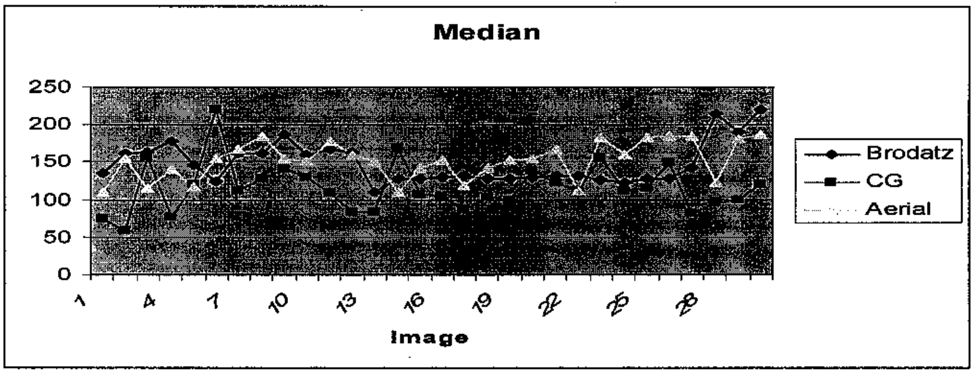


Figure 21 Graph representation of Median value

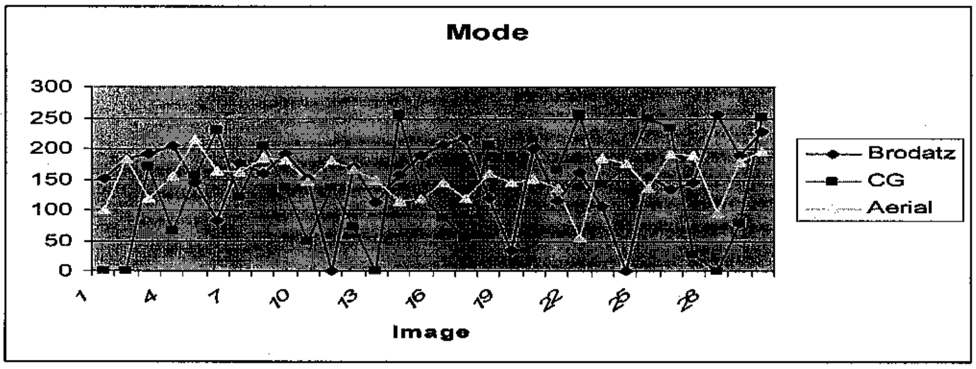


Figure 22 Graph representation of Mode value

4.1.4 Data Analysis and Classification

When a set of values in an image has a sufficiently strong central tendency, that is a tendency to cluster around some particular value, then it may be useful to characterize the set by a few numbers that are related to its moments or features. In this project, there are nine features extracted from each image as shown in figures above.

Mean estimates the value around which central clustering of the pixel occurs according to their intensity. For a histogram distribution with a very broad 'tails', the mean may converge poorly or not at all as the number of sampled points is increased. High mean value represents a low intensity image and low mean value indicates a high intensity image.

Variance however characterizes the width or variability of the histogram distribution. A texture with a small variance represents one in which the image tends to be relatively smooth. An opposite features of it is represented by coarseness which measures how coarse the image is.

The skewness characterizes the degree of symmetry of a distribution around its mean. While mean is dimensional that is having the same units as the measured quantities of pixels, the skewness is a conventionally defined in such a way as to make it non-dimensional. It is a pure number that characterizes only the shape of the histogram distribution.

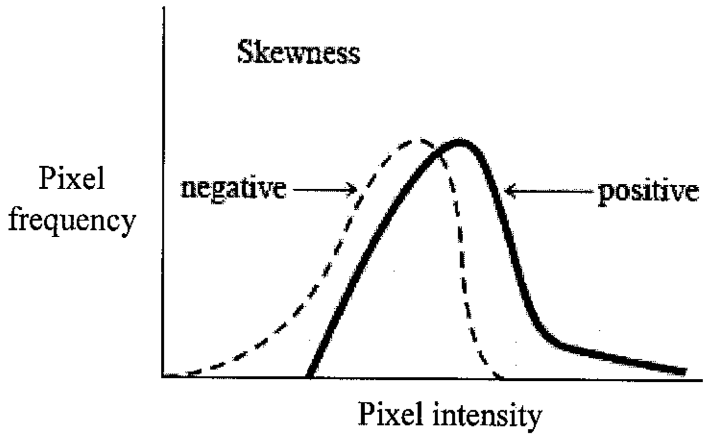


Figure 23 Skewness distribution

Figure 23 explains that a positive value of skewness signifies a distribution with an asymmetric tail extending out towards low pixel intensity (255 which represents white). When an image has zero skewness, the distribution is in fact symmetrical.

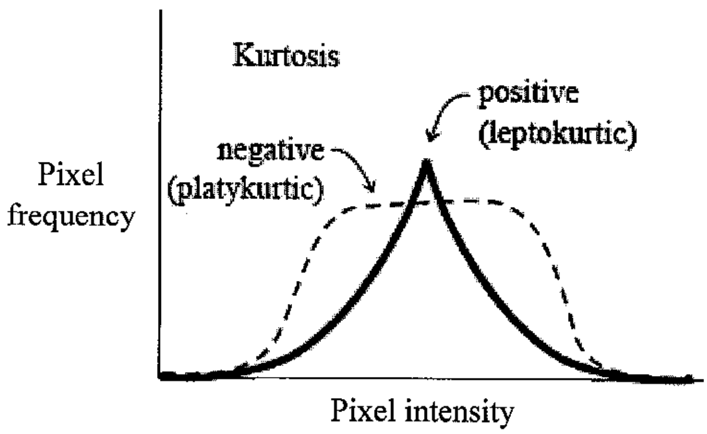


Figure 24 Kurtosis representation

Figure 24 illustrates the shape of the histogram which is having a positive and negative value of kurtosis. The kurtosis is also a non-dimensional quantity. It measures the relative peakedness or the flatness of a distribution to a normal distribution. A distribution with a positive kurtosis is termed *leptokurtic*; the outline of a mountain peak as an example. However, a distribution with negative kurtosis is termed *platykurtic*; the outline of a loaf of bread for an example. Another shape of kurtosis is termed *mesokurtic* which represents an in-between distribution [13].

Median gives the value of the middle gray level in the distribution and mode gives the most frequently occurring gray level in a distribution. The mode is useful primarily when there is a single sharp maximum point in the histogram.

4.2 Second Order Statistics Implementation

4.2.1 Algorithm Development

As applied to develop the first order statistics, the algorithm of second order statistics is also written by using MATLAB. The structure of the algorithm is attached in *Appendix F* for reference.

4.2.2 Verification

Verification is done in mathematical approach. A set of array is selected and the features are calculated for all four directions.

4.2.3 GLRLM Approach

Since no image has been simulated yet, an array is considered as image at this stage. Figure 25 represents the sample array used.

1	1	2	2	2
1	1	2	2	2
1	3	3	3	3
3	3	4	4	4
3	3	4	4	4

Figure 25 Array representing an image

The pixels intensity located in each coordinate in the array is analyzed and arranged back into a new table consisting run length data and gray level. The table is constructed for all four directions and represented in Figure 26. From these tables, data for g(i), r(j) and S are extracted and used as inputs for the equations as stated in Chapter 2.

Run length

Gray level		1	2	3	4	g(i)
	1	1	2	0	0	3
	2	0	0	2	0	2
	3	0	2	0	1	3
	4	0	0	2	0	3
	r(j)	1	4	4	1	S = 10

P(i.j) | 0°

Run length

Gray level		1	2	3	4	g(i)
	1	0	1	1	0	2
	2	0	3	0	0	3
	3	3	1	1	0	5
	4	0	3	0	0	3
	r(j)	3	8	2	0	S = 13

P(i.j) | 90°

Run length

Gray level		1	2	3	4	g(i)
	1	1	2	0	0	3
	2	2	2	0	0	4
	3	2	1	1	0	4
	4	2	2	0	0	4
	r(j)	7	7	1	0	S = 15

P(i.j) | 45°

Run length

		1	2	3	4	g(i)
Gray level	1	3	1	0	0	4
	2	2	2	0	0	4
	3	6	1	0	0	7
	4	2	2	0	0	4
	r(j)	13	6	0	0	S = 19

P(i.j) | 135°

Figure 26 Table of GLRLM element values of four orientations

4.2.4 Data Analysis and Classification

From research done on the subject, it shows that the average run length values change almost linearly with the perception distance. This indicates that the run length matrix responses to the perception distance change directly. After all computational of the GLRLM's, the features can be extracted. With these features, the image can be classified in the texture classification part. The features are short run emphasis (SRE), long run emphasis (LRE), gray level distribution (GLN), run length distribution (RLN) and run percentages (RP).

Short run emphasis is used to measure the distribution of short runs. The SRE is highly dependent on the occurrence of short runs and is expected large for fine textures. Long run emphasis measures distribution of long runs. The LRE is highly dependent on the occurrence of long runs and is expected large for coarse structural textures. The gray level distribution however measures the similarity of the length of runs through out the image. The RLN is expected small if the run lengths are alike through out the image and the gray level distributions measures the similarity of gray level values through out the image. The GLN is expected small if the gray level values are alike through out the image. Lastly, the run percentage measures the homogeneity and the distribution of runs of an image in a specific direction. The RP is the largest when the length of runs is 1 for all gray levels in specific direction. Other extra features can be referred in *Appendix M*.

CHAPTER 5
CONCLUSION

This chapter highlights the summary and the most significant findings of the project. Together with the conclusion derived from the project work, future recommendation is also described in this chapter.

5.1 Summary

The first order and the second order statistics have been successfully developed in MATLAB. Through this project, it is learned that the statistical method developed are capable in discriminating image.

5.2 Future Recommendation

As future work, further investigation can be done on the run-length statistic for to determine the most relevant features among the five features presented in this paper. This investigation will allow the removal of the highly correlated features, while keeping the most important ones.

A test to this approach on CT studies can be done in future for comparison and classification on medical imaging field. As a final goal, successful use of the texture features presented in this paper to develop an automated and reliable system for analysis and classification for medical images can be revised and developed.

REFERENCES

[1] Final Year Project Committee, Electrical & Electronics Department, University of Technology PETRONAS, Bandar Sri Iskandar, 31750 Tronoh, Perak, Malaysia, October 2005.

[2] Robert M. Haralick. K Shanmugam and Its'hak Dinstein, "Textural Features for Image classification, IEEE Transaction on system", vol.SMC3, No.6, pp. 610-621, November 1973

[3] Harry WECHSLER, Dept. of Electrical Engineering and Computer Science, University of Wisconsin, Milwaukee, WI 53211, USA, 26 November 1979.

[4] http://artworks.avalonweb.net/gallery/gallery_main.php

[5] R. M. Pickett, "Visual analyses of texture in the detection and recognition of objects", in *Picture Processing and Psychopictorics*, Lipkin and Rosenfeld, Eds. New York: Academic Press, pp. 289-308, 1970.

[6] Fritz Albregtsen, Department of Informatics, University of Oslo, Selected Themes from Digital Image Analysis: *Statistical Texture Analysis Static or Adaptive*, INF 5300, V-2004, 18 February 2004.

[7] Moses Amadasun, Member IEEE, and Robert King, "Textural Features Corresponding to Textural Properties", *IEEE Trans. on Systems, Man and Cybernetics*, Vol. 19, No. 5, September/October 1989.

[8] Robert M. Haralick, "Statistical and Structural Approaches to Texture", IEEE vol.67, No.5, May 1979 pp.786-804.

[9] L. Davis, S. Johns and J. K. Aggarwal, "Texture analysis using generalized co-occurrence matrices", IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 1, No. 3, July 1979, pp. 251-259.

[10] M. M. Galloway, "Texture analysis using gray level run lengths", Computer Graphics Image Processing, Vol. 4, pp. 172-179, June 1975.

[11] http://www.google.com dictionary search: Define aerial.

[12] http://www.google.com dictionary search: Define computer graphic.

[13] Horng-Hai Loh, Jia-Guu Leu, "The Analysis of Natural Textures Using Run Length Features", IEEE Trans. On Industrial Electronics, Vol. 35, No. 2, May 1988.

[14] M. Tuceryan and A.K. Jain, "Texture Analysis", Chapter 11 in *The Handbook of Pattern Recognition and Computer Vision*, C.H. Chen, L.F. Pau, P. S. P. Wang (eds) World Scientific Publishing Co., pp. 235-276, 1993.

[15] L. Van Gool, P. Dewaele and A. Oosterlinck, Texture Analysis Anno 1983, *Computer Vision, Graphics and Image Processing*, Vol. 29, pp. 336-357, 1985.

[16] A. K. Jain and F. Farrokhnia, Unsupervised Texture Segmentation Using Gabor Filters, *Pattern Recognition*, Vol. 24, No. 12, pp. 1167-1186, 1991.

[17] D. Blostein, N. Ahuja, Shape from texture: Integrating texture-element extraction and surface estimation, *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11(12), pp. 1233-1251, 1989.

[18] Kalle Karu, "Is there any Texture in the Image?", Dept of Computer Science, Michigan State University, East Lansing, MI 48824.

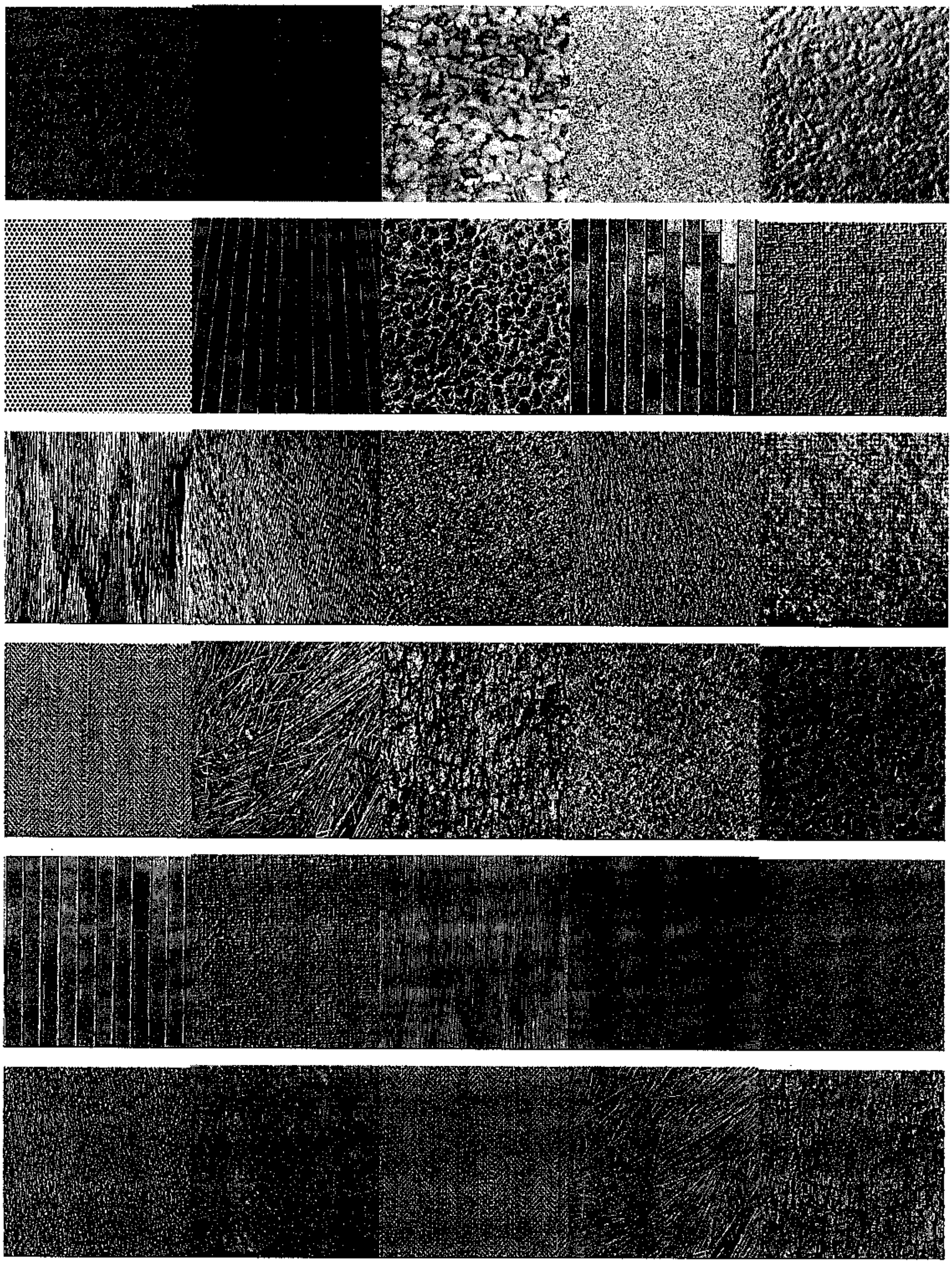
[19] Richard W. Conners, "A Theoretical Comparison of Texture Algorithms, IEEE Transactions on Pattern Analysis and Machine Intelligence", vol.PAMI-2, No.3, May 1979

[20] http://sipi.use.edu/database.

APPENDICES

APPENDIX A

SAMPLE OF BRODATZ TEXTURE



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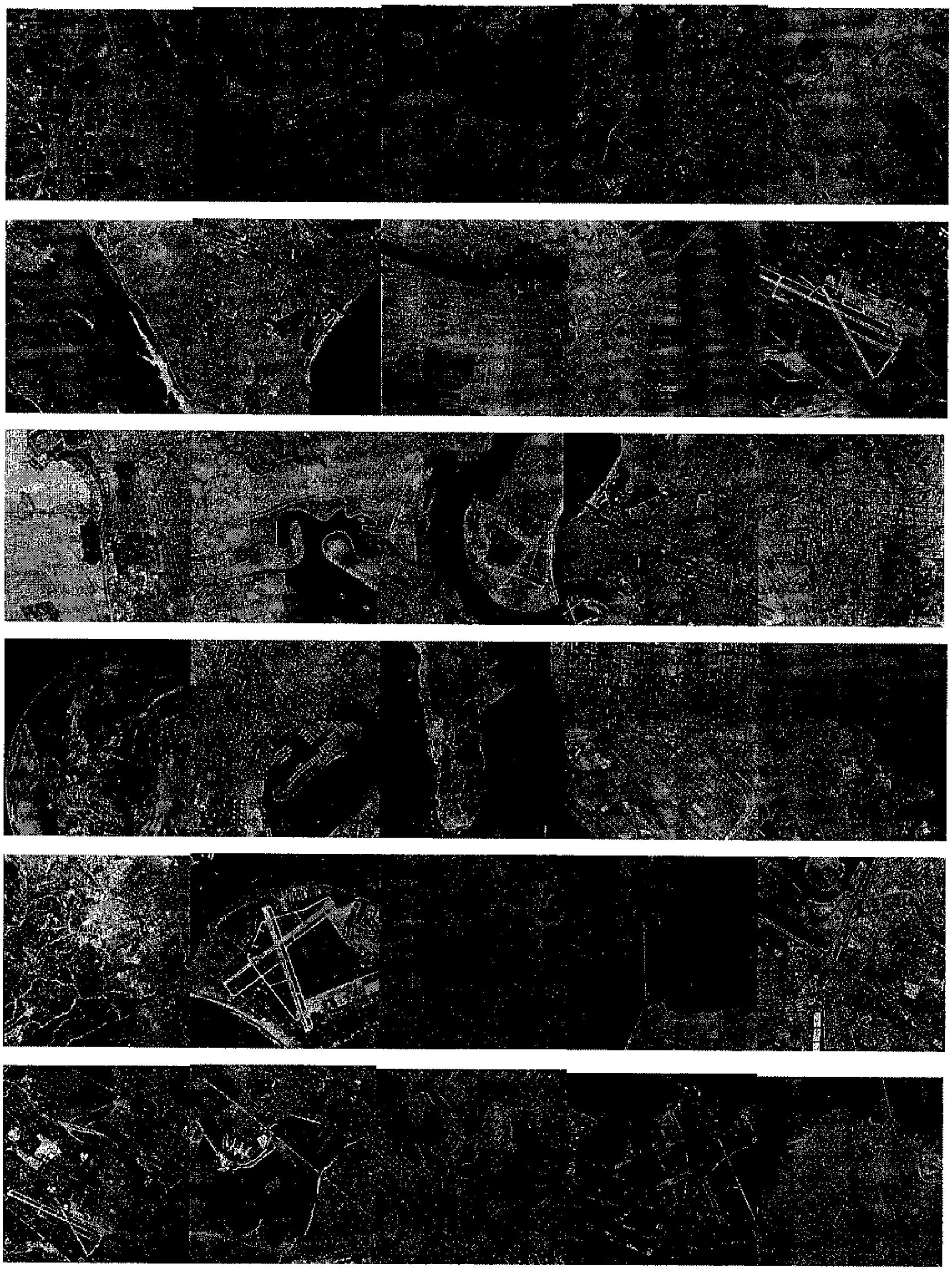
APPENDIX B
SAMPLE OF AERIAL IMAGES



Published with courtesy of http://sipi.use.edu/database/

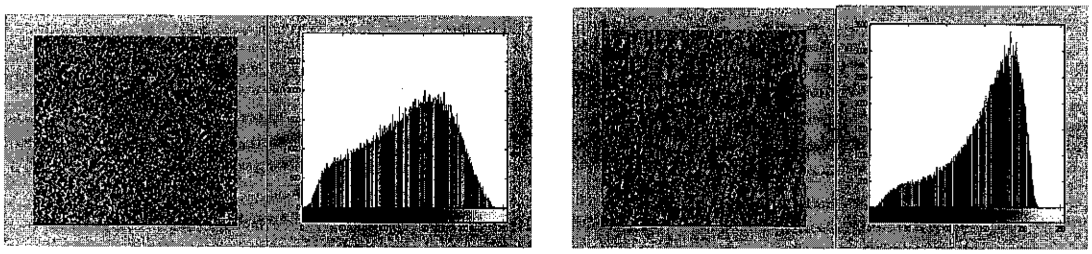
APPENDIX C

SAMPLE OF COMPUTER GRAPHIC IMAGES

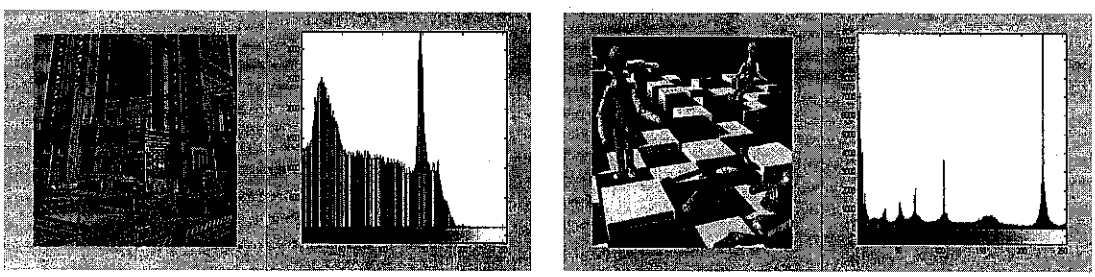
Published with courtesy of http://artworks.avalonweb.net/gallery/gallery_main.php

APPENDIX D

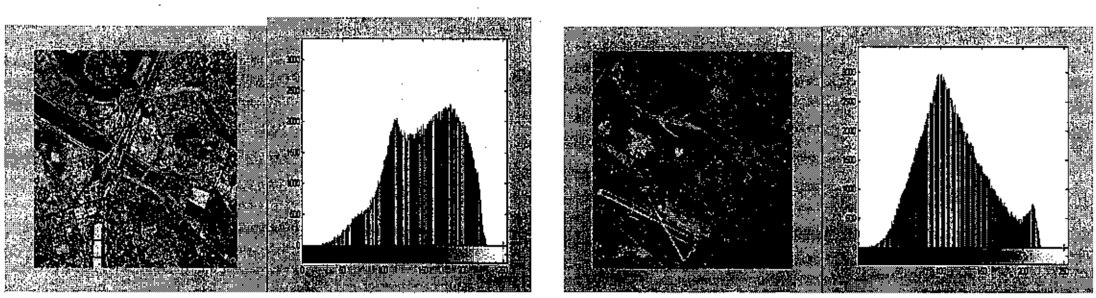
HISTOGRAM REPRESENTING EACH IMAGE



Brodatz Image



Computer Graphic Image



Aerial Image

APPENDIX E
FIRST ORDER STATISTICS ALGORITHM

```
% read the input of the image.
I = imread('30.tiff');
figure, imshow(I);
% define the image in the histogram.
% intensity of the image can be determined from the histogram.
figure,imhist(I);
N = imhist(I);
% N is the number of pixels for each intensity.
% M represents the size of the image.
% find the total pixel (M) if the image.
[a c] = size(I)
M = a*c
% range of the intensity.
% 0 is black and 255 is white.
% b represents pixel intensity.
% P is corresponding histogram of the image.
b = (0:255);
P = N/M;
end
%**************************FIRSTORDER STATISTICS****************************
% determine the mean of the texture.
% the mean gives the average gray level of the image.
m = sum(b*P);
Mean = m
% determine the variance if the image.
% small variance represents smooth image.
v = sum(((b-m).^2)*P);
```

```
Variance = v

% determine the coarseness of the image.

c = 1-(1/(1+v));

Coarseness = c

% determine the skewness of the image.

% skewness represents the measure of the symmetry of the histogram.

s = (1/v.^(3/2)).* sum(((b - m).^3)*P);

Skewness = s

% determine kurtosis of the image.

% kurtosis indicates the flatness of the histogram.

k = (1/v.^2).*sum(((b-m).^4)*P);

Kurtosis = k

% determine the energy.

% large value of energy coreesponds to homogenous regions.

eng = sum(P.^2);

Energy = eng

% calculate the entropy.

% function 'find' is to find the indices of the probabilities non equal to zero.

% large value of entropy imply a more uniform distribution of gray levels.

f = find(P>0);

etp = sum(P(f).*log10(P(f)));

Entropy = etp

% calculate the median.

% median gives the value of the middle gray level.

somme = 0;

i = 0;

while(somme<=0.5)

   i = i+1;

   somme = somme+P(i);

end

Median = i-1
```

```
% calculate the mode.

% mode gives the most frequently occuring gray level.

d = max(P);

Mode = find(P>=d)-1


%***********************************END*************************************
```

APPENDIX F

SECOND ORDER STATISTICS ALGORITHM

```
I = [1 1 4 4 1;3 4 0 1 1;5 4 2 2 2;2 1 1 4 4;0 2 2 5 1]

[a b] = size(I)          % size of input array

R = zeros(1,10);         % declare R as 1 by 10 matrix of zeros

G = zeros(1,10);         % declare G as 1 by 10 matrix of zeros

for x = 2:(a-1)                              % x range of ROI matrix

  for y = 2:(a-1)                            % y range of ROI matrix

    M = (a-2) * (b-2);                       % size of ROI matrix

    S = sum(R(j=1:R);                        % total no of runs in an image

    P(I(x,y)+1) = (P(I(x,y)+1)*(1/S));       % element of normalized GLRLM

    for i=1:G

      R = P(i,j);                            % no of runs of length

      for j = 1:R

        G = P(i,j);                          % no of runs having gray level i

      end

    end

  end

end

%********************SECOND ORDER STATISTICS*********************

c = 1/S;

for j=1:10

  d = R(j)/j^2;

end

SRE = c*sum(d)     % calculate short run emphasis
```

```
for j=1:10
   e = R(j)*j^2;
end
LRE = c*sum(e)     % calculate long run emphasis
for i=1:10
   h = (G(i))^2;
end
GLN = c*sum(h)     % calculate the gray level distribution
for j=1:10
   k = (R(j))^2;
end
RLN = c*sum(k)     % calculate the run length distribution
n = 1/M;
for i=1:10
   l = sum(R(j));
end
RP = n*l           % calculate the run percentage
for i=1:10
   m = G(i)/(i^2);
end
LRGE = c*sum(m)    % calculate the low gray run emphasisfor i=1:10;
   q = G(i)*(i^2);
end
HRGE = c*sum(q)    % calculate the high gray run emphasis


%********************************END**********************************
```

APPENDIX G

FIRST ORDER ALGORITHM VERIFICATION

Array 1: **y = [1 3 2]**

a = 1 N = sum(y) = 1 + 3 + 2 = 6

c = 3 P = N/M = 6/3 = 2

M = 3 b = y = [1 3 2]

1. Mean

$$m = \sum_{b=0}^{L-1} bP(b)$$

$$m = (1)(2) + (3)(2) + (2)(2)$$
$$m = 12$$

2. Variance

$$\sigma^2 = \sum_{b=0}^{L-1} (b-m)^2 P(b)$$

$$\sigma^2 = \left[(1-12)^2(2)\right] + \left[(3-12)^2(2)\right] + \left[(2-12)^2(2)\right]$$
$$\sigma^2 = 242 + 162 + 200$$
$$\sigma^2 = 604$$

3. Coarseness

$$Coarseness = 1 - \frac{1}{1+\sigma^2}$$

$$= 1 - \frac{1}{1+604}$$
$$= 0.9983$$

4. Skew

$$skew = \frac{1}{\sigma^3} \sum_{b=0}^{L-1} (b-m)^3 P(b)$$

$$= \frac{1}{14844.1525} \left[\left[(1-12)^3(2)\right] + \left[(3-12)^3(2)\right] + \left[(2-12)^3(2)\right] \right]$$
$$= \frac{1}{14844.1525}(-6120)$$
$$= -0.4123$$

5. Kurtosis $$Kur = \frac{1}{\sigma^4}\sum_{b=0}^{L-1}(b-m)^4 P(b)$$

$$= \frac{1}{364815.3198}\left[\left[(1-12)^4(2)\right]+\left[(3-12)^4(2)\right]+\left[(2-12)^4(2)\right]\right]$$
$$= 0.1711$$

6. Energy $$eng = \sum_{b=0}^{L-1}\left[P(b)^2\right]$$

$$= 2^2$$
$$= 4$$

7. Entropy $$etp = \sum_{b=0}^{L-1}P(b)\log\left[P(b)\right]$$

$$= 2\log(2)$$
$$= 0.6021$$

Array 2: **y = [2 4 6]**

a = 1 N = sum(y) = 2 + 4 + 6 = 12

c = 3 P = N/M = 12/3 = 4

M = 3 b = y = [2 4 6]

1. Mean $$m = \sum_{b=0}^{L-1} bP(b)$$

$$m = (2)(4)+(4)(4)+(6)(4)$$
$$m = 48$$

2. Variance $$\sigma^2 = \sum_{b=0}^{L-1}(b-m)^2 P(b)$$

$$\sigma^2 = \left[(2-48)^2(4)\right]+\left[(4-48)^2(4)\right]+\left[(6-48)^2(4)\right]$$
$$\sigma^2 = 8464+7744+7056$$
$$\sigma^2 = 23264$$

3. Coarseness $$Coarseness = 1 - \frac{1}{1+\sigma^2}$$

$$= 1 - \frac{1}{1+23264}$$
$$= 0.99996$$
$$\approx 1.0000$$

4. Skew $$skew = \frac{1}{\sigma^3}\sum_{b=0}^{L-1}(b-m)^3 P(b)$$

$$= \frac{1}{3548351.085}\left[\left[(2-48)^3(4)\right]+\left[(4-48)^3(4)\right]+\left[(6-48)^3(4)\right]\right]$$
$$= \frac{1}{3548351.085}\left[(-389344)+(-340736)+(-296352)\right]$$
$$= -0.2893$$

5. Kurtosis $$Kur = \frac{1}{\sigma^4}\sum_{b=0}^{L-1}(b-m)^4 P(b)$$

$$= \frac{1}{541213586.4}\left[\left[(2-48)^4(4)\right]+\left[(4-48)^4(4)\right]+\left[(6-48)^4(4)\right]\right]$$
$$= 0.0838$$

6. Energy $$eng = \sum_{b=0}^{L-1}\left[P(b)^2\right]$$

$$= 4^2$$
$$= 16$$

7. Entropy $$etp = \sum_{b=0}^{L-1} P(b)\log\left[P(b)\right]$$

$$= 4 \log (4)$$
$$= 2.4082$$

Array 3: **y = [1 6 8]**

a = 1 N = sum(y) = 1 + 6 + 8 = 15

c = 3 P = N/M = 15/3 = 5

M = 3 b = y = [1 6 8]

1. Mean $$m = \sum_{b=0}^{L-1} bP(b)$$

$$m = (1)(5) + (6)(5) + (8)(5)$$
$$m = 75$$

2. Variance $$\sigma^2 = \sum_{b=0}^{L-1} (b-m)^2 P(b)$$

$$\sigma^2 = [(1-75)^2(5)] + [(6-75)^2(5)] + [(8-75)^2(5)]$$
$$\sigma^2 = 27380 + 23805 + 22445$$
$$\sigma^2 = 73630$$

3. Coarseness $$Coarseness = 1 - \frac{1}{1+\sigma^2}$$

$$= 1 - \frac{1}{1+73630}$$
$$= 0.999986$$
$$\approx 1.0000$$

4. Skew $$skew = \frac{1}{\sigma^3} \sum_{b=0}^{L-1} (b-m)^3 P(b)$$

$$= \frac{1}{19979392.35} \left[[(1-75)^3(5)] + [(6-75)^3(5)] + [(8-75)^3(5)] \right]$$
$$= \frac{1}{19979392.35} [(-2026120) + (-1642545) + (-1503815)]$$
$$= -0.2589$$

5. Kurtosis $$Kur = \frac{1}{\sigma^4} \sum_{b=0}^{L-1} (b-m)^4 P(b)$$

$$= \frac{1}{5421378145} \left[[(1-75)^4(5)] + [(6-75)^4(5)] + [(8-75)^4(5)] \right]$$
$$= 0.0671$$

6. Energy $$eng = \sum_{b=0}^{L-1} \left[P(b)^2 \right]$$

$$= 5^2$$
$$= 25$$

7. Entropy $$etp = \sum_{b=0}^{L-1} P(b) \log[P(b)]$$

$$= 5 \log (5)$$
$$= 3.4949$$

APPENDIX H

FOS RESULT FOR BRODATZ TEXTURE

Image	a	c	M	Mean	Variance	Coarseness	Skewness	Kurtosis	Energy	Entropy	Median	Mode
1	512	512	262144	128.6726	2803.9	0.9996	-0.3070	2.2189	0.0074	-2.3090	135	152
2	512	512	262144	148.5144	2208.3	0.9995	-0.9651	3.2330	0.0053	-2.2051	161	184
3	512	512	262144	156.7717	1507.8000	0.9993	-0.8175	3.4694	0.0079	-2.1528	164	192
4	512	512	262144	173.5653	940.6339	0.9989	-1.2400	6.3651	0.0107	-2.0279	178	204
5	512	512	262144	145.6593	718.9750	0.9986	-0.5747	5.6054	0.0110	-2.0211	146	144
6	512	512	262144	128.8649	1534.0000	0.9993	0.1549	2.2043	0.0078	-2.1320	125	83
7	512	512	262144	155.7015	809.5788	0.9988	-1.5134	7.2020	0.0122	-2.0037	161	176
8	512	512	262144	161.4082	258.8626	0.9962	-3.9732	40.6608	0.0220	-1.7147	162	160
9	512	512	262144	178.5995	760.3266	0.9987	-2.0578	9.9864	0.0159	-1.9134	187	192
10	512	512	262144	158.0319	908.8854	0.9989	-0.6657	4.7095	0.0095	-2.0530	159	152
11	512	512	262144	157.5754	1784.3000	0.9994	-2.5270	10.0567	0.0143	-1.9375	166	0
12	512	512	262144	158.1817	1051.8000	0.9991	-1.4908	6.3208	0.0117	-2.0467	164	170
13	512	512	262144	111.3804	1546.8000	0.9994	0.1418	2.5830	0.0070	-2.1962	110	112
14	512	512	262144	127.8073	5463.2000	0.9998	-0.0048	1.7926	0.0056	-2.2644	128	158
15	512	512	262144	127.6333	5495.5000	0.9998	-0.0050	1.7973	0.0078	-2.1470	128	190
16	512	512	262144	127.6581	5482.5000	0.9998	-0.0053	1.7924	0.0082	-2.1147	129	206
17	512	512	262144	129.9838	5543.6000	0.9998	-0.0354	1.7938	0.0109	-1.9932	132	217
18	512	512	262144	127.7675	5511.8000	0.9998	-0.0153	1.7899	0.0112	-1.9892	128	120
19	512	512	262144	127.8537	5450.1000	0.9998	6.2907E-04	1.7981	0.0079	-2.1207	127	33
20	512	512	262144	129.4034	5527.8000	0.9998	-0.0372	1.7898	0.0124	-1.9596	130	199
21	512	512	262144	130.0839	5467.5000	0.9998	-0.0444	1.8031	0.0221	-1.7017	131	115
22	512	512	262144	128.8975	5569.1000	0.9998	-0.0194	1.7882	0.0161	-1.8750	131	161
23	512	512	262144	127.8088	5463.1000	0.9998	-4.8191E-05	1.8019	0.0096	-2.0328	126	106
24	512	512	262144	122.7092	5922.1000	0.9998	-0.0123	1.7775	0.0146	-1.9098	122	0
25	512	512	262144	128.1240	5504.4000	0.9998	-0.0197	1.7908	0.0121	-1.9809	128	156
26	512	512	262144	128.1747	5477.0000	0.9998	-0.0227	1.7911	0.0072	-2.1588	128	133
27	512	512	262144	141.9726	236.0116	0.9958	0.2555	5.8906	0.0296	-1.7106	142	144
28	512	512	262144	162.3809	9867.8000	0.9999	-0.4286	1.4366	0.1388	-1.7503	215	255
29	512	512	262144	184.6066	1092.8000	0.9991	-0.9728	4.5946	0.0097	-2.1029	189	190
30	512	512	262144	212.8173	646.2825	0.9985	-1.7171	7.2548	0.0150	-1.9312	219	227
Sum Value			7864320	4328.609	100554.7564	29.9764	-18.9194	147.0984	0.4815	-60.4559	4451	4531
Average Value			262144	144.287	3351.8252	0.9992	-0.6306	4.9033	0.0161	-2.0152	148.3667	151.0333

APPENDIX I

FOS RESULT OF COMPUTER GRAPHIC IMAGE

Image	a	c	M	Mean	Variance	Coarseness	Skewness	Kurtosis	Energy	Entropy	Median	Mode
1	512	512	262144	81.2447	2920.6000	0.9997	0.2254	1.7621	0.0065	-2.2402	75	0
2	512	512	262144	88.7258	8319.5000	0.9999	0.5054	1.6413	0.0645	-1.8430	58	0
3	512	512	262144	151.1337	2907.1000	0.9997	-0.6954	3.3612	0.0060	-2.2933	156	170
4	512	512	262144	95.7109	3845.5000	0.9997	1.1308	3.5490	0.0063	-2.2807	77	67
5	512	512	262144	115.7522	2975.8000	0.9997	-0.1758	2.2189	0.0053	-2.3205	121	156
6	512	512	262144	216.1798	254.5578	0.9961	-1.4653	6.9079	0.0230	-1.7377	219	229
7	512	512	262144	106.0007	1762.7000	0.9994	-0.1784	2.8121	0.0074	-2.2119	111	121
8	512	512	262144	130.3005	4607.2000	0.9998	-0.0220	1.8147	0.0057	-2.3122	127	205
9	512	512	262144	128.4537	2388.4000	0.9996	-0.7689	2.9705	0.0085	-2.2018	140	137
10	512	512	262144	118.1154	3788.9000	0.9997	0.0299	1.7925	0.0059	-2.3029	129	49
11	512	512	262144	105.9319	3425.9000	0.9997	0.2167	2.1300	0.0051	-2.3350	108	137
12	512	512	262144	89.2515	3024.4000	0.9997	0.3872	2.4325	0.0054	-2.3071	84	72
13	512	512	262144	94.4363	3767.6000	0.9997	0.5630	2.4297	0.0051	-2.3407	83	0
14	512	512	262144	157.9308	4106.4000	0.9998	-0.3479	1.9241	0.0049	-2.3414	168	255
15	512	512	262144	113.4433	3485.9000	0.9997	0.2555	2.1580	0.0055	-2.3076	106	124
16	512	512	262144	118.1125	3609.4000	0.9997	0.3135	1.9425	0.0056	-2.3097	104	88
17	512	512	262144	93.6787	2691.8000	0.9996	0.5161	2.7404	0.0056	-2.3028	87	55
18	512	512	262144	116.2245	5109.1000	0.9998	0.2179	1.6499	0.0058	-2.3198	103	207
19	512	512	262144	118.5245	3674.0000	0.9997	0.5833	2.0588	0.0066	-2.2643	99	187
20	512	512	262144	146.0386	5498.3000	0.9998	-0.0910	1.5564	0.0062	-2.3087	139	214
21	512	512	262144	114.6461	2480.9000	0.9996	0.1817	2.3965	0.0074	-2.2272	122	166
22	512	512	262144	116.2946	4153.9000	0.9998	0.1895	2.1638	0.0043	-2.3824	112	255
23	512	512	262144	156.3260	2428.9000	0.9996	-0.1599	2.4898	0.0060	-2.2820	156	142
24	512	512	262144	117.4129	3402.2000	0.9997	0.2115	2.1440	0.0049	-2.3444	112	169
25	512	512	262144	119.6963	7052.5000	0.9999	0.2414	1.7405	0.0088	-2.2865	115	250
26	512	512	262144	145.8466	6087.8000	0.9998	-0.2039	1.5375	0.0086	-2.2531	149	235
27	512	512	262144	96.9573	3927.1000	0.9997	0.4208	1.9704	0.0050	-2.3337	82	27
28	512	512	262144	98.2111	3809.8000	0.9997	0.2805	2.1259	0.0048	-2.3482	95	0
29	512	512	262144	103.5888	1120.9000	0.9991	0.4179	2.8647	0.0086	-2.1164	100	78
30	512	512	262144	137.7887	5198.6000	0.9998	0.1737	1.7004	0.0050	-2.3498	121	252
Sum Value			7864320	3591.9584	111825.6578	29.9872	2.9532	69.2239	0.2583	-67.8050	3458	4047
Average Value			262144	119.7319	3727.5219	0.9996	0.0984	2.3075	0.0086	-2.2602	115.2667	134.9

APPENDIX J

FOS RESULT OF AERIAL IMAGES

Image	a	c	M	Mean	Variance	Coarseness	Skew	Kurtosis	Energy	Entropy	Median	Mode
1	512	512	262144	115.3449	1699.9	0.9994	0.4548	2.7553	0.0071	-2.208	110	101
2	512	512	262144	150.8738	1799.4	0.9994	-3.623	2.3989	0.0066	-2.2142	155	184
3	512	512	262144	117.8217	430.4416	0.9977	1.3156	6.516	0.0263	-1.7727	116	120
4	512	512	262144	133.3738	881.5418	0.9989	-0.6145	2.5775	0.0105	-2.0448	140	156
5	512	512	262144	125.9169	2377.8	0.9996	0.405	2.2437	0.0066	-2.231	117	215
6	512	512	262144	150.3559	1689.8	0.9994	-0.1571	2.0608	0.0067	-2.197	154	164
7	512	512	262144	166.4329	409.5339	0.9976	-0.4009	3.2628	0.015	-1.9079	167	161
8	512	512	262144	183.6457	259.4701	0.9962	-0.5459	3.3576	0.0181	-1.8086	185	186
9	512	512	262144	138.948	2615.9	0.9996	-0.4839	1.945	0.0065	-2.2312	154	180
10	512	512	262144	156.2185	588.1118	0.9983	0.716	2.9479	0.0143	-1.9434	150	147
11	512	512	262144	174.2573	457.4511	0.9978	-0.5525	2.6359	0.0139	-1.9124	178	180
12	512	512	262144	159.2339	530.6256	0.9981	-0.0326	2.7751	0.0122	-1.9735	160	165
13	512	512	262144	153.1385	314.5343	0.9968	0.2113	3.4879	0.0192	-1.834	150	148
14	512	512	262144	111.909	576.5831	0.9983	0.6846	4.1569	0.00126	-1.9806	110	114
15	512	512	262144	144.6376	612.6372	0.9984	0.5697	2.6512	0.012	-1.9769	141	119
16	512	512	262144	157.2889	428.3985	0.9977	0.1989	2.6719	0.0161	-1.8919	153	144
17	512	512	262144	122.8241	722.0885	0.9986	0.8587	3.8907	0.013	-2.0001	119	119
18	512	512	262144	141.63	739.2124	0.9987	0.0234	2.106	0.0098	-2.0448	142	160
19	512	512	262144	154.893	690.6942	0.9986	0.2881	2.7335	0.0107	-2.025	153	145
20	512	512	262144	161.3564	437.7648	0.9977	1.1678	3.6701	0.0213	-1.8131	155	152
21	512	512	262144	166.5935	715.177	0.9986	0.1554	1.7636	0.0125	-1.9585	167	137
22	512	512	262144	114.6489	1877.7	0.9995	0.2987	2.071	0.0078	-2.1539	111	55
23	512	512	262144	180.1378	414.8029	0.9976	-0.4152	2.4729	0.0138	-1.9011	182	186
24	512	512	262144	148.627	1990.4	0.9995	-0.6963	2.481	0.0074	-2.1941	160	177
25	512	512	262144	174.5868	737.8039	0.9986	-0.2519	1.6496	0.0136	-1.9105	182	137
26	512	512	262144	179.4462	454.3743	0.9978	-0.5201	2.1499	0.0154	-1.8551	184	192
27	512	512	262144	176.4888	614.5237	0.9984	-0.9931	3.3222	0.0156	-1.9278	185	190
28	512	512	262144	132.4828	1720.9	0.9994	0.5464	2.253	0.0077	-2.1623	123	96
29	512	512	262144	180.2412	259.9171	0.9962	-0.5335	3.9483	0.0185	-1.804	180	178
30	512	512	262144	179.7145	525.942	0.9981	-0.6411	2.2588	0.0149	-1.8926	187	195
AVERAGE	512	512	262144	151.767	919.1	0.9983	0.0857	2.84	0.0125	-1.9923	152.33	153.43

APPENDIX K

TABULATED RESULTS OF ARRAY VERIFICATION

Table: Verification Through MATLAB Code

Array	a	c	M	Mean	Variance	Coarseness	Skewness	Kurtosis	Energy	Entropy	Median	Mode
1	1	3	3	12	604	0.9983	-0.4123	0.1711	4	0.6021	0	0
2	1	3	3	48	23264	1.0000	-0.2893	0.0838	16	2.4083	0	0
3	1	3	3	75	73630	1.0000	-0.2589	0.0671	25	3.4949	0	0

APPENDIX L

TABULATED RESULT OF MATHEMATICAL CALCULATION

Table: Verification Through Calculation

Array	a	c	M	Mean	Variance	Coarseness	Skewness	Kurtosis	Energy	Entropy	Median	Mode
1	1	3	3	12	604	0.9983	-0.4123	0.1711	4	0.6021	0	0
2	1	3	3	48	23264	1.0000	-0.2893	0.0838	16	2.4083	0	0
3	1	3	3	75	73630	1.0000	-0.2589	0.0671	25	3.4949	0	0

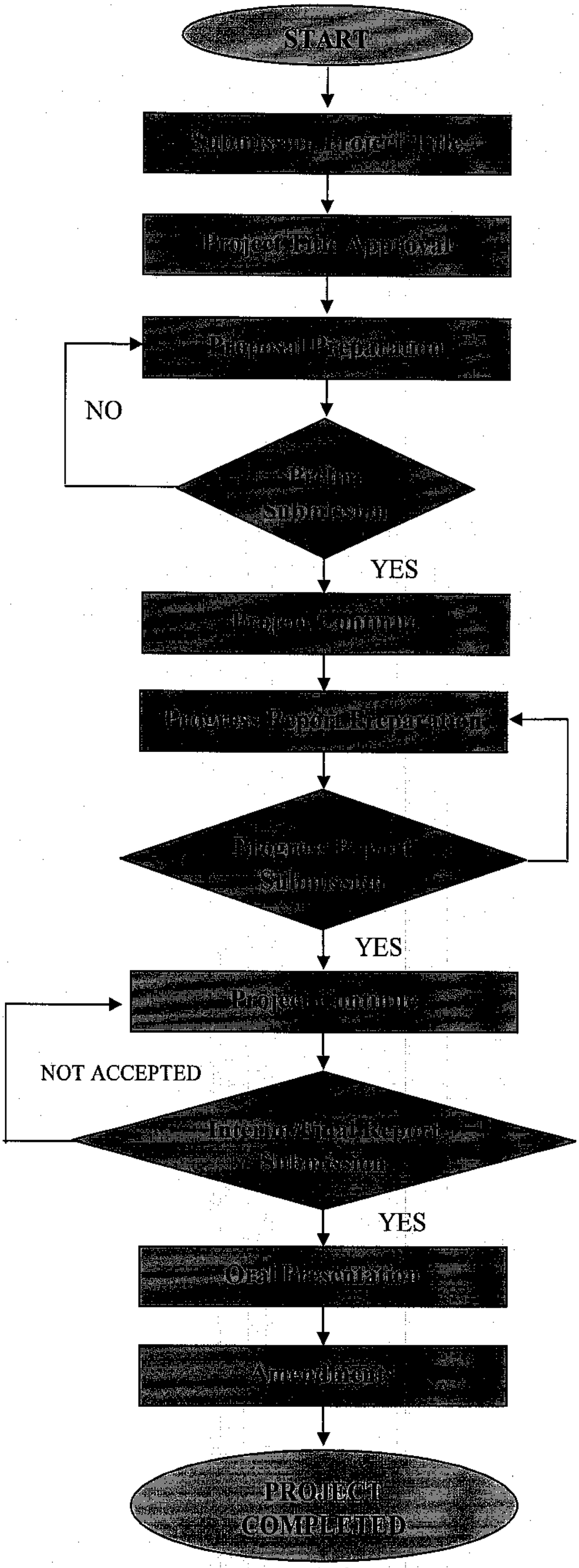
APPENDIX M

OTHER SOS FEATURES

Feature	Formula	What is measured?
Short Run Emphasis	$SRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{j^2}$	Measures the distribution of short runs. The SRE is highly dependent on the occurrence of short runs and is expected large for fine textures.
Long Run Emphasis	$LRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j)*j^2$	Measures distribution of long runs. The LRE is highly dependent on the occurrence of long runs and is expected large for coarse structural textures.
Low Gray-Level Run Emphasis	$LGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{i^2}$	Measures the distribution of low gray level values. The LGRE is expected large for the image with low gray level values.
High Gray-Level Run Emphasis	$HGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j)*i^2$	Measures the distribution of high gray level values. The HGRE is expected large for the image with high gray level values.
Short Run Low Gray-Level Emphasis	$SRLGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{i^2*j^2}$	Measures the joint distribution of short runs and low gray level values. The SRLGE is expected large for the image with many short runs and lower gray level values
Short Run High Gray-Level Emphasis	$SRHGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)*i^2}{j^2}$	Measures the joint distribution of short runs and high gray level values. The SRHGE is expected large for the image with many short runs and high gray level values
Long Run Low Gray-Level Emphasis	$LRLGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)*j^2}{i^2}$	Measures the joint distribution of long runs and low gray level values. The LRLGE is expected large for the image with many long runs and low gray level values
Long Run High Gray-Level Emphasis	$LRHGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j)*i^2*j^2$	Measures the joint distribution of long runs and high gray level values. The LRHGE is expected large for images with many long runs and high gray level values
Gray-Level Non-uniformity	$GLNU = \frac{1}{n_r}\sum_{i=1}^{M}\left(\sum_{j=1}^{N}P(i,j)\right)^2$	Measures the similarity of gray level values through out the image. The GLN is expected small if the gray level values are alike through out the image.
Run Length Non-uniformity	$RLNU = \frac{1}{n_r}\sum_{j=1}^{N}\left(\sum_{i=1}^{M}P(i,j)\right)^2$	Measures the similarity of the length of runs through out the image. The RLN is expected small if the run lengths are alike through out the image.
Run Percentage	$RPC = \frac{n_r}{P(i,j)*j}$	Measures the homogeneity and the distribution of runs of an image in a specific direction. The RPC is the largest when the length of runs is 1 for all gray levels in specific direction.

APPENDIX N

FLOW DIAGRAM OF THE WHOLE PORJECT WORK


START
Project Title Approval
Proposal Preparation
NO
Prelim Submission
YES
Project Continue
Progress Report Preparation
NO
Progress Report Submission
YES
Project Continue
NOT ACCEPTED
Interim/Final Report Submission
YES
Oral Presentation
Amendment
PROJECT COMPLETED

APPENDIX O

PROJECT MILESTONE

Name : Siti Hajar Mohd Yakop **ID : 2845**

No.	Detail/ Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Project Work Continue		■	■											
	-Develop second order Statistic														
2	Submission of Progress Report 1			●											
3	Project Work Continue				■	■	■	■							
	-Verification of algorithm -Analyzing images														
4	Submission of Progress Report 2								●						
5	Project work continue								■	■	■	■			
	-Enhancement of algorithm -Data analysis and classification														
6	Submission of Dissertation Final Draft												●		
7	Oral Presentation													●	
8	Submission of Project Dissertation														●

● Suggested milestone

■ Process