ABSTRACT

The process of the characteristic feature extraction is one of the adopted techniques for the purpose of pattern recognition in the images. The process of the characteristic feature extraction numerically is one of the adopted techniques for the purpose of pattern recognition in the digital images, and the process of the characteristic feature extraction depending on the Co-occurrence matrices is one of the most important techniques for the purpose of pattern recognition in the textured images.

This work aim to study the characteristic features for the textured images, eight characteristic features are selected to investigate the aim of this work. These selected features are:

Maximum probability, entropy, homogeneity, cluster shade, cluster prominence, contrast, angular second moment, and the inverse difference moment.

In this research, the characteristic features depending on the Co-occurrence matrix are extracted in two ways. In the first one, the characteristic features are extracted depending on average Co-occurrence matrices which be extracted for four angles (0^o, 45^o, 90^o, and 135^o). While in the second method, the characteristic features are extracted depending on the Co-occurrence matrix for each angle of the following angles (0^o, 45^o, 90^o, and 135^o). In this method, four values for each of the selected characteristic features are extracted. Then the average values for each of the characteristic features are extracted depending on the extracted four values.

To study the effect of block size on the calculation of the statistical characteristic features, the statistical features are calculated for the whole image and for each block in the image after dividing the image into blocks with block size (32x32) and for each block in the image after dividing the image into blocks with block size (64x64). In addition, to

study the effect of quantization level on the calculation of the statistical characteristic features three values (8, 16 and 32) of quantization level are adopted in this research.

All the calculations are applied on the three textured images with 256 gray levels selected from Brodatz album.

The results show the calculation for most the selected features not change except the feature of the entropy where the difference in the extracted value of the entropy in the two ways is perceptible. This property can be utilized to increase the discrimination power in the classification process.

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Sarah
2006

Appendix A

BMP Image File Format

<u>BMP Image File Format</u> [Sama99]

The BMP file format divides a graphics file into four major parts, these are:

- <u>Bitmap File Header:</u> The bitmap header is 14-bytes long and is formatted as follows:

  UNIT bfType (*holds the signature value 0x4d42, which identifies the file as BMP*)

  DWORD bfSize (*holds the file size*)

  UNIT bfReserved (*not used, set to zero*)

  UNIT bfReserved (*not used, set to zero*)

  DWORD bfOffBits (*specifies the offset, relative to the beginning of the file, where the data representing the bitmap itself begins*)

- <u>Bitmap Information Header:</u> The bitmap information contains important information about the image. The windows format for this header is:

  DWORD biSize (*holds the header length in bytes*)

  LONG biWidth (*identify the image width*)

  LONG biHeight (*identify the image height*)

  WORD biplanes

  Word biBitCount (*identify number of bits/pixel in the image and thus the maximum number of colors that the bitmap can contain*)

  DWORD biCompression (*identify the compression scheme that the bitmap employs. It will contain zero if the bitmap uncompressed*)

  DWORD biSizeImage (*set to zero for uncompressed image, else it holds the size (in bytes) of the bits representing the bitmap image for compressed images*)

  LONG biXPelsPerMeter

  LONG biXPelsPerMeter

  DWORD biClrUsed

  DWORD biClrImportant

- <u>Palette (Color table containing RGB quad or RGB triple structure:</u> the color table specifies the colors used in the bitmap. The BMP files come in four color formats

1. 2-color *one-bit per pixel*
2. 16-color *four-bits per pixel*

3. 256-color *eight-bits per pixel*
4. 16.7 million-color *24-bits per pixel*

The number of bits per pixel -and hence the color format- can be determined from the biBitCount shown above.

In the 2-color, 16-color, and 256-color BMP formats, the color table contains one entry for each color. Each entry specifies the intensities of a color's *red*, *green*, and *blue* components and it is of 4-bytes long as shown below:

BYTE rgbBlue
BYTE rgbGreen
BYTE rgbRed
BYTE rgbReserved

Each color-table entry can specify a range of red, green, and blue values from 0 to 255. True-color BMP files do not contain color tables, because a single color table with 16.7 million entries of 4-bytes each would require 64MB of storage space.

- Bitmap Bits: The bitmap bits is the set of bits defining the image-the bitmap itself. In the 2-color, 16-color, and 256-color BMP formats, each entry in the bitmap is an index to the color table. In 16.7 million-color bitmap, where is no color table, each bitmap entry directly specifies a color. The first 3-bytes in each 24-bit entry specifies the pixel colors red component, the second specifies green component and the third specifies blue.

The bitmap bits representing a single line are stored in left-to-right, the same way that the pixels they represent line up on the screen. The first row pixel data in the bitmap responds to the bottom row of pixels on the screen, the second row corresponds the row of pixels second from the bottom, and so on.

The size of one bitmap entry is determined by the number of bits per pixel as shown in the following table:

NUMBER OF COLORS	NUMBER OF BITS PER PIXEL REQUIRED
2	1
16	4 (1/2 byte)
256	8 (1 byte)
16.7 million	24 (3 bytes)

Supervisor Certification

I certify that this thesis was prepared under my supervision at the department of Computer Science/College of Science/Al-Nahrain University, by **Sarah Abbas Asem Al-Naqshbandi** as partial fulfillment of the requirements for the degree of Master of Science in Computer Science.

Signature:

Name:**Dr. Laith Abdul Aziz Al-Ani**

Title:**Assistant Professor**

Date: / /**2006**

In view of the available recommendations, I forward this thesis for debate by examination committee.

Signature:

Name:**Dr. Taha S. Bashaga**

Title:**Head of the department of Computer Science**

Date: / /**2006**

Chapter One

Overview

1.1 Introduction

With the advent of high speed general purpose digital computers it is becoming possible to perform mathematical or algorithmic processes on pictorial data from images of photographic quality. In most of these processes, the pictorial information is represented as a function of two variables(x,y). The image in its digital form is usually stored in the computer as a two dimensional array. Various two-dimensional analyses are performed on image to achieve specific image processing tasks such as coding, restoration, enhancement, and classification. In recent years a tremendous amount of computer processing of photographs has occurred, with facilities having been developed to process anything from aerial photographs to photomicrographs [Hara73].

Computer vision refers to the field of computer science that is concerned with the design and implementation of algorithms that allow machines to simulate human's vision. Various fields related to computer processing of images are categorized according to the type of input it take and type of results they produce (Table 1-1) [Nibl86].

Table (1-1): Categorize of image-computer processing [Nibl86]

		OUTPUT	
		Image	**Description**
INPUT	**Image**	Image Processing	Pattern Recognition & Computer Vision
	Description	Computer Graphics	Other Data Processing

It is clearly seen (from the table) that image processing takes an image as an input, perform some operation on it (such as: enhancement, transformation, rotation, etc.), then produce the processed image as output. Computer graphics produce image according to received description information (such as: line drawing or use 3 dimensional view of an object with effect for shading, lighting, etc.) [Umba98].

Automatic machine pattern recognition, description, and classification have become important activities in a variety of engineering and scientific disciplines such as biology, psychology, medicine, computer vision, artificial intelligence, remote sensing, and pattern recognition. A pattern could be defined as an entity that could be given a name. It is represented by a vector of measured properties or features and their interrelationships. Pattern recognition systems are expected to automatically classify, describe, or cluster complex patterns or objects based on their measured properties or features. They are expected to identify a given pattern as a member of already known or defined classes (Supervised classification), or assign a pattern to a so far unknown class of patterns (Unsupervised classification or clustering). Designing a pattern recognition system involves the following main steps: (i) data acquisition and preprocessing, (ii) representation or feature extraction, and (iii) decision making or clustering [Gonz00, Mao94].

1.2 Image Classification

The objective of this operation is to replace visual analysis of the image data with quantitative techniques for automating the identification of features in a scene.

The classification of pictorial data can be done on a resolution cell basis or on a block of contiguous resolution cells. The most difficult step in categorizing pictorial information from a large block of resolution cells is that of defining a set of meaningful features to describe the pictorial information from a large block of resolution cells from the block of resolution cells. Once these features are defined, image blocks can be categorized using any one of a multitude of pattern recognition techniques. The most important features to be extracted about regions in pattern recognition or image classification problems are through their texture analysis [Alan96, Mao94].

Texture features could be derived using various approaches such as: Co-occurrence matrices, Fourier power spectrum and signal processing (Gabor and wavelet transformation), correlation features, structural features, features extracted using neural networks, etc. Due to the increasing amount of texture features, it becomes a very hard task to select an appropriate set of texture features for classification purposes. Finding an appropriate set of features-vector that represent observations with reduced dimensionality without sacrificing the discrimination power, along with finding the specific features-vector that has the best discrimination power has been one of the most important problems in the field of pattern analysis and texture classification [Sama99].

1.3 Texture Analysis

Texture analysis is one of the most important techniques used in analysis and classification of images presenting repetition of fundamental image elements. It is widely used in interpretation and classification of terra in images, radiographic and microscopic cell images, and many other domains of pattern recognition [Guib88]. Texture can be recognized when it is seen, but it is a very difficult concept to define [Roan87]. Generally, attributed to images containing repetitive patterns in which elements or primitives are arranged according to certain placement rules. Number of times the basic pattern element repeats inside that given area is inversely proportional to the image resolution, which might be defined as the distance between the observer and the textural surface. Texture analysis research attempts to solve the following problems [Gonz87, Chel93]:

- Texture Segmentation: The goal of texture segmentation is to subdivide the image into its constituent parts for further subsequent processing such as texture classification.

- Texture Classification: Refer to the problem of identifying a particular class label of the input texture. The pattern classification techniques may be applied by assuming that there is only one texture in the image (the image being constructed from a single segmented region).

Texture analysis systems that are used for texture classification, segmentation, or labeling should consist of two phases: (i) feature extraction phase, and (ii) texture discrimination phase.

Texture is interesting because it allows easy discrimination of objects from background, using local features, and global information such as luminance [Dupa89]. The general approach to textural classification is based on global measures and feature extraction using: (i) *statistical methods* (used to describe the texture of a region; statistical approaches yield characterizations of textures as smooth, coarse, grainy etc.), (ii) *structured techniques* (that deal with arrangement of image primitives such as the description of texture based on regularly spaced parallel lines)[Shou05].

Statistical methods for feature extraction are one of the early methods proposed in the literature. It is used to detect texels (texels are the basic primitives from which the texture is constructed or composed) and relationships among them. Such measures include entropy, energy, and correlation based on gray tone Co-occurrence matrices [Sama99].

1.4 Review of Previous Studies

Several researches in the field of pattern recognition developed texture classification system. The scope of this survey is limited to the researches that works of image classification with texture analysis, some of the previous studies are tabulated as follows:

Author, Year, Reference	*Remarks*
Robert M. Haralick, 1973 [Hara73]	**Described some easily computable textural features based on gray tone spatial dependencies, and illustrates their application in category identification tasks of three different kinds of image data. The data set was divided into two parts, a training set and test set. The results showed that the test set identification accuracy is 89 percent for the photographs, 82 percent for the aerial photograph imagery, and 83 percent for the satellite imagery. These results indicate that the easily computable textural features probably have a general applicability for a wide variety of image classification applications.**
Patrick C. Chen, 1978 [Chen78]	**Applied split and merge segmentation algorithm based on Co-occurrence matrix, this combination is took in one direction. It is first evaluated on a set of regions forming two levels of the quadratic picture tree. This work showed the combination of the Co-occurrence matrices as a texture features with a split and merge algorithm.**
L.S. Davis, 1979 [Davi79]	**Described Generalized Co-occurrence Matrices (GCM) for texture discrimination. They do not describe texture directly but rather describe the spatial arrangement of local image features such as edges and lines. The description of (GCM) is based on three attributes: image feature prototype, spatial predicate and prototype attribute. The prototype is regarded as the structural definition of the image features of interest. The authors compare three prototypes, namely pixel intensity, edge pixel, and extended edge. For each of the three categories, their spatial predicates are defined. The following features are extracted from GCM: contrast, uniformity, entropy, and correlation. In their first study, classification experiments are performed on 30 texture samples. They found by comparing with the Co-occurrence matrix approach, their method performs much better (an average of 60 percent versus 43 percent for single features, and 68 percent versus**

	43 percent for pairs of features).
Michal Unser, 1986 [Unse86]	**Proposed a simplification of the very popular grey level dependence method for texture analysis. The usual Co-occurrence matrices are replaced by their associated sum and difference histogram. Two maximize likelihood texture classifiers have been introduced. The first one considers the sum and difference histogram as the component of feature vector. The second classifier is based on global measurements extracted from the histograms. The experiment results indicate that sum and difference histograms are almost as powerful as Co-occurrence matrices for texture discrimination.**
Roan, ggarwal, and Martin, 1987 [Roan87]	**Developed a method that classifies textures at different resolutions. The statistical features used for classification are derived from the Fourier power spectrum and Co-occurrence matrices. The relationships between feature properties and image resolution were studied. Four types of texture features were calculated and used as the basis for a "leave-one-out" classification scheme. The texture feature types, power spectrum (the intersection between rings and edges), Co-occurrence features (contrast, entropy, and uniformity) were selected. The classification scheme incorporates "confidence" levels from the various measures. The experimental results indicate the effectiveness of the classification process on several texture classes with the added dimension of resolution variation.**
He, Wang, and Guibert, 1988 [Guib88]	**Presented a new approach for texture discrimination based on an algorithm that automatically selects the texture features best suited to a particular classification problem. Three sets of texture features from Co-occurrence matrix with different displacements, and from its Fourier transforms, have been computed. In all, 173 texture features for each (32×32) sample image were used with statistical classifiers. The mean recognition rate was 95%. This approach could be used to classify images of various textural properties.**
Laith A-A. Al-Ani,	**Adopted Texture classification technique based on the Co-occurrence matrices. A set of 13 textural features, extracted from**

1996 **[Alan96]**	**Co-occurrence matrices have been investigated and used to discriminate image regions extracted from the split and merge technique.**
Ban Abdul Razzak, **1997** **[Razz97]**	**This research implemented image regions classification for remotely sensing image, with two different supervised classification methods; i.e. minimum distance method and texture method. The first method adopted some useful statistical features; the second "texture method" utilized the power of the Co-occurrence matrices to classify image regions.**
Venus W. Samawi, **1999** **[Sama99]**	**Proposed a method for the classification of natural-textured image, using neural networks, and suggested the best neural network architecture leading towards the goal of high accuracy texture image classification. Five different feature sets of features (statistical, spectral, direct features, or the combination of statistical and spectral features) were used to train a number of texture classification neural networks to find the best feature set that could be used to discriminate texture images and improve the overall performance. From the experimental result it was found that training a neural network texture classifier using statistical, spectral features are improves the texture classification results.**
C. Rosenberger, **1999** **[Rose99]**	**Studied and analyzed the complementarities of some texture attributes and in the other hand, quantified their efficiency through experimental results in texture recognition. He also presents a texture model derived from the Wold decomposition of the 1D autocorrelation function.**
P. Dulyakarn, **2000** **[Duly00]**	**Described a comparison study of two texture features derived from gray level Co-occurrence matrix and Fourier transform. By comparing results between these two texture features he showed that the feature derived from gray-level Co-occurrence matrices give the better result than Fourier transform.**
	The purpose of this work was to apply and test Haralick's Gray Level Co-occurrence Matrix (GLCM) technique for automatic

A. Usinskas, 2002 [Usin02]	**calculation and segmentation of the ischemic stroke volume from images. For this task, the 3- nearest neighbor's classifier was trained to perform stroke and non-stroke area classification. The segmentation and classification results were compared versus a manual segmentation. Approximately half of the automatically computed and segmented stroke volumes from images differed less than 15 % from the corresponding manually segmented stroke volumes.**
M. Sharma, 2002 [Shar02]	**In this work five different feature extraction methods have been evaluated. These are auto-correlation, edge Frequency, primitive-length, Law's method, and co-occurrence matrices. The results showed that the Law's method and Co-occurrence matrix method yield the best results. The overall best results are obtained when they used features from all five methods. Results are produced using leave-one-out method. The results showed that there is considerable performance variability between the various texture methods.**
M. Wilkinson, 2003 [Wilk03]	**Present multi-resolution method for use in texture, classification, a connected operator similar to the morphological hat-transform is defined, and two scale-space representations are built. The most important features were extracted from the scale spaces by unsupervised cluster analysis, and the resulting pattern vectors provided the input of a decision tree classifier. It obtained 93.5% correct classification for the Brodatz texture database.**
Alyaa H. Ali, 2004 [Ali04]	**A digital image system was suggested to define the regions of cold and high clouds. The classification process was applied by using the K- mean clustering algorithm. The textural analysis is used where six parameters are calculated from the Co-occurrence matrix. These parameters were inserted in the Clustering method. The best classifier feature is the angular second moment. She used the angular second moment with any textural feature; get a good result of the cloud classification, since the angular second moment gives indication on the cloud homogeneity.**
Omran M.,	**Investigated the application of an efficient optimization method,**

2005 **[Omra05]**	**known as Particle Swarm Optimization (PSO), to the field of pattern recognition and image processing. First a clustering method that is based on PSO is proposed. The application of the proposed clustering algorithm to the problem of unsupervised classification and segmentation of images is investigated. A new automatic image generation tool tailored specifically for the verification and comparison of various unsupervised image classification algorithms is then developed. A dynamic clustering algorithm which automatically determines the "optimum" number of clusters and simultaneously clusters the data set with minimal user interference is then developed. Finally, PSO-based approaches are proposed to tackle the color image quantization and spectral. Un-mixing problems. In all the proposed approaches, the influence of PSO parameters on the performance of the proposed algorithms is evaluated.**

1.5 Research Objective

This project aimed to extract and analysis some of the extracted characteristic features from some of the textured images depending on Co-occurrence matrix. The process of feature extraction will be passing in two ways.

This study will be taken in the consideration the effect of block size and the quantization level on the behavior of the extracted features.

This study can be led us to the way which can be increased the discrimination power in process of pattern recognition.

1.6 Chapters Overview

In this section, the contents of individual chapters of this thesis are briefly reviewed:

- Chapter two (Texture Analysis) consists of all methodology deals with image classification and details of texture analysis, texture features with statistical classifier.
- Chapter used three (System Development and Implementation) describes image data used, then applied Co-occurrence matrices classification, and then selected feature sets that are for comparison.
- Chapter four (Conclusions and Suggestions for Future Work) concentrates on conclusions with recommendations for the future work.

Chapter Two
Texture Analysis

2.1 Introduction

Texture is an important characteristic for the analysis of many types of images. It can be seen in all images from multi-spectral scanner images obtained from aircraft or satellite platforms (which the remote sensing community analysis) to microscopic images of cell cultures or tissue samples (which the biomedical community analysis), it has a wide range of applications. Millions of digital images are created throughout the World Wide Web, digital cameras, different kinds of sensors, medical scanners, etc.

In a search for meaningful features for describing pictorial information, it is only natural look toward the types of features which human beings use in interpreting pictorial information. Spectral, textural, and contextual features are three fundamental pattern elements used in human interpretation of color photographs [Hara73].

•Spectral Features:-Describe the average tonal variations in various bands of the visible and/ or infrared portion of an electromagnetic spectrum.

•Textural Features:-Contain information about the spatial distribution of tonal variations.

•Contextual Features:-Contain information derived from blocks of pictorial data surrounding the area being analyzed.

2.2 Texture

Quantitative study of images is often concerned with four types of parameters, which are of fundamental importance. These are Contrast (Is very important measure in image processing which often determine the quality of an image, Color (Add more useful discriminatory information to the image), Shape (Is a measure which is used in recognizing the various object contained in an image), and Texture (Describe the spatial distribution of tonal value within band and provide useful information for performing automatic interpretation and recognition) [Alan96].

Although texture can be recognized when it is seen, it is very difficult to define. This difficulty is demonstrated by the number of different texture definitions attempted by vision researchers. The following are some of these definitions:

•"A region in an image has a constant texture if a set of local statistics or other local properties of the picture function are constant, slowly varying, or approximately periodic." [Tuce93].

•"The image texture we consider is nonfigurative and cellular. An image texture is described by the number and types of its (tonal) primitives and the spatial organization or layout of its (tonal) primitives. A fundamental characteristic of texture: it cannot be analyzed without a frame of reference of tonal primitive being stated or implied. For any smooth gray-tone surface, there exists a scale such that when the surface is examined, it has no texture. Then as resolution increases, it takes on a fine texture and then a coarse texture." [Hara79].

•"The notation of texture appears to depend upon three ingredients: (i) some local 'order' is repeated over a region which is large in comparison to the order's size,(ii) the order consists in the nonrandom arrangement of elementary parts, and (iii) the parts are roughly uniform entities having approximately the same dimensions everywhere within the textured region." [Tuce93].

These definitions of texture indicate that a key point of texture definition is that the basic pattern elements (texels) must appear with a characteristic repetition inside a given area [Roan87].

Image texture, defined as a function of the spatial variation in pixel intensities (gray level) which is useful in a variety of applications [Sonk98]. One immediate application of image texture is the recognition of image regions using textural properties. Texture properties are used to discriminate: (i) one object from other, (ii) an object from background, (iii) to draw inference about 3D world. For that, any machine vision system must be able to deal with texture [Jain94].

Among the main tasks of texture analysis are segmentation and classification. The typical approach to texture segmentation or classification consists of two phases:

•First phase: textural features are computed over a local neighborhood of a pixel. The features may be local statistics in case of statistical methods, or parameters of an underlying model in structural methods.

•Second phase: a suitable clustering or classification algorithm including neural networks, is used to cluster or classify the external pattern vectors. In texture classification task where the texture categories are known, a supervised classification technique can be used to classify a pattern vector. When textural categories are unknown, an unsupervised classification (clustering) technique can be used to classify a pattern vector [ferr02].

This chapter reviews and discusses various aspects of texture analysis. The concentration is on the various methods of feature extraction and classification.

2.3 Taxonomy of Texture Models

Identifying the perceived qualities of texture in an image is an important first step toward building mathematical models for texture. In spite of the fact that there is no general definition of texture, texture has number of properties that are assumed to be true. These properties are [Tuce93]:

•Texture is a property of area. So texture is a contextual property where its definition must involve gray values in spatial neighborhood. The size of this neighborhood depends upon the texture type, or size of primitive defining texture.

•Texture involves spatial distribution of gray levels. Thus, two-dimensional histograms or Co-occurrence matrices are reasonable texture analysis tools

.

•Texture in an image can be perceived at different scales or level of resolution. For example, consider the texture represented as formed by the individual brick in the wall; the interior details in brick are lost. At higher resolution when only a few bricks are in the field of view, the received texture shows the details in the brick.

•A region is perceived to have texture when the number of primitive objects in the region is large. If only a few primitive objects are presented, then a group of countable objects is perceived instead of a textured image. In other words, a texture is presented when significant individual “forms” are not presented.

Uniformity, density, coarseness, roughness, regularity, linearity, directionality, frequency, and phase, are important properties used to describe textures. Some of these properties are not independent. For example, frequency is not independent of density, and the direction property only applies to directional textures. The fact that the perception of texture has so many different dimensions is an important reason why there is no single method of texture representation that is adequate for variety of textures. For that, different types of textures may need different features to represent and classify them.

2.4 Texture Problem

Texture processing problems can be divided into feature extraction, and discrimination. Various methods for extracting texture features can be applied in four broad categories of problems: texture segmentation, texture classification, texture synthesis, and shape from texture. The concentration is on texture segmentation and classification. The following is a review for these two areas [Gonz87, Shou05]:

2.4.1 Texture Segmentation

Segmentation is the process that subdivides an image into its constituent parts or objects [Gonz87]. One does not need to know which specific textures exist in the image in order to do texture segmentation. All that is needed is a way to tell that two textures (usually in adjacent regions of an image) are different [Chel93]. Segmentation is a difficult, yet very important task in many image analysis or computer vision applications. Differences in the mean gray level or in color within small neighborhoods alone are not always sufficient for image segmentation. Rather, one has to rely on differences in the spatial arrangement of gray values of neighboring pixels (i.e. difference in texture). The problem of segmenting an image based on texture segmentation properties is referred to as the texture segmentation problem [Jain94].

2.4.2 Texture Classification

Texture can be considered to be repeating patterns of local variation of pixel intensities. Despite its importance and ubiquity in image data, a formal approach or precise definition of texture does not exist, it is one of those words that we all know but have a hard time defining. When two different textures seen, one can clearly recognize their similarities or differences, but may have a hard time verbalizing them. Textures mainly could be used to [Sali05]:

1. Discriminate between different (already segmented) regions or to classify them,
2. Produce descriptions so that textures can be reproduced, and
3. Segment an image based on textures.

Texture classification involves deciding to what texture category an observed textured region or pixel belongs. In order to accomplish this, one needs to have a priori knowledge of the classes to be recognized. Once this knowledge is available and the texture features are extracted, one then uses classical pattern classification techniques to do classification. Thus, standard pattern classification techniques may be applied to the image pixels. The three most well known models for designing a classification system are: statistical, syntactical or structural, and artificial neural networks methods, the concentration will be on statistical classifiers. Statistical classifiers are of two basic categories: supervised and unsupervised classification [Sama99].

•Supervised Classification

There are a number of separable pattern cover real images. Automatically, separating these patterns is performed by estimating some of the statistical properties within a series of templates. In fact, each of these templates represents an ideal pattern. So individual pixels can be compared with each template to determine the closest match. Each pixel is then assigned to a class representing the most similar templates. With supervised classification, the analyst defines on the image a small area, called a training site, which is representative of each class. The value of each pixel in a training site is used to define the decision space for that class. After the clusters for each training site are defined, the computer then classifies all the remaining pixels in the image [Jano01].

• Unsupervised Classification

Unsupervised classification is a method which examines a large number of unknown pixels and divides into a number of classed based on natural groupings present in the image values. Unlike supervised classification, unsupervised classification does not require analyst-specified training data. The basic premise is that values within a given cover type should be close together in the measurement space (i.e. have similar gray levels), whereas data in different classes should be comparatively well separated (i.e. have very different gray levels). The classes that resulted from unsupervised classification are based on natural groupings of the image values, the identity of the class will not be initially known, must compare classified data to some from of reference data (such as larger scale imagery, maps, or site visits) to determine the identity and informational values of the classes. Thus, in the supervised approach, to define useful information categories and then examine.

Their reparability; in the unsupervised approach the computer determines spectrally separable class, and then defines their information value, the analyst attempts a posterior to assign these (natural) or spectral classes to the information classes of interest. This method is, usually, used when less is known about the data before classification [Jano01].

2.5 Feature Extraction

Feature extraction refers to the process of finding a mapping that reduces the dimensionality of the patterns by extracting some numerical measurements from raw input patterns [Seti97]. It is also defined as the process of forming a new “often smaller” set of features (refined representation) from the original feature set. Feature extraction can avoid the curse of dimensionality, improves the generalization ability of classifiers, and reduces the computational requirements of the classifier [Mao94].

There is no well-developed theory for feature extraction; most of these features are very application oriented and often found by heuristic methods and iterative data analysis. Number of factors should be taken into-consideration before choosing the appropriate learning method for feature extraction. Some of these factors are: (i) the feature extractor should provide a high compression ratio (to reduce the classification computational time), (ii) the extracted features must be independent of class membership.

Many types of representations and features have been proposed for attempting to maximize the classification task with a minimal set of compact discriminates. To discriminate images with different textural characteristics, it is essential to extract texture features that most completely embody information about the spatial distribution of intensity variations in each image. These features can be extracted either directly from image statistics or spatial frequency domain [Andr02, Guib88].

Classically, figure (2.1) shows the major categories of texture measure methods which have been identified: structural, statistical.

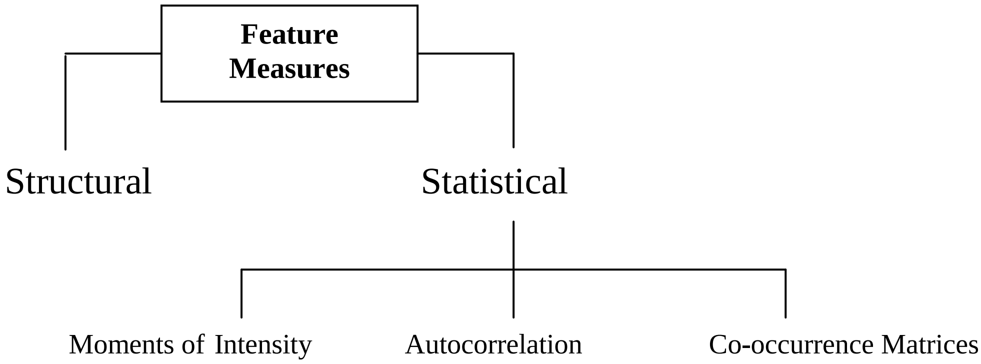


Figure 2.1: Major categories of features for texture identification [Andr02]

2.5.1 Structural Approaches

A first way of defining the texture in a region is to define a grammar for the way that the pattern of the texture produces structure.

The basic scheme is to build a grammar for the texture and then parse the texture to see if it matches the grammar. The idea can be extended by defining texture primitives, simple patterns from which more complicated ones can be built. The parse tree for the pattern in a particular region can be used as a descriptor. For example: suppose that we have a rule of the form $S \rightarrow aS$, then three applications to this rule would yield the string “aaaS”. Let “a” represent a primitive (let it be a circle) and assign the meaning of “circle to the right” to a string of the form “aaa....”, then the rule $S \rightarrow aS$ allows us to generate a texture pattern of the form shown if figure (2.2) [Gonz87].

Figure2.2: (a) Texture Primitive. (b) Pattern Generated [Sama99]

2.5.2 Statistical Approaches

One of the defining qualities of texture is the spatial distribution of gray values. The use of statistical features is therefore one of the early methods proposed in the machine vision literature [Tuce93]. Since textures may be random, but with certain consistent properties, one obvious way to describe such textures is through their statistical properties, textural properties are characterized by statistics derived from gray-level distributions or from the textural local feature distributions, moment of intensities, autocorrelation features, and Co-occurrence matrices approaches are the most popular statistical features[ferr02].

The moments beyond this are harder to describe intuitively, but they can also describe the texture.

- **Gray-level Co-occurrence Matrices**

An important and powerful statistical texture analysis algorithm is the Co-occurrence matrices [Alan96]. It is statistical way to describe shape by statistically sampling the way certain gray-levels occur in relation to other grey-levels [Web3].

One aspects of texture is concerned with the spatial distribution and spatial dependence among the gray tones in local area.

The Co-occurrence matrix is a two dimensional histogram of a number of times that pairs of intensity values occur in given spatial relationship. In 1973, Haralick, et.al. have utilized extended blocks of size (64×64) for imagery that were quantized into 16 levels. Haralick (1979) proposed a variety of measures to extract useful textural information form the Co-occurrence matrices.

The Co-occurrence matrices are constructed by considering that every pixel have eight neighbors (horizontally, vertically and diagonally at 45 degrees), see figure (2.3) a. It is also assumed that the matrix of relative frequencies of gray levels Co-occurrence can specify the texture-context information. Some of the texture measures can be obtained from these matrices like homogeneity and the contrast [Web1].

Suppose an image to be analyzed is rectangular and has resolution cells in the horizontal direction and resolution cells in the vertical direction. Suppose that the gray tone appearing in each resolution cell is quantized to levels, in order to keep the size of the Co-occurrence matrix manageable since pixel amplitude is re-quantized over the range 0<=a,b<=1.during the computation four brightness value spatial dependency matrices are derived, each matrix correspond to the spatial dependency along certain orientation (0°, 45°, 90°, 135°), see figure (2-3)b.

(a) (b)

Figure 2.3:(a) The neighbor's index of the pixels in eight directions. (b) The angels.

The texture is specified by the matrix of relative frequencies of Co-occurrence p(i,j), which indicate the number of times that each two neighboring pixels of an image, separated by a distance (d), will have gray tone (i) for one pixel and (j) gray tone for the other pixel, matrix A, Such matrices of gray tone spatial dependence frequencies are the function of the angular relationship between the neighboring pixels, as well as a function of the distance between them [Alan96].

Matrix A-general form of any gray tone spatial dependence matrix (i, j) stands for number of times gray tones (i, j) has neighbors.

	0	1	2	3
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)

The Co-occurrence matrices are based on the repeated occurrence of the gray-level configuration in the considered texture. This configuration varies rapidly in fine textures, more slowly in coarse textures.

As very simple example, if a small segment of a digital image quantized into four gray levels (0-3),matrix (B), the number of adjacent pixels with gray levels i and j is counted and placed in element (i,j) of the gray spatial dependency matrix (A). Four type of adjacency orientations may use (ϴ=0°, 45°, 90°, 135°),matrix(C), for example the element (0,0) at ϴ=0 and d=1 is the number of times a pixel with gray scale value 0 is horizontally adjacent to another pixel of value 0, counted from left to right as well as right to left) [Jano01,Davi79].

$$\begin{pmatrix} 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 2 & 2 & 2 \\ 2 & 2 & 3 & 3 \end{pmatrix}$$

Matrix B-gray level image

$$A\,(1,0°) = \begin{pmatrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 6 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{pmatrix} \qquad A\,(1,45°) = \begin{pmatrix} 2 & 1 & 3 & 0 \\ 1 & 2 & 1 & 0 \\ 3 & 1 & 0 & 2 \\ 0 & 0 & 2 & 0 \end{pmatrix}$$

$$A\,(1,90°) = \begin{pmatrix} 6 & 0 & 2 & 0 \\ 0 & 4 & 2 & 0 \\ 2 & 2 & 2 & 2 \\ 0 & 0 & 2 & 0 \end{pmatrix} \qquad A\,(1,135°) = \begin{pmatrix} 4 & 1 & 0 & 0 \\ 1 & 2 & 2 & 0 \\ 0 & 2 & 4 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

Matrix C- the Co-occurrence matrices for the four orientations (ϴ=0°, 45°, 90°, 135°) and distance =1.

It is often convenient to normalize the Co-occurrence matrices. When the relationship is the nearest horizontal neighbor (d=1, ϴ=0) there will be $2(N_X-1)$ neighboring resolution cell pair on each row, and there are N_Y rows, providing a total of $2N_Y(N_X-1)$. The normalized Co-occurrence matrices

$P_N(i, j, \theta)$ Is Then

$$P_N(i, j, \theta) = \frac{1}{N_\theta} P(i, j, \theta) \cdots\cdots\cdots (2-1)$$

$$N_\theta = \begin{pmatrix} 2N_y(N_x - 1) & \theta = 0^\circ \\ 2(N_x - 1)(N_y - 1) & \theta = 45^\circ \ \& 135^\circ \\ 2N_x(N_y - 1) & \theta = 90^\circ \end{pmatrix}$$

The Co-occurrence texture features are computed from spatial gray dependence. Matrix (p) contains the relative frequencies with which two pixels (one with gray level value i and the other with gray level j) separated by distance d at a certain angle Θ occur in the image. It is important to note that when computing Co-occurrence features from images with relative high number of possible pixel intensity values (e.g. 256) it is not wise to use all possible discrete signal levels. If all original intensity levels were employed, the derived texture information could be easily blurred by a noise in the image. The major difficulties in using Co-occurrence matrices is their large dimension, this can be overcome by coarse quantization [Alan96].

Hence it is preferable to transform the original intensity values into a smaller number of possible levels via a quantization method [Web2].
Quantization has two types these are divided into:

- Uniform Quantization: In order to be in a form suitable for computer processing, an image function f (x, y) must be digitized in amplitude and it is called gray-level quantization.
- Nonuniform Quantization: For a fixed value of N (N: N×N size of image), it is possible in many cases to improve the appearance of an image by using an adaptive scheme. When the number of gray levels must be kept small, it is usually desirable to use unequally spaced levels in the quantization process .

The texture classification can be based on criteria (features) derived from Co-occurrence matrices [Sama99].

If an image region contains fine texture, the occurrence matrix of pair of pixels will tend to be uniform, while for coarse texture the matrix values will be skewed toward the diagonal of the matrix. Using statistics derived from the Co-occurrence matrix Haralick in 1973 performed a number of identification experiments on a set of imagery. It is found many properties for the matrix P are obvious from the way it is constructed:

1 .Its diagonal elements are approximately equal to the areas of regions with the p(i, j) element (i=j) equal to the area of regions whose pixels have value i.

2. The off diagonal elements have values approximately equal to the length of the boundaries between regions with p(i,j) element equal to the contour length between regions whose pixels have value i and j.

For image with low contrast, elements far from the diagonal should be zero or very small, while the opposite will be true for high contrast images [Ali04].

2.6 Statistical Texture Features

Haralick (1973) have proposed a variety of measures that can be employed to extract useful textural information from Co-occurrence matrices. The equations which define a set of 13 measures of textural features are given in last section. Some of these measures relates to specific textural characteristics of the image such as homogeneity, contrast, and the presence of organized structure within the image. Other measures characterize the complexity and nature of gray tone transition which occur in the image. Even thought these features contain information about the textural characteristics of the image, it is hard to identify which specific textural characteristic is represented by each of these features. The Co-occurrence matrix p(i ,j) is the

(i , j)th element of the given quantized matrix of size (Ng×Ng), normalized by the total number of paired occurrences. For a chosen distance (d) we have four angular gray tone spatial dependency matrices. The mean and the range of these features, averaged over the four values, comprise the set of features which can be used as inputs to the classifiers [Alan96].

The spatial gray-level Co-occurrence matrix estimates image properties related to second order statistics. A set of texture features can be computed from Co-occurrence matrix, these descriptors include [Hara79, Guib88]:

1.Maximum Probability (MPR):

$$\text{MPR}=\max_{i,j} p_d(i,j) \qquad (2.2)$$

2. Element Difference moment of order K (EDM):

$$\text{EDM}=\sum_i\sum_j (i,j)^k p_d(i,j) \qquad (2.3)$$

3.Entropy (ENT):

$$\text{ENT}=-\sum_i\sum_j p_d \log p_d(i,j) \qquad (2.4)$$

4.Homogeneity (HOM):

$$\text{HOM}=\sum_i\sum_j \frac{p_d(i,j)}{1+|i-j|} \qquad (2.5)$$

The value of the local homogeneity is high when the diagonal concentration is high.

5.Energy or Uniformity (ENE):

$$\text{ENE}=\sum_i\sum_j p_d^2(i,j) \qquad (2.6)$$

6.Correlation (COR):

$$\text{COR}=\frac{\sum_{i}\sum_{j}(i-\mu_x)(j-\mu_y)P(i,j)}{\sigma_x\sigma_y} \qquad (2.7)$$

Where μ_x, μ_y are the mean, and σ_x, σ_y are the standard deviations of P (x) and P (y), where $P_d(x)=\sum_j P_d(x,j)$, and $P(y)=\sum_i P(i,y)$. Since the Co-occurrence matrix is square matrix $\therefore \sigma_x=\sigma_y$, and $\mu_x=\mu_y$

7.Cluster Shade (CLS):

$$\text{CLS}=\sum_i\sum_j(i+j-M_x-M_y)^3\ P(i,j) \qquad (2.8)$$

8.Cluster Prominence (CLP):

$$\text{CLP}=\sum_i\sum_j(i+j-M_x-M_y)^4\ P(i,j) \qquad (2.9)$$

Where $M_x=\sum_i\sum_j iP(i,j)$, and $M_y=\sum_i\sum_j jP(i,j)$

9. Contrast (CNT):

$$\text{CNT}=\sum_i\sum_j(i,j)^2\,p(i,j) \qquad (2.10)$$

This is the moment of inertia of the matrix around its main diagonal. It is a natural measure of the degree of spread of the matrix value.

10. Angular Second Moment (ASM):

$$ASM=\sum_{i}\sum_{j} p(i,j)^{2} \qquad (2.11)$$

The Angular Second Moment features are a measure of homogeneity of the image. In a homogeneous image there are very few dominate gray tone transition. Hence the matrix for this type of image will have fewer entries of large magnitude and vice versa.

11. Inverse difference Moment (INV):

$$INV=\sum_{i}\sum_{j}\frac{P(i,j)}{1+(i-j)^{2}} \qquad (2.12)$$

The value of the local homogeneity is high when the diagonal concentration is high .

The Co-occurrence features suffer from a number of difficulties, these are [Tuce93]:

1. There is no well-established method for selecting the displacement vector d; computing Co-occurrence matrices for different values of d is not feasible.
2. For a given d, a large number of features can be computed from Co-occurrence matrix. This means that some sort of feature selection method must be used to select the most relevant features.

The Co-occurrence matrix-based features have been primarily used for classification tasks and not for segmentation tasks [Tuce93].

Chapter Three

System Development and Implementation

3.1 Introduction

The theoretical concepts of texture analysis and image classification were discussed in the previous chapter. This chapter is devoted to describe the computer programs design and implementation to offer the facilities, which may be required to perform the classification process.

To perform the texture classification process, three textured images from Brodatz album are chosen and implemented for this purpose. These are (D17, D18, and D84) as shown in figure (3-1). Each of these images has been digitized into 128×128 pixels of 256 gray-level. The screen images are of bit-map (BMP) type. A detailed description of the BMP file format is presented in the Appendix (A).

D17 D18 D84

Figure (3-1): The three textured images used as test material

The system was implemented and written using visual Basic version 6.0 on a personal computer (Pentium IV processor with 256 RAM and 20 GB hard disk that works under windows XP).

3.2 Features Set

The goal in image analysis is to extract data useful for solving application based problem. This is done by intelligently reducing the amount of image data with the tools have explored. A feature vector is one method to represent an image, or part of an image object, by finding measurements on a set of features. Therefore, finding a specific features-vector that has the best discrimination power has been one of the most important problems in the field of texture analysis and image classification. The statistical features is one of the most important features that is used to evaluate the performance of Co-occurrence matrices for solving texture classification problem, thus, the statistical feature is adopted in work.

- **Statistical Feature Set**

The texture statistical features are known to contain significant discriminatory information for image classification. Some of the commonly used statistical features are based on gray-level Co-occurrence matrix. In this work the statistical feature is extracted for different window sizes (sub-image of size M×M) with different quantization level. The head line of the presented work can be summarized by the following two modules:

Module-1: For each image, the Co-occurrence matrix P is extracted with different quantization levels 8, 16 and 32; eight statistical texture features are calculated depending on the extracted Co-occurrence matrix P. These eight statistical texture features which are chosen and adopted in this work are:

1. Maximum probability	2.Entropy	3. Homogeneity
4. Cluster-Shade	5. Cluster-Prominence	6. Contrast
7. Angular Second Moment.	8. Inverse Difference Moment.	

These statistical features are defined in eq's (2.2), (2.4), (2.5), (2.7), (2.8), (2. 9), (2.10), and (2.11) respectively.

Module-2: In this module the same procedure presented in set -1 is applied but with different block size M×M of the original image (the original image is divided into sub images with block size 32X 32 and 64 X 64), then the Co-occurrence matrix P is extracted for each block size, then the selected features (presented in ***module-1***) is calculated depending on the extracted Co-occurrence matrix P.

3.3 TICS System Structure

The features extraction is performed through the user interface. The user interface includes two choices, through which the user can perform the following operations (see figure (3-2)):

- Apply Co-occurrence matrix on original image.
- Apply Co-occurrence matrix on sub images.

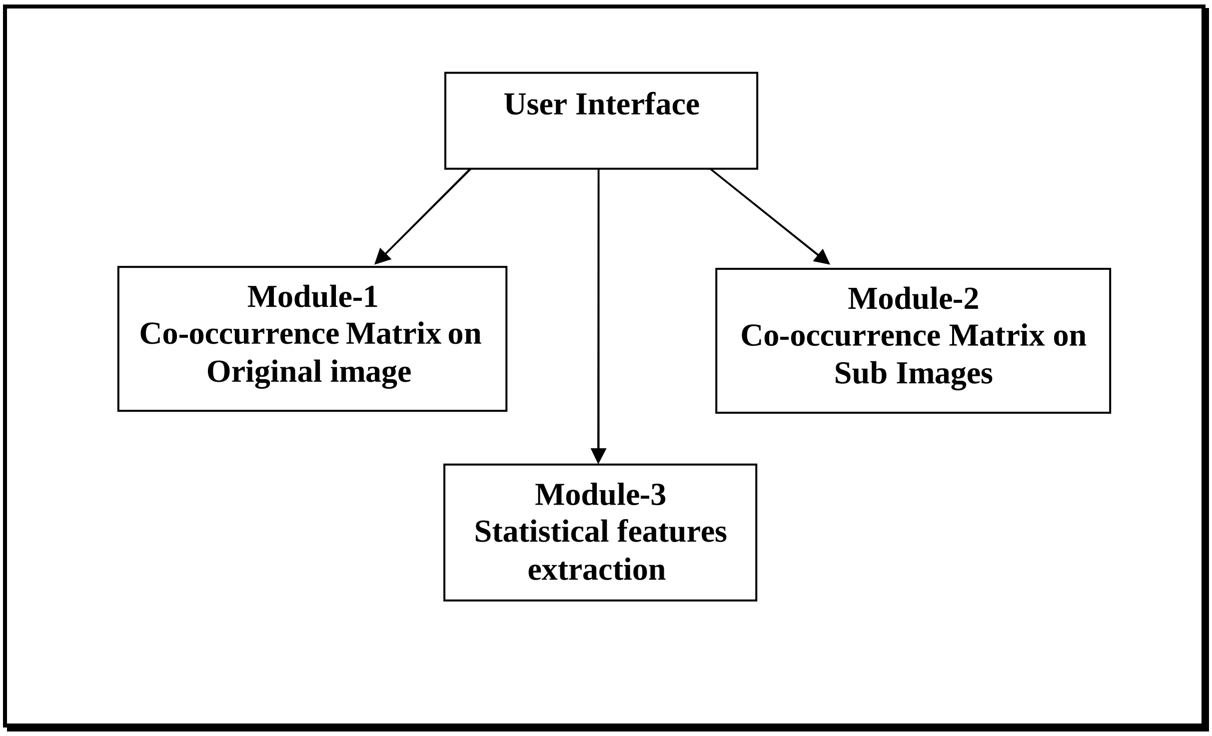


Figure (3-2): The Main Modules

When applying Module-1 and Module-2, one can make a comparison and the analysis between the results by extract features from module-3.

3.4 The Design Approach

For a typical texture classification system, the determination of the class is one of the aspects of overall task. Texture classification system generally contains several modules.

In this work, a Texture-Image Classification System "TICS" was implemented by using Co-occurrence matrices algorithm. During the early stages of the system design, the designer needs to specify the input image format (to analyze the input image and extract the image-data), determine the feature set that should be calculated (from image data). Finally, specify the Co-occurrence matrices (using new way to calculate the features set and comparing the results).

Considering the above argument, TICS was constructed using number of modules, each module performs specific task. Collectively, these modules combine to perform the overall texture classification task (using the selected features). From the functional point of view, TICS consists of seven modules (see figure (3-3)).

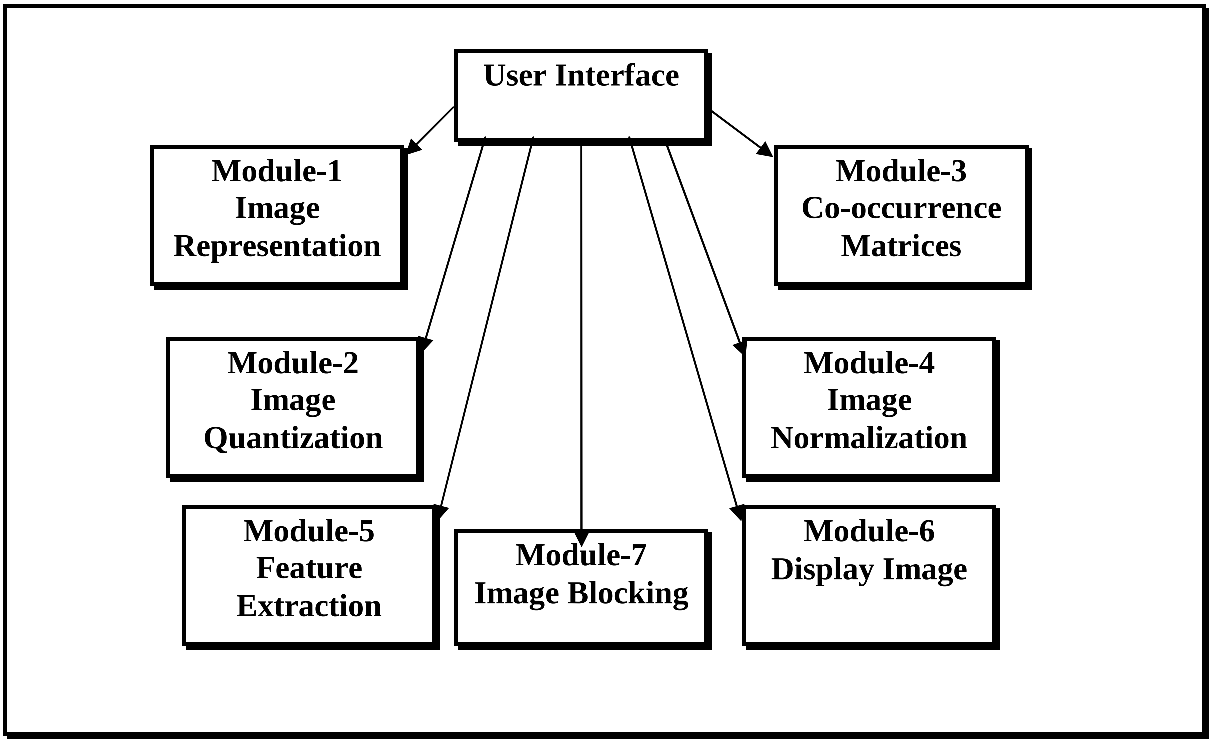


Figure (3-3): Texture Image Classification System (TICS) Sub Modules.

The Flow Control of TICS is presented in Figure (3-4).

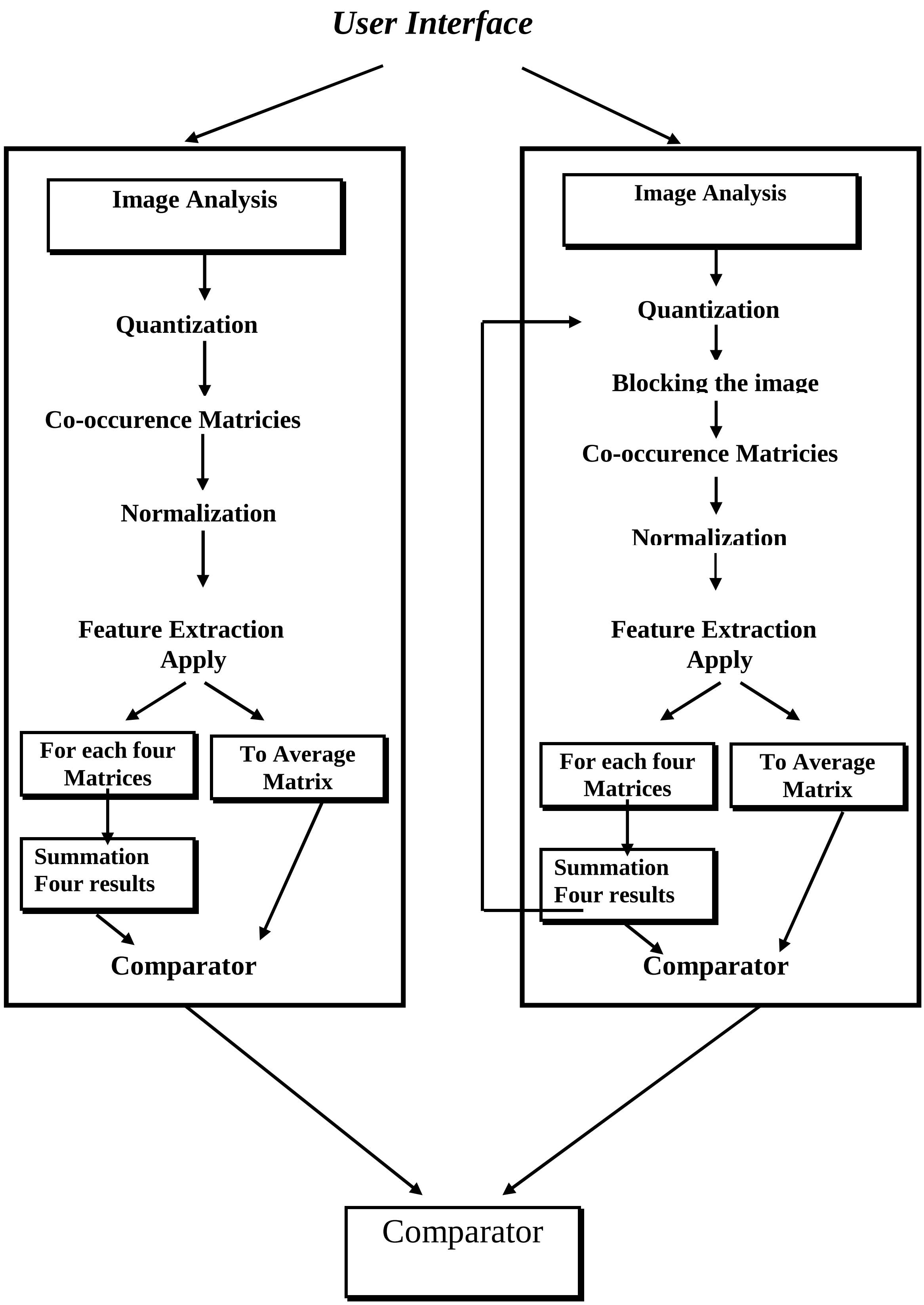


Figure (3-4):Flow Control of TICS

3.4.1 Module-1: Image Representation

Scanners are capable of producing image representation in a variety of formats. One of the most popular of these formats is the bit-map (BMP) format. BMP files consist of three parts (the detailed structure of the BMP files is shown in appendix A). These three parts are header (provides essential information about the image such as image-width, image-height, number of bit/pixel, and a pointer to the beginning of the image-data), color palette (represent the intensities in red, green, and blue (RGB)), and image-data (represents the pixel values). In the present work only the gray images are adopted .

Image representation module concerned with analyzing the image file to get information about the input image (image-width, image-height, and the image-data), and pass this information to the next modules.

3.4.2 Module-2: Image Quantization

The main draw back in using the spatial gray level dependence method is the large memory requirement for storing the Co-occurrence matrices. Sometimes the Co-occurrence matrices used for texture characterization are more voluminous than the original images from which they are derived. Quantization process overcomes this problem. For this reason image quantization process is adopted in this work.

Image quantization is the process of reducing the image data by removing some of detail information by mapping groups of data points to a single point. This can be done to the pixel values themselves. In the present work the gray level reduction is achieved by taking the data and reducing the number of bits per pixel.

3.4.3 Module-3: Co-occurrence Matrices

Algorithm (3.1) Co-occurrence Matrices

As be mentioned before, the gray level Co-occurrence matrix is the two dimensional matrix of joint probability P (I, J) between pairs of pixel separated by a distance d in a given direction.

This algorithm is executed on a two matrices the first one is the input BMP file image (original image) and the second one is the matrix indices that is depend on quantization and blocking size input.

Step 0: Read BMP file.

Step 1: ***For K = 0 to width-image - 1***

For L = 0 to height-image - 1

For I = 0 to width-image-index - 1

For J = 0 to height –image-index - 1

***If (Bmp image (K, L) = I) Then Go To* Step2**

{Check all array contents with the each index I if it is equal to it then now enter in four different angles (0°, 45°, 90°, and 135°)} for specific pixel value check the neighbors in 4 angles if it found equal to J index, increment the counter when complete search for specific value store the value of counter in new array of (i, j)}.

Next J

Next I

Initialize again all counters of four angles to search to next indices

Next L

Next K

Step 2: Calculate the Average of the Co-occurrence matrix (since the result from step 1 is four matrices according to four angles 0°, 45°, 90°, and 135°) by applying the following equation :

$$p_{ave}(i,j)=\frac{1}{4}\sum_{j=0}^{hight-1}\sum_{i=0}^{width-1}p_{\vartheta=0}(i,j)+p_{\vartheta=45}(i,j)+p_{\vartheta=90}(i,j)+p_{\vartheta=135}(i,j)$$

Step 3: End.

3.4.4 Module-4: Normalization of the Co-occurrence Matrix

This step is accomplished by dividing each entry in the Co-occurrence matrix by the total number of paired occurrences (equation 2-1).

3.4.5 Module-5: Feature Extraction

Features extraction abstracts high-level information about individual patterns to facilitate texture classification. Therefore, to discriminate images with different textural characteristics, it is essential to extract texture features. Feature set (presented in section 3.2.1) were extracted from selected textured images.

3.4.6 Module-6: Display-Image

This module used for displaying the processed image at the end of any executing module when the user desire that.

3.4.7 Module-7: Image Blocking

In this module the image can be divided into array of blocks (sub-images), usually of size $2^k \times 2^k$ (where *k* is integer input value).

<u>Algorithm (3.2): Image Blocking</u>

<u>Step 0</u>: Block size (*k*).

Let M=128 div 2^k : Let N be number of blocks (N=M^2)

<u>Step 1:</u> Read image blocks.

For Y = 0 to height \ 2^k - 1

For X = 0 to width \ 2^k - 1

For y2 = 0 to 2^k - 1

For x2 = 0 to 2^k - 1

Store-image(X, Y, x2, y2) = image(X * 2^k + x2, Y * 2^k + y2)

Next x2

Next y2

Next X

Next Y

Step 2: End.

3.5 The Implementation Approach

This section (implementation approach) explains the details of implementation of this work. Algorithm (3.3) explain the followed steps of the image analysis based on texture feature.

Algorithm (3.3): Image Analysis Based on Texture features

Step 0: Read BMP file (image).

Step 1: Apply Quantization method on the data of BMP file.

Step 2: Apply Co-occurrence matrices method (see Algorithm 3.1).

Step 3: Calculate the average of the Co-occurrence matrix and normalize it. by applying the related equations (see chapter 2).

Step 4: Extract features for the average Co-occurrence matrix.

Step 5: Calculate the Co-occurrence matrix for each angle and normalize it. In this process four matrices are extracted.

Step 6: Extract features for the four matrices.

Step 7: Select the block size needed for dividing the original image (see Algorithm 3.2) and select the number of level needed for quantization process.

Step 8: For each sub-image go to step 2 until finishing the process of the last sub-image.

Step 9: Compare the result of features of original image with each sub image and analysis it.

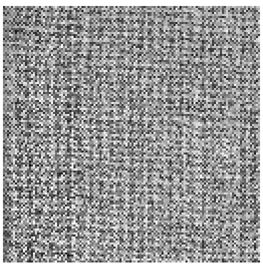
Step 10: End.

3.5.1 Experiment1 (D17) :

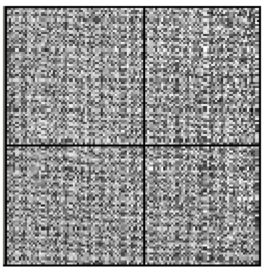
The first selected textured image used as a test material is D17 image. The D17 is of a size of (128 × 128) with 256 gray levels. The eight selected features (MPR, ENT, HOM, CLS, CLP, CNT, ASM, and INV) are calculated for the original image and for the sub image for different block sizes 32 x 32 and 64 x 64 as be shown in figure (3-5) with different quantization levels 8, 16, and 32.

It should be mentioned that the features are calculated in two ways, the first one for the average Co-occurrence matrix (first case named before) and the second one for the Co-occurrence matrix of angle 0°, 45°, 90°, and 135°(second case named after). Four values for the same feature is extracted (one for each angle) for the second case, and then the average value for the four features is calculated .

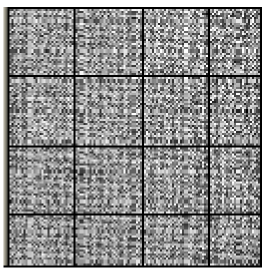
The calculated values for the eight features for D17 image for the two cases with 8, 32, and 64 level is presented in tables (3-1), (3-2), and (3-3) respectively.



(A)



(B)



(C)

Figure (3-5): Experiment 1
(A) Original Image D17,
(B) Extracted Features with window size 64×64.
(C) Extracted Features with window size 32×32.

Table 3-1: The value of statistical features for textured image D17 with quantization level =8

	8 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	6.0865	0.3700	4.1253	2.4458	0.0390	0.0447	679.67	6798.2
After	6.0865	0.3713	5.5127	2.4272	0.0388	0.0446	682.27	6823.7

Table 3-2: The value of statistical features for textured image D17 with quantization level =16

	16 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	23.881	0.2159	5.5649	0.0063	0.0109	0.3099	6333.1	131753
After	23.881	0.2167	7.4654	0.0062	0.0103	0.3000	6357.3	132249

Table 3-3: The value of statistical features for textured image D17 with quantization level =32

	32 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	95.4240	0.1177	7.0477	0.0016	0.0033	0.2035	54601	231892
After	95.4240	0.1181	9.4552	0.0015	0.0030	0.2033	54813	232765

It is clear from these tables that most of the selected features are stable in the two cases before and after except the feature of the entropy since the difference in the feature value of the two cases (before and after) is perceptible. This property can be utilized in the process of the discrimination pattern.

Figure (3-6) shows the behavior of the selected features in the case of before and after. As be mentioned before that the entropy feature gives perceptible slope in the case of before and after.

Figure (3-7) shows the behavior of the selected features with different quantization levels. It is clear from the figure that some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.

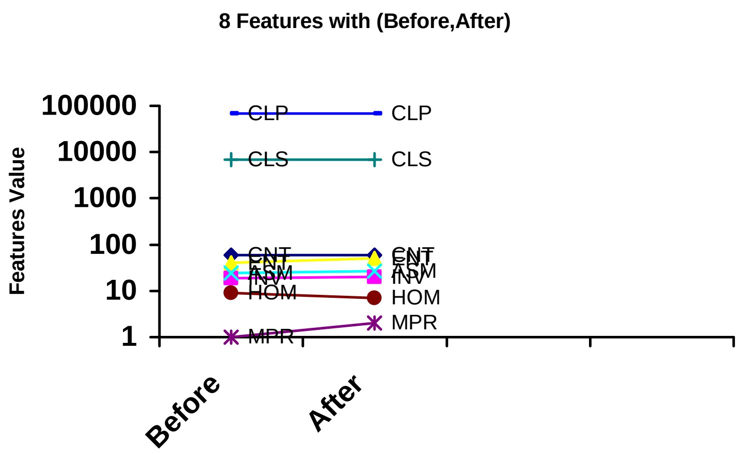


Figure (3-6): The behavior of the selected features in the case of before and after.

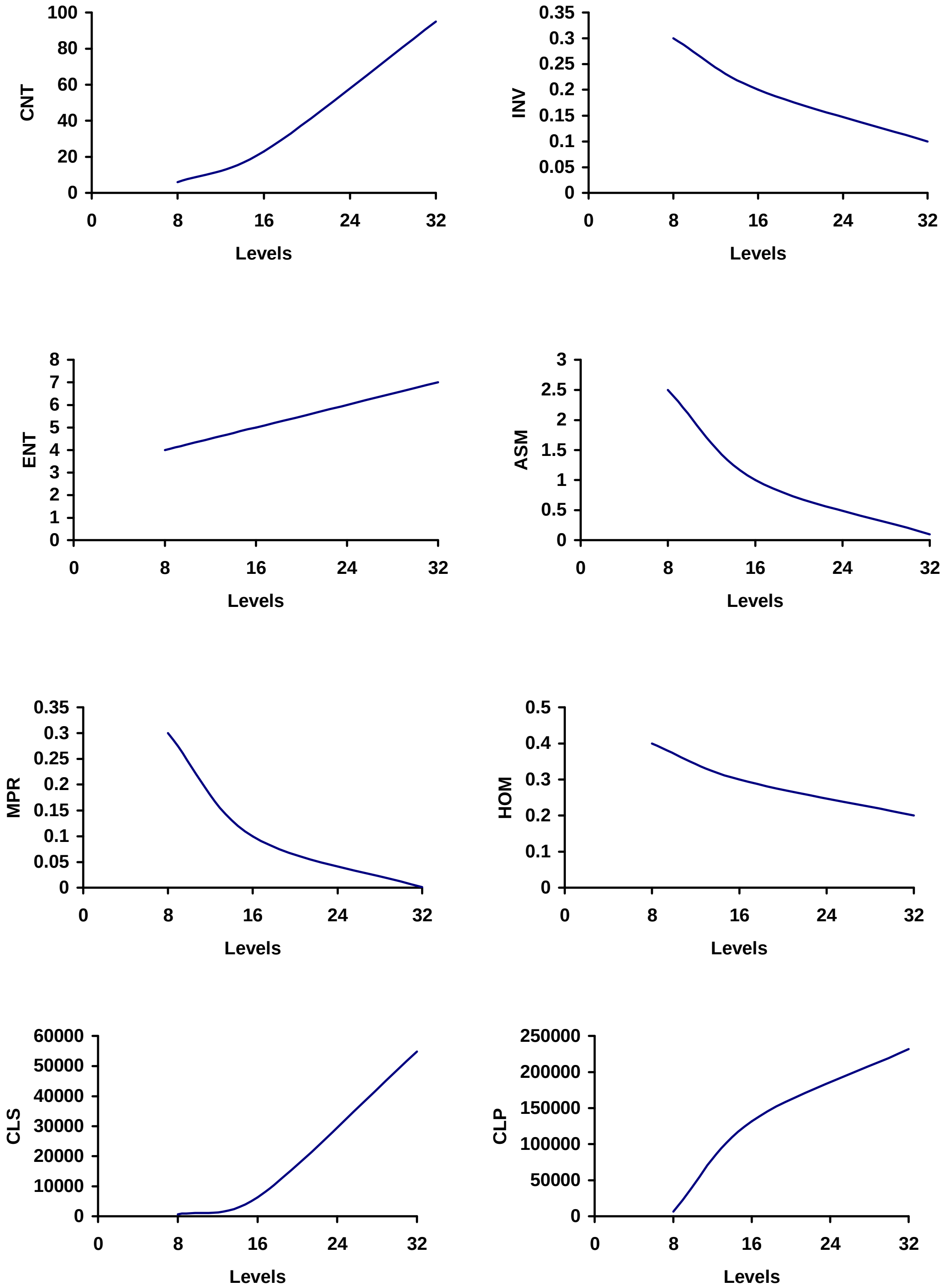


Figure (3-7): The behavior of the selected features with different quantization level (8, 16, and 32).

Table (3-4) shows the extracted features from D17 image with block size (64 x 64) and with different quantization level (8, and 16).

Table (3-4): Extracted features for each block (block size 64×64) of the D17 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
CNT	Block1	5.9644	6.0185	23.426	23.640
	Block2	5.5802	5.5803	21.746	21.943
	Block3	6.7693	6.8294	26.906	27.147
	Block4	6.0044	6.0585	23.466	23.680
INV	Block1	0.3716	0.3743	0.2175	0.2190
	Block2	0.3822	0.3825	0.2266	0.2238
	Block3	0.3510	0.3536	0.2003	0.2017
	Block4	0.4116	0.4143	0.2575	0.2500
ENT	Block1	4.1089	5.5185	5.5501	7.4709
	Block2	4.0030	5.3787	5.4251	7.3083
	Block3	4.1919	5.6119	5.6328	7.5808
	Block4	4.1489	5.5585	5.5901	7.5109
ASM	Block1	0.0242	0.0241	0.0063	0.0062
	Block2	0.0278	0.0278	0.0074	0.0073
	Block3	0.0217	0.0217	0.0056	0.0056
	Block4	0.0242	0.0241	0.0046	0.0046

To be continue

Table (3-4): Extracted features for each block (block size 64×64) of the D17 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
MPR	Block1	0.0366	0.0366	0.0113	0.0104
	Block2	0.0501	0.0526	0.0158	0.0141
	Block3	0.0332	0.0293	0.0095	0.0078
	Block4	0.0766	0.0766	0.0051	0.0050
HOM	Block1	0.4479	0.4513	0.3110	0.3133
	Block2	0.4569	0.4603	0.3194	0.3218
	Block3	0.4310	0.4342	0.2952	0.2974
	Block4	0.4879	0.4913	0.3510	0.3530
CLS	Block1	631.71	636.575	5913.7	5959.3
	Block2	660.34	665.461	6161.3	6209.2
	Block3	701.24	706.64	6537.1	6587.5
	Block4	631.75	636.61	5913.7	5959.3
CLP	Block1	6209.5	6265.1	121004	121916
	Block2	6500.1	6528.9	125705	126741
	Block3	27230.1	7235.8	214033	140411
	Block4	6259.9	6256.2	121618	121916

Table (3-5) shows the extracted features from D17 image with block size (32 x 32) and with quantization level 8.

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
CNT	Block1	5.6940	5.7987
	Block2	5.9577	6.0708
	Block3	5.5607	5.6625
	Block4	5.4083	5.5076
	Block5	5.9259	6.0325
	Block6	5.9456	6.0546
	Block7	5.8314	5.9379
	Block8	5.4378	5.5374
	Block9	6.5039	6.6255
	Block10	6.3089	6.4192
	Block11	6.0802	6.0930
	Block12	5.4403	5.5400
	Block13	6.9222	7.0503
	Block14	7.0390	7.1667
	Block15	6.5002	6.6238
	Block16	5.6940	5.7987

		Level -8	
		Before	After
INV	Block1	0.3783	0.3839
	Block2	0.3652	0.3705
	Block3	0.3823	0.3881
	Block4	0.4215	0.4272
	Block5	0.3669	0.3725
	Block6	0.3630	0.3684
	Block7	0.3693	0.3747
	Block8	0.3852	0.3910
	Block9	0.3553	0.3605
	Block10	0.3562	0.3616
	Block11	0.3599	0.3600
	Block12	0.3752	0.3807
	Block13	0.3436	0.3438
	Block14	0.3423	0.3474
	Block15	0.3626	0.3678
	Block16	0.3783	0.3839

To be continue

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
ENT	Block1	4.0420	5.4855
	Block2	4.0402	5.4300
	Block3	3.9605	5.3688
	Block4	3.9566	5.3634
	Block5	4.0348	5.4576
	Block6	4.0193	5.4421
	Block7	3.9948	5.4171
	Block8	3.9749	5.3879
	Block9	4.0882	5.5015
	Block10	4.1076	5.5468
	Block11	4.0613	5.4944
	Block12	3.9519	5.3515
	Block13	4.1710	5.6330
	Block14	4.2032	5.6714
	Block15	4.1563	5.6174
	Block16	4.0420	5.4855

		Level -8	
		Before	After
ASM	Block1	0.0255	0.0255
	Block2	0.0253	0.0260
	Block3	0.0279	0.0282
	Block4	0.0696	0.0698
	Block5	0.0259	0.0260
	Block6	0.0262	0.0264
	Block7	0.0264	0.0265
	Block8	0.0278	0.0280
	Block9	0.0242	0.0244
	Block10	0.0234	0.0234
	Block11	0.0251	0.0251
	Block12	0.0277	0.0279
	Block13	0.0213	0.0213
	Block14	0.0210	0.0212
	Block15	0.0223	0.0227
	Block16	0.0255	0.0256

To be continue

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
MPR	Block1	0.0501	0.0463
	Block2	0.0482	0.0469
	Block3	0.0525	0.0521
	Block4	0.0502	0.0498
	Block5	0.0458	0.0450
	Block6	0.0485	0.0470
	Block7	0.0493	0.0486
	Block8	0.0525	0.0523
	Block9	0.0443	0.0439
	Block10	0.0385	0.0380
	Block11	0.0474	0.0434
	Block12	0.0454	0.0434
	Block13	0.0340	0.0310
	Block14	0.0338	0.0317
	Block15	0.0357	0.0356
	Block16	0.0501	0.0463

		Level -8	
		Before	After
HOM	Block1	0.4537	0.4607
	Block2	0.4410	0.4477
	Block3	0.5556	0.5626
	Block4	0.4945	0.5015
	Block5	0.4443	0.4512
	Block6	0.4413	0.4480
	Block7	0.4454	0.4521
	Block8	0.4579	0.4650
	Block9	0.4336	0.4462
	Block10	0.4354	0.4422
	Block11	0.4366	0.4433
	Block12	0.4497	0.4566
	Block13	0.4225	0.4290
	Block14	0.4232	0.4298
	Block15	0.4396	0.4462
	Block16	0.4537	0.4607

To be continue

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
CLS	Block1	584.29	589.47
	Block2	708.42	719.54
	Block3	648.96	659.26
	Block4	652.87	663.22
	Block5	725.81	737.35
	Block6	733.29	744.87
	Block7	666.35	676.84
	Block8	639.91	650.01
	Block9	776.66	788.37
	Block10	702.11	710.25
	Block11	648.48	658.66
	Block12	622.93	632.69
	Block13	656.66	666.87
	Block14	676.00	686.58
	Block15	666.39	676.69
	Block16	584.29	593.74

		Level -8	
		Before	After
CLP	Block1	5613.4	5699.8
	Block2	7254.4	7260.4
	Block3	6432.9	6440.6
	Block4	6463.9	6472.8
	Block5	7469.9	7472.8
	Block6	7552.9	7554.4
	Block7	6692.9	6695.8
	Block8	6318.9	6321.4
	Block9	8239.5	8248.1
	Block10	7238.9	7240.2
	Block11	6515.9	6524.2
	Block12	6118.9	6128.1
	Block13	6775.3	6785.9
	Block14	6096.9	6105.0
	Block15	6824.6	6834.6
	Block16	5688.8	5699.8

It is clear from the values of the calculated features, which are presented in table (3-4) that most of the selected features not affected by the size of the block; these results led us to the following remarks:

- The definition of the texture is verified, sine it represent the repetition of fundamental image elements.
- It is preferable to select the sample of the texture with minimum size of block to extract the statistical texture features.

Same thing noticed in the previous tables can be notice from the results of table (3-5), since that most of the selected features are stable in the two cases before and after except the feature of the entropy since the difference in the feature value of the two cases (before and after) is perceptible.

Figure (3-8) reflects the behavior of the selected features in the case of before and after. It is clear from this figure that the entropy feature gives perceptible slope in the case of before and after, and this result is similar to the result obtained from figure (3-9).

Figure (3-10) reflects the behavior of the selected features with 16 levels. Same thing can be seen, some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.

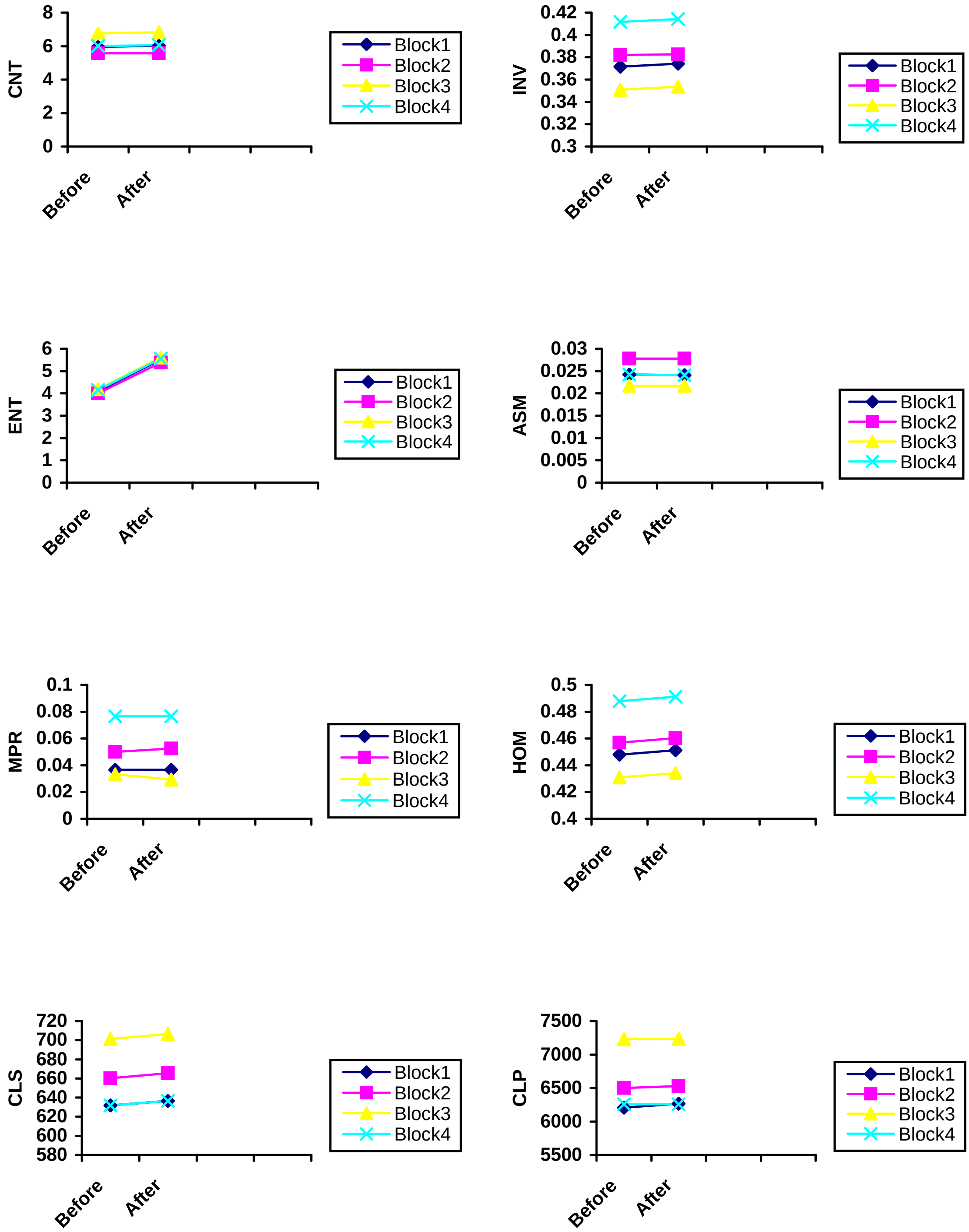


Figure (3-8): The behavior of the selected features in each block (block size 64×64) of the D17 image with quantization level 8 in the two cases of before.

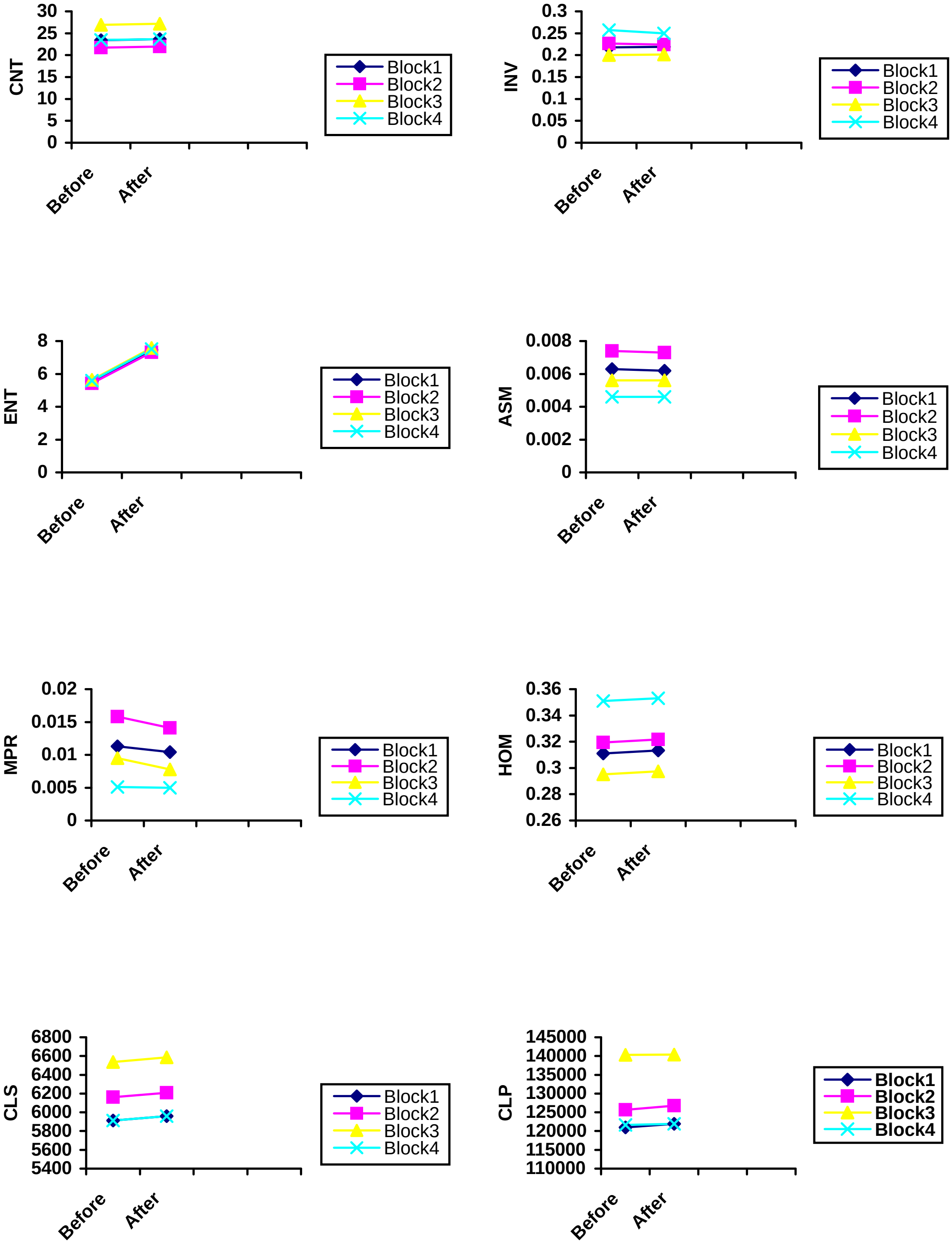


Figure (3-9): The behavior of the selected features in each block (block size 64×64) of the D17 image with quantization level 16 in the two cases of before.

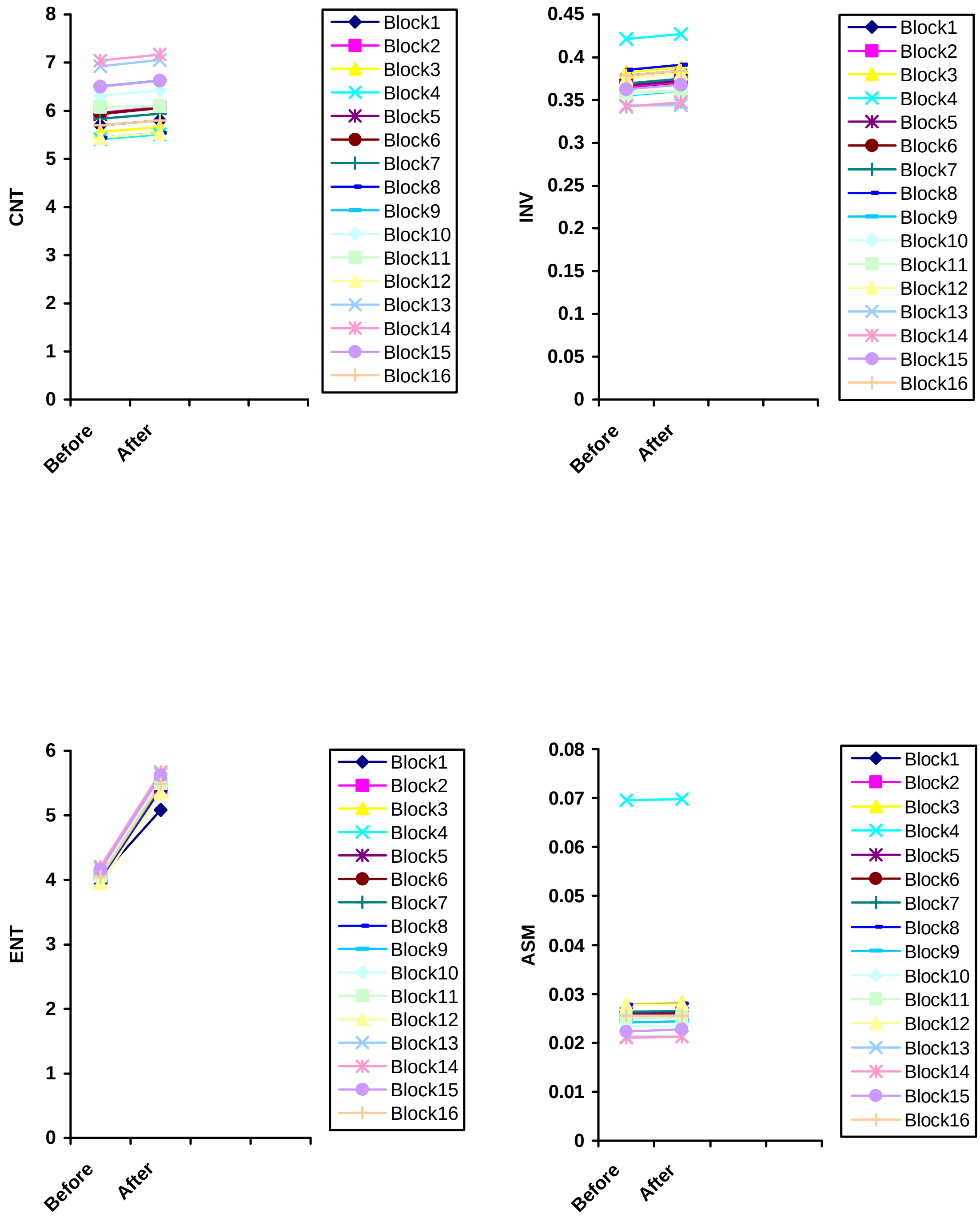


Figure (3-10): The behavior of the selected features in each block (block size 32×32) of theD17 image with quantization level 8 in the two cases of before and after.

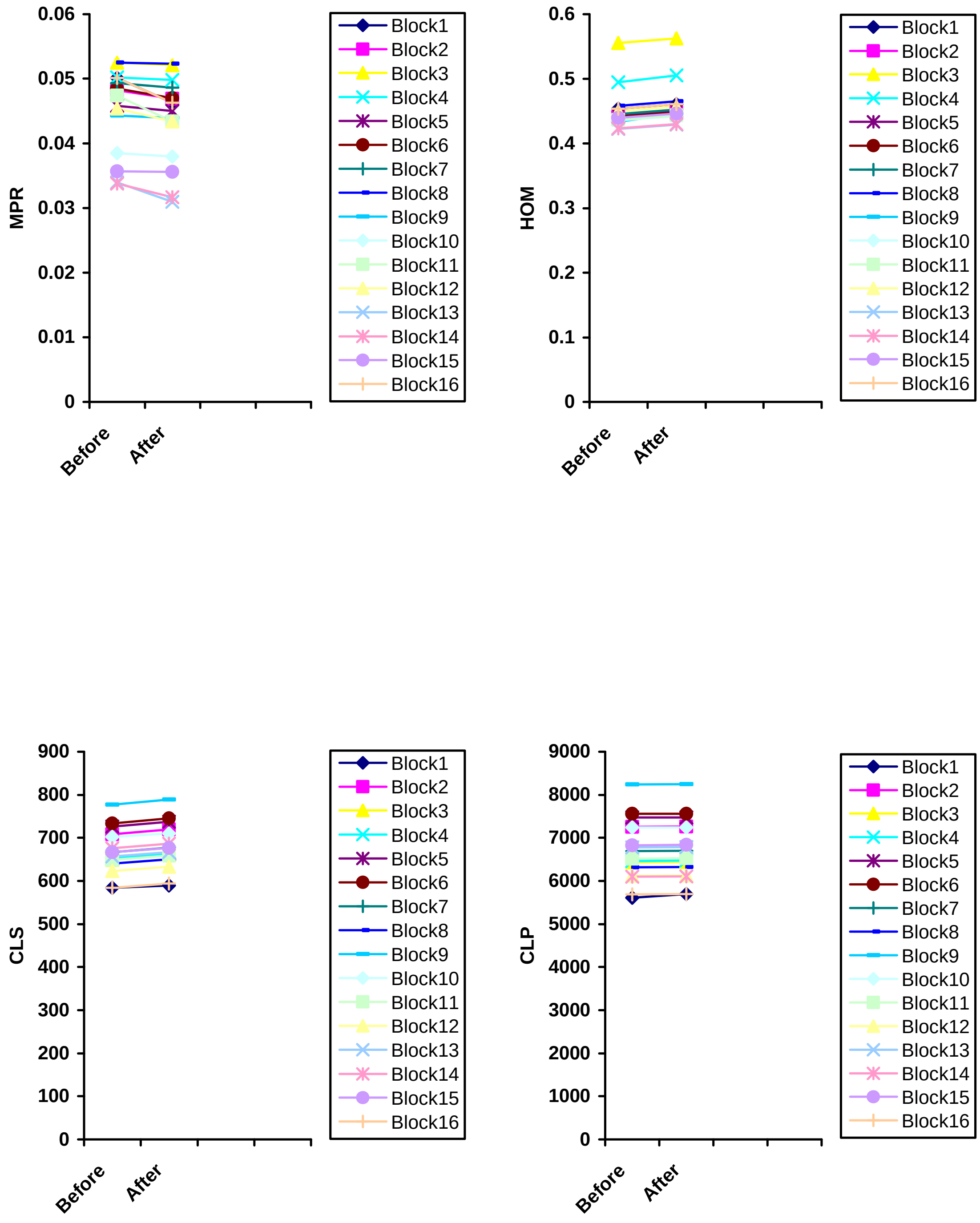
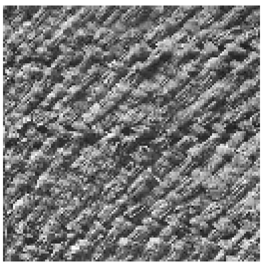


Figure (3-10): The behavior of the selected features in each block (block size 32×32) of theD17 image with quantization level 8 in the two cases of before and after.

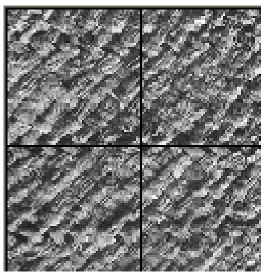
3.5.2 Experiment 2 (D18):

The second selected textured image used as a test material is D18 image. The D18 is of a size of (128 × 128) with 256 gray levels. The eight selected features are calculated for the original image and for the sub image for different block size 32 x 32 and 64 x 64 as be shown in figure (3-11) with different quantization level 8, 16, and 32.

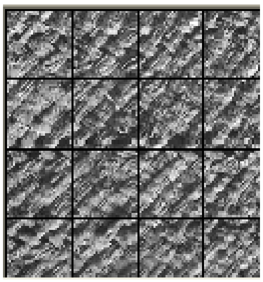
The features are calculated in two ways, the first one for the average Co-occurrence matrix and the second one for the Co-occurrence matrix of angle 0°, 45°, 90°, and 135° as be mentioned before that the two ways named before and after respectively. Four values for the same feature is extracted (one for each angle) for the second case, and then the average value for the four features is calculated.



(A)



(B)



(C)

Figure 3-11: Experiment 2
(A) Original Image D18,
(B) Extracted Features with window size 64×64.
(C) Extracted Features with window size 32×32.

Table 3-6: The value of statistical features for textured image D18 with quantization level =8

	8 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	2.9560	0.5212	3.7328	3.8060	0.0798	0.5681	375.31	3354.9
After	2.9560	0.5233	3.0284	3.8070	0.0801	0.5704	376.80	3368.3

Table 3-7: The value of statistical features for textured image D18 with quantization level =16

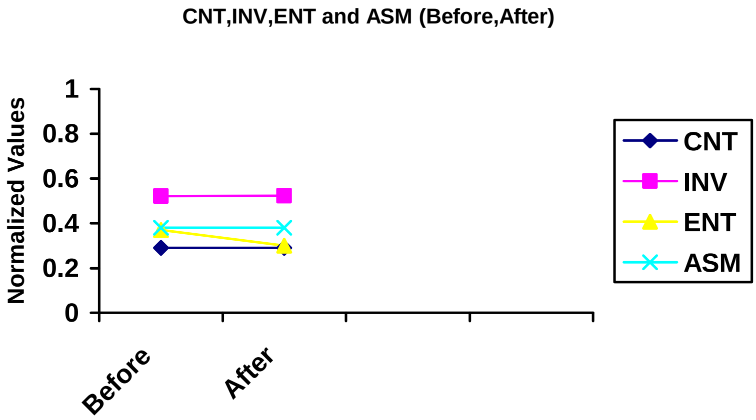
	16 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	11.343	0.3430	5.1631	0.0104	0.0305	0.4207	3572.7	66315
After	11.343	0.3444	6.9524	0.0104	0.0306	0.4224	3586.9	66578

Table 3-8: The value of statistical features for textured image D84 with quantization level =32

	32 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	44.774	0.2024	6.6243	0.0027	0.0084	0.2921	31141	1179058
After	44.774	0.2051	8.9182	0.0027	0.0083	0.2932	31265	1183749

It is clear from these tables and from figure (3-12) that most of the selected features except the entropy feature are stable in the two cases before and after since the values of entropy feature have perceptible slope in the two cases before and after.

Figure (3-13) shows the behavior of the selected features with different quantization level. It is clear from the figure that some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.



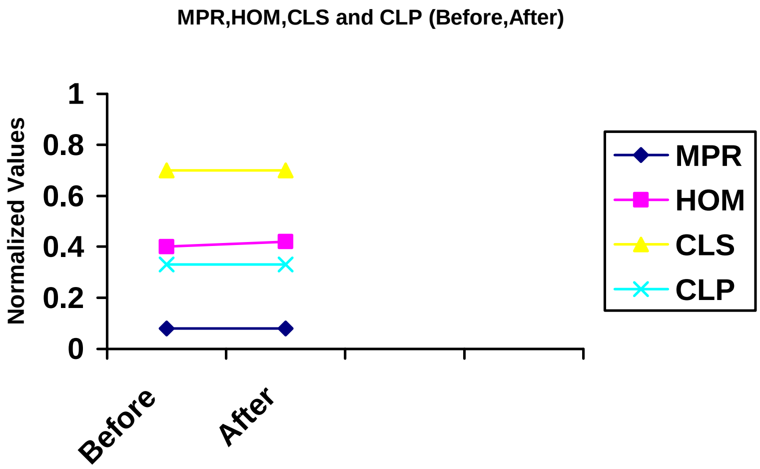


Figure (3-12): The behavior of the selected features in the two cases of before and after.

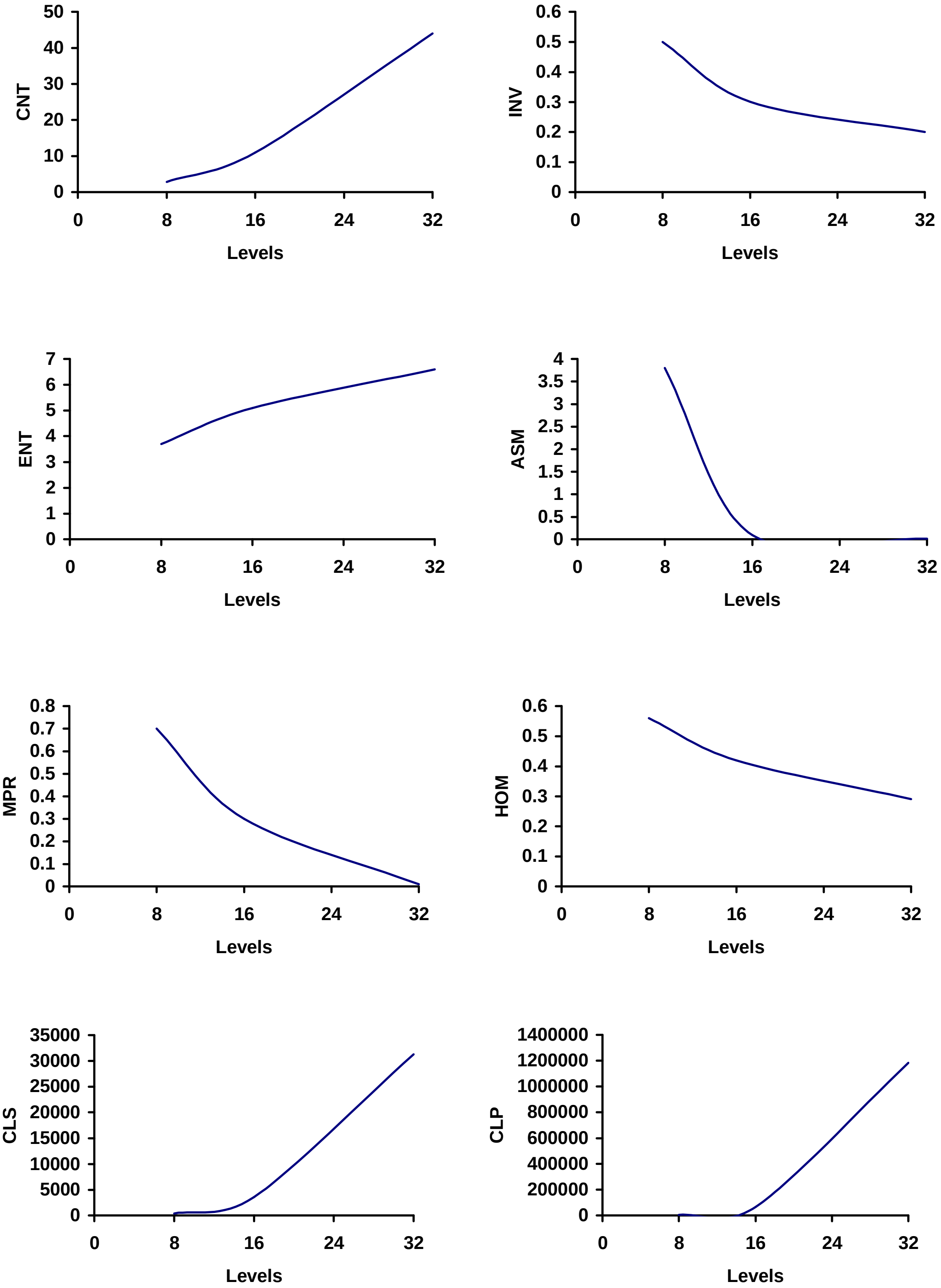


Figure (3-13): The behavior of the selected features with different quantization level (8, 16, and 32)

Table (3-9) shows the extracted features from D18 image with block size (64×64) and with different quantization level (8, and 16).

Table (3-9): Extracted features for each block (block size 64×64) of the D18 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
CNT	Block1	2.9018	2.9242	11.149	11,234
	Block2	2.6433	2.6636	10.174	10.252
	Block3	3.1608	3.1847	12.153	12.244
	Block4	2.9418	2.9642	11.894	11.274
INV	Block1	0.5154	0.5196	0.3368	0.3395
	Block2	0.5417	0.5461	0.3611	0.3640
	Block3	0.5056	0.5097	0.3301	0.3328
	Block4	0.5554	0.5559	0.3768	0.3790
ENT	Block1	3.1778	5.0305	5.1501	6.9633
	Block2	3.6190	4.9619	5.0348	6.8132
	Block3	3.7465	5.0663	5.1632	6.9783
	Block4	3.7578	5.0705	5.1901	7.0033
ASM	Block1	0.0374	0.0377	0.0101	0.0100
	Block2	0.0418	0.0420	0.0118	0.0117
	Block3	0.0376	0.0380	0.0106	0.0107
	Block4	0.0774	0.0772	0.0501	0.0500

To be continue

Table (3-9): Extracted features for each block (block size 64×64) of the D18 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
MPR	Block1	0.0814	0.0821	0.0252	0.0254
	Block2	0.0864	0.0871	0.0387	0.0390
	Block3	0.0812	0.0819	0.0326	0.0329
	Block4	0.0812	0.0813	0.0652	0.0654
HOM	Block1	0.5627	0.5672	0.4154	0.4188
	Block2	0.5841	0.5888	0.4351	0.4386
	Block3	0.5552	0.5597	0.4097	0.4130
	Block4	0.6070	0.6076	0.4554	0.4588
CLS	Block1	389.49	392.61	3699.7	3729.3
	Block2	344.56	347.31	3300.7	3446.9
	Block3	363.44	366.35	3446.9	3474.6
	Block4	389.53	392.65	3699.8	3729.8
CLP	Block1	3492.3	3520.3	68907	69460
	Block2	3000.5	3008.2	59720	59908
	Block3	3290.4	3296.3	64730	64746
	Block4	3516.5	3520.3	69455	69460

The results of the previous tables would be presented in a different way as be presented in Experiment (1), Figure (3-13) and figure (3-14) presents the behavior of the selected features for each block in the D18 image, since block size in this case 64×64 with quantization level 8 and 16 respectively. It should be mentioned that the values of the features are normalized to the value one. The results shows that there is no clearly difference in the extracted feature value in the two cases before and after expect the entropy feature, where the changes is perceptible in the two cases before and after.

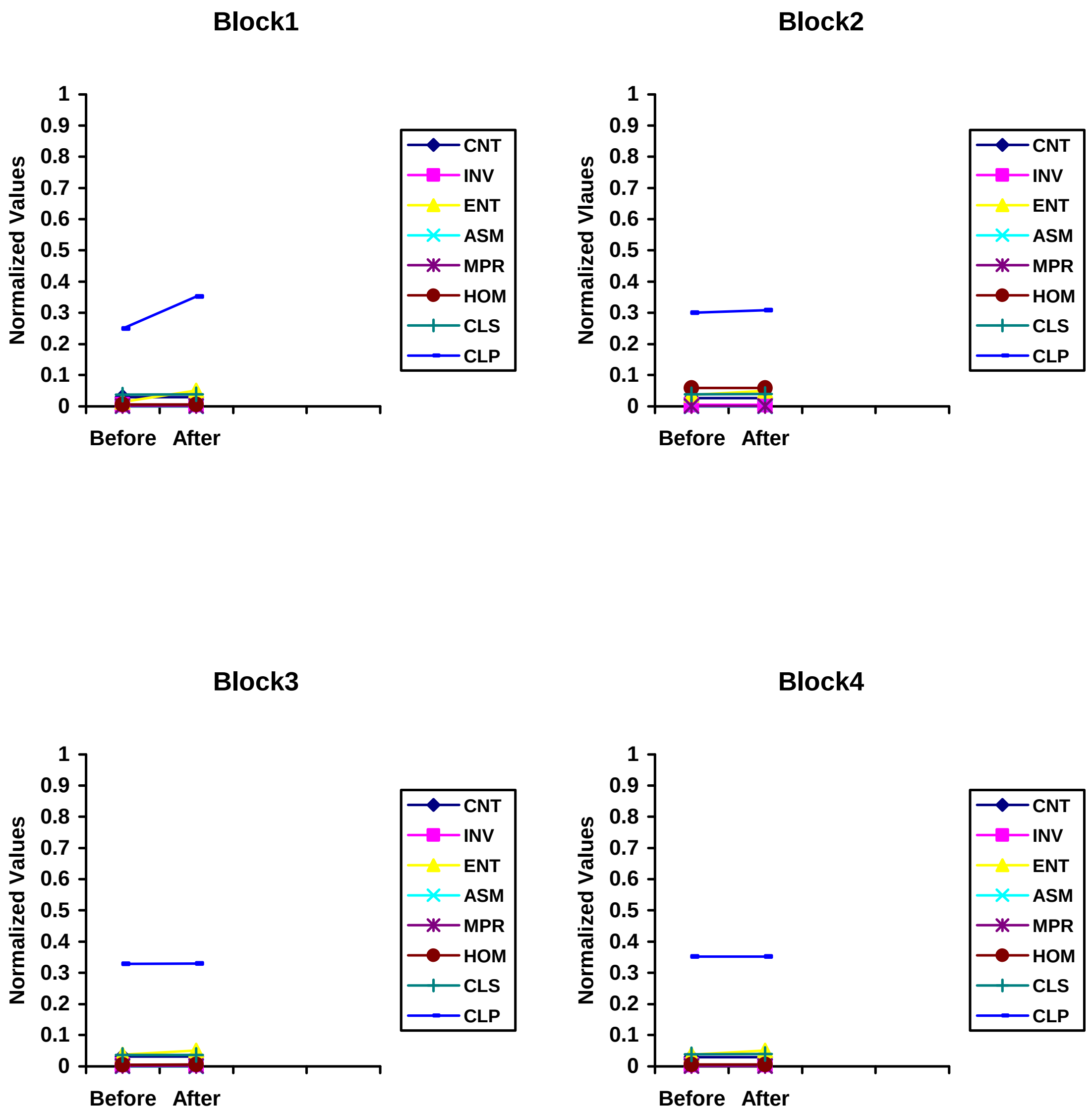


Figure (3-13): The behavior of blocks with selected features of the D18 image, with block size 64×64 and quantization level 8 in the two cases of before and after.

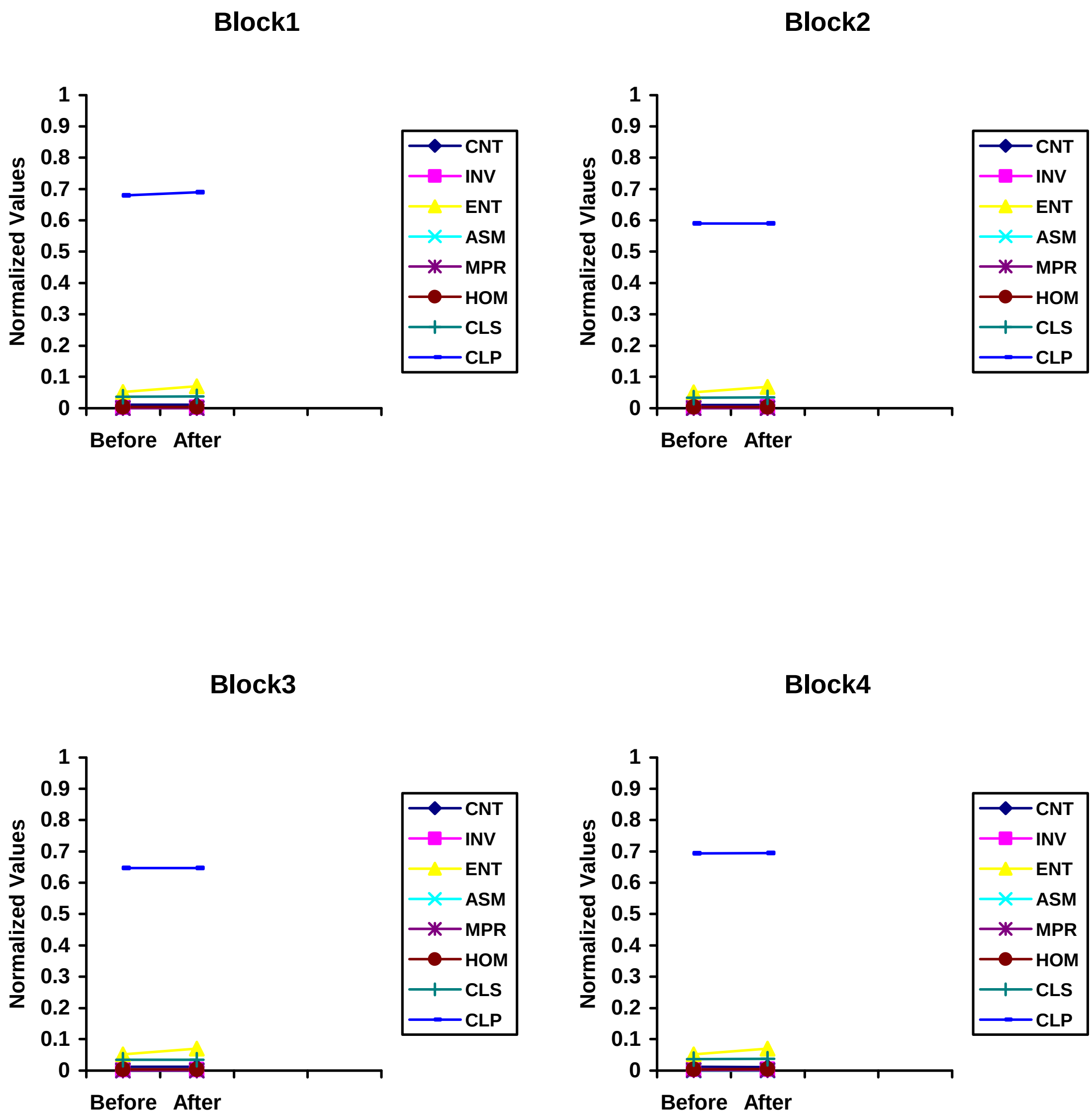


Figure (3-14): The behavior of blocks with selected features of the D18 image, with block size 64×64 and quantization level 16 in the two cases of before and after.

Tables(3-10) shows the extracted features from D18 image with quantization level 8.

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	**After**
CNT	Block1	2.9030	2.9475
	Block2	2.7702	2.8138
	Block3	2.7235	2.7665
	Block4	2.9455	2.9901
	Block5	3.1217	3.1706
	Block6	2.7870	2.8309
	Block7	2.4627	2.5023
	Block8	2.4416	2.4793
	Block9	3.1460	3.1945
	Block10	2.8919	2.9373
	Block11	2.9092	2.9556
	Block12	2.3283	2.3651
	Block13	3.4984	3.5529
	Block14	2.9946	3.0398
	Block15	3.4098	3.4630
	Block16	2.9031	2.9475

		Level -8	
		Before	**After**
INV	Block1	0.5071	0.5154
	Block2	0.5279	0.5376
	Block3	0.5304	0.5390
	Block4	0.5644	0.5732
	Block5	0.5082	0.5166
	Block6	0.5345	0.5432
	Block7	0.5354	0.5442
	Block8	0.5615	0.5708
	Block9	0.5073	0.5156
	Block10	0.5086	0.5170
	Block11	0.5061	0.5144
	Block12	0.5433	0.5522
	Block13	0.4935	0.5016
	Block14	0.5035	0.5119
	Block15	0.4917	0.4998
	Block16	0.5071	0.5154

To be continue

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
ENT	Block1	3.6875	5.0307
	Block2	3.7022	5.0540
	Block3	3.5649	4.8682
	Block4	3.7026	5.0563
	Block5	3.6778	5.0185
	Block6	3.5518	4.8474
	Block7	3.5244	4.7997
	Block8	3.5372	4.8573
	Block9	3.7268	5.0882
	Block10	3.6454	4.9605
	Block11	3.7381	5.0873
	Block12	3.4960	4.7657
	Block13	3.7785	5.1306
	Block14	3.7018	5.0530
	Block15	3.7753	5.1410
	Block16	3.3687	5.0307

		Level -8	
		Before	After
ASM	Block1	0.0373	0.0381
	Block2	0.0357	0.0363
	Block3	0.0437	0.0452
	Block4	0.0796	0.0801
	Block5	0.0401	0.0409
	Block6	0.0466	0.0474
	Block7	0.0427	0.0437
	Block8	0.0434	0.0439
	Block9	0.0376	0.0380
	Block10	0.0392	0.0401
	Block11	0.0348	0.0353
	Block12	0.0461	0.0469
	Block13	0.0360	0.0369
	Block14	0.0383	0.0391
	Block15	0.0350	0.0356
	Block16	0.0373	0.0381

To be continue

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
MPR	Block1	0.0716	0.0720
	Block2	0.0615	0.0612
	Block3	0.1036	0.1053
	Block4	0.1373	0.1389
	Block5	0.0989	0.1006
	Block6	0.1158	0.1177
	Block7	0.0887	0.0901
	Block8	0.0924	0.0931
	Block9	0.0868	0.0818
	Block10	0.0843	0.0857
	Block11	0.0730	0.0715
	Block12	0.0989	0.1005
	Block13	0.0787	0.0776
	Block14	0.0761	0.0771
	Block15	0.0815	0.0828
	Block16	0.0716	0.0728

		Level -8	
		Before	After
HOM	Block1	0.5547	0.5638
	Block2	0.5714	0.5808
	Block3	0.5742	0.5836
	Block4	0.6095	0.6190
	Block5	0.5567	0.5659
	Block6	0.5789	0.5883
	Block7	0.5768	0.5862
	Block8	0.5998	0.6097
	Block9	0.5540	0.5631
	Block10	0.5564	0.5656
	Block11	0.5539	0.5630
	Block12	0.5843	0.5938
	Block13	0.5463	0.5552
	Block14	0.5522	0.5614
	Block15	0.5431	0.5522
	Block16	0.5547	0.5638

To be continue

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
CLS	Block1	370.32	376.38
	Block2	485.07	492.92
	Block3	306.07	311.05
	Block4	362.45	368.33
	Block5	349.31	354.98
	Block6	303.85	308.79
	Block7	330.08	335.43
	Block8	374.44	380.55
	Block9	389.66	396.03
	Block10	337.54	343.05
	Block11	439.90	447.53
	Block12	317.70	322.88
	Block13	361.17	367.04
	Block14	358.59	364.45
	Block15	413.39	420.14
	Block16	370.32	376.38

		Level -8	
		Before	After
CLP	Block1	3321.4	3376.3
	Block2	4550.3	4606.4
	Block3	2510.4	2626.2
	Block4	3210.7	3264.2
	Block5	3125.3	3171.6
	Block6	2579.4	2625.3
	Block7	2760.4	2816.4
	Block8	3354.4	3389.5
	Block9	3590.4	3637.9
	Block10	2935.4	2988.4
	Block11	4085.6	4130.6
	Block12	2634.2	2686.3
	Block13	3282.4	3333.5
	Block14	3242.0	3294.0
	Block15	3710.9	3844.0
	Block16	3334.5	3376.3

Figure (3-15) shows the results of selected features for each block normalization to the value one, with 16 block, it is clearly from the graph the similarity and satiability of feature values, between all blocks that see it in figure (3-13) and (3-14).

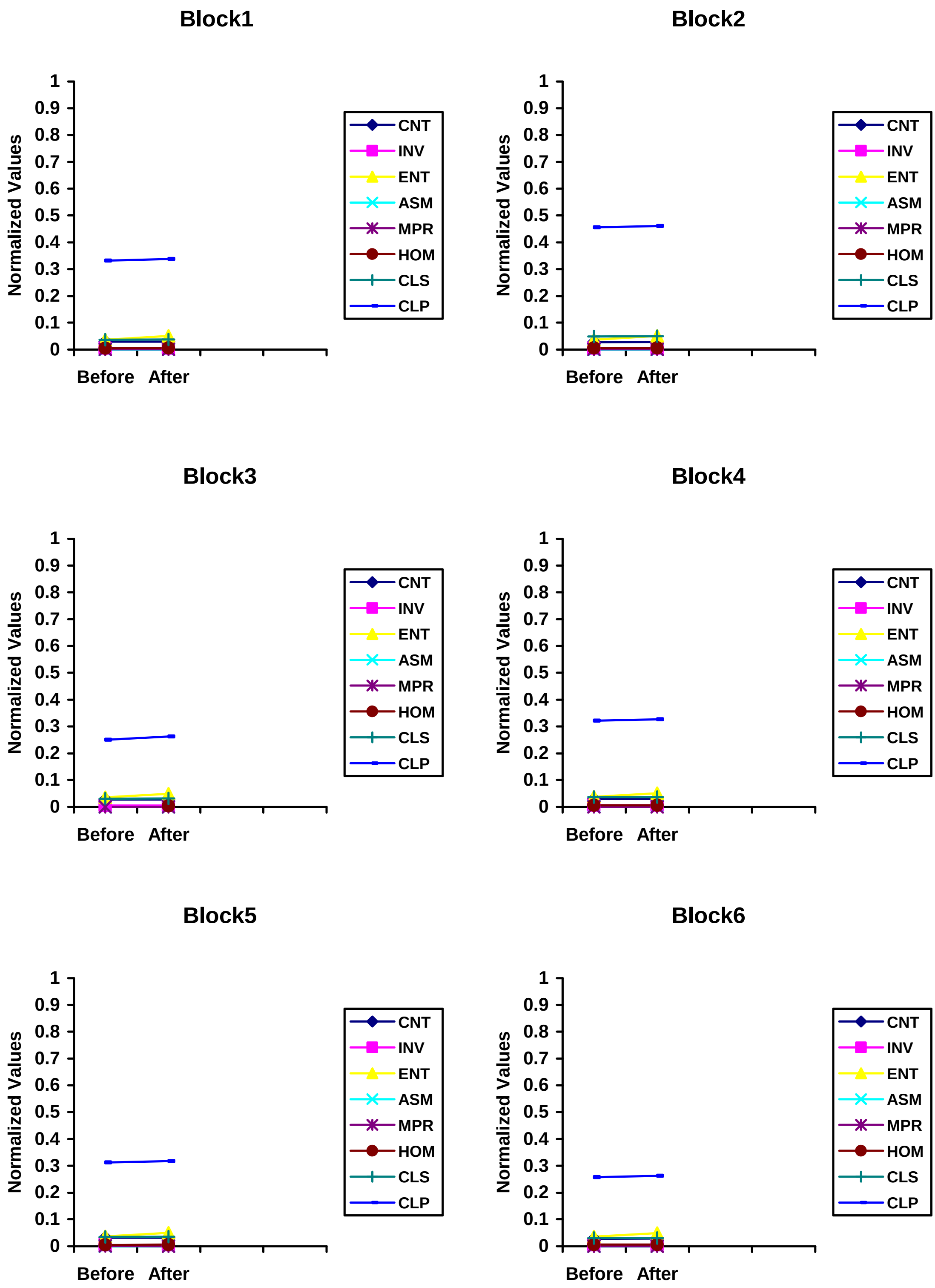


Figure (3-15): The behavior of blocks with selected features of the D18 image, with block size 32×32 and quantization level 8 in the two cases of before and after.

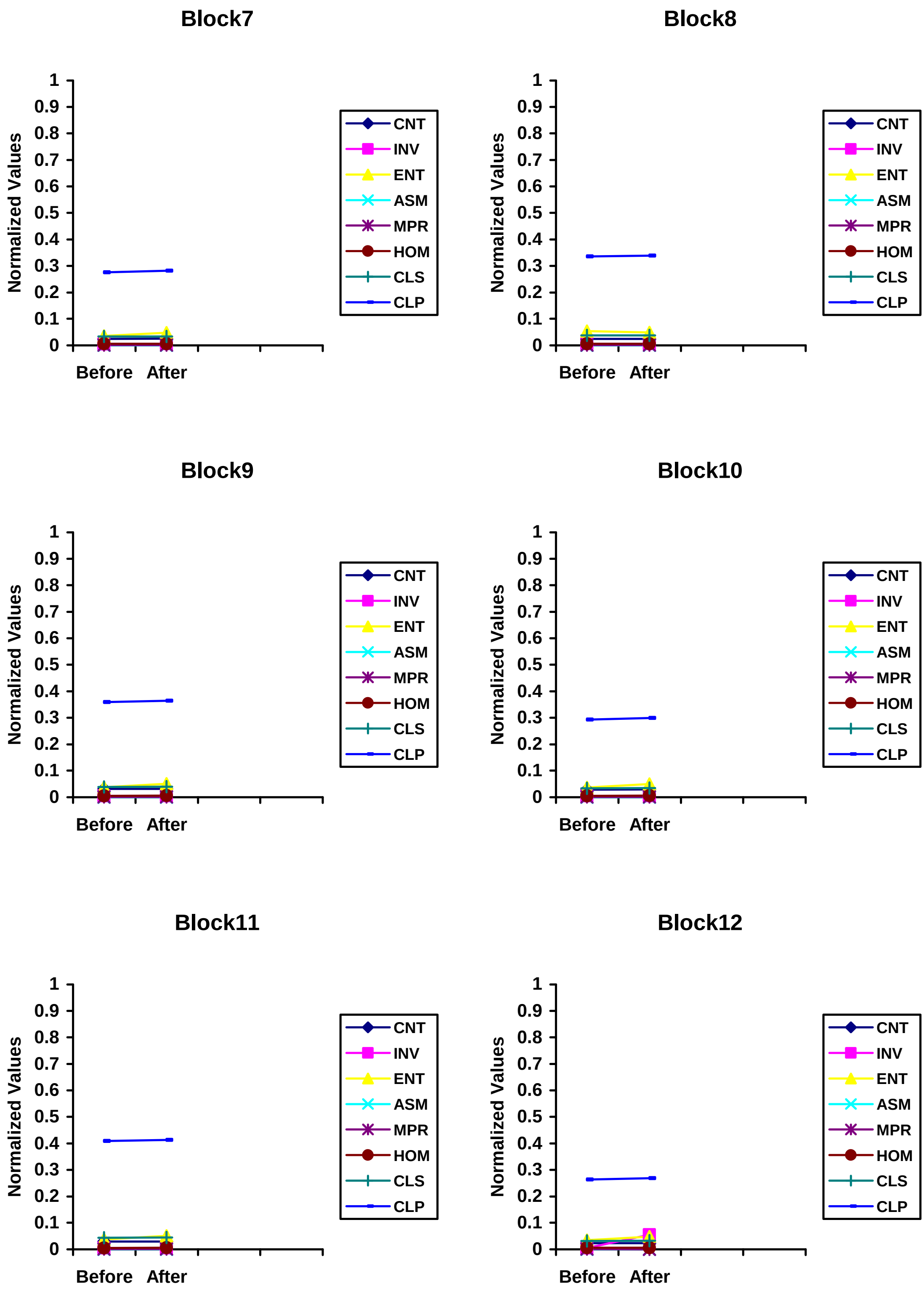


Figure (3-15): The behavior of blocks with selected features of the D18 image, with block size 32×32 and quantization level 8 in the two cases of before and after.

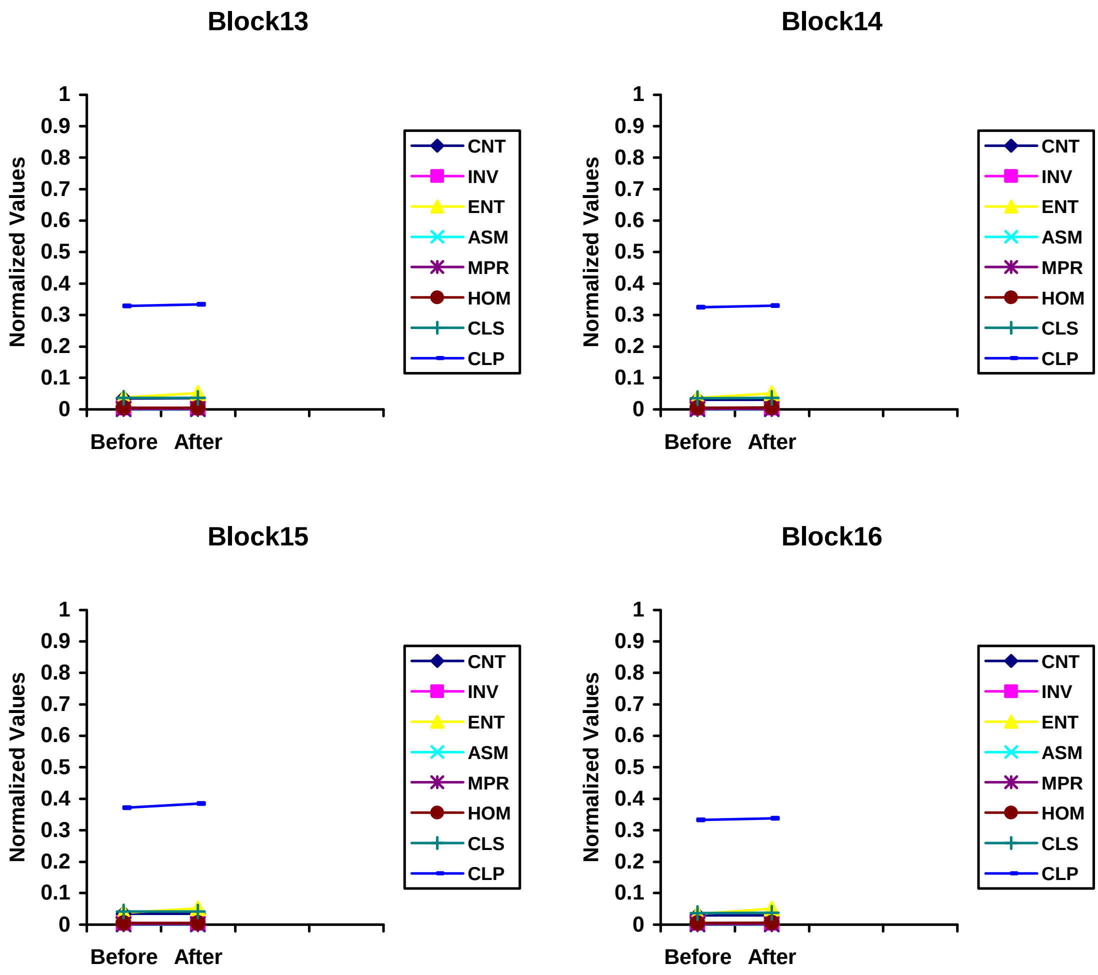
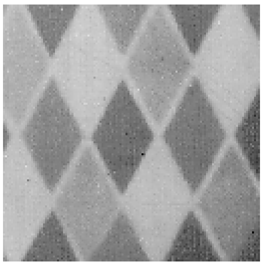


Figure (3-15): The behavior of blocks with selected features of the D18 image, with block size 32×32 and quantization level 8 in the two cases of before and after.

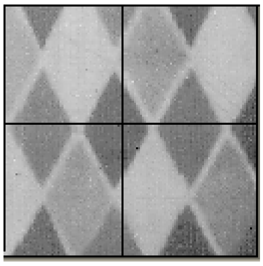
3.5.3 Experiment 3 (D84):

The third selected textured image used as a test material is D84 image. The D84 is of a size of (128 × 128) with 256 gray levels. The eight selected features are calculated for the original image and for the sub image for different block size 32 x 32 and 64 x 64 as be shown in figure (3-16) with different quantization level 8, 16, and 32.

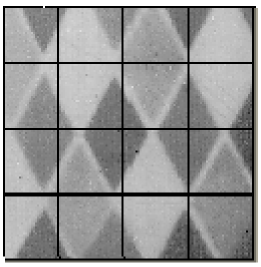
The features are calculated in two ways, the first one for the average Co-occurrence matrix and the second one for the Co-occurrence matrix of angle 0°, 45°, 90°, and 135° as be mentioned before that the two ways named before and after respectively. Four values for the same feature is extracted (one for each angle) for the second case, and then the average value for the four features is calculated.



(A)



(B)



(C)

Figure 3-16: Experiment 3
(A) Original Image D84,
(B) Extracted Features with window size 64×64.
(C) Extracted Features with window size 32×32.

Table 3-11: The value of statistical features for textured image D84 with quantization level =8

	8 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	0.2741	0.8688	2.2929	0.1651	0.3044	0.8697	789.42	7879.9
After	0.2741	0.8732	3.0804	0.1663	0.3056	0.8731	792.53	7911.0

Table 3-12: The value of statistical features for textured image D84 with quantization level =16

	16 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	0.6691	0.7723	3.2014	0.0707	0.1720	0.7802	7376.1	153101
After	0.6691	0.7754	4.4260	0.0711	0.1727	0. 7833	7405.2	153704

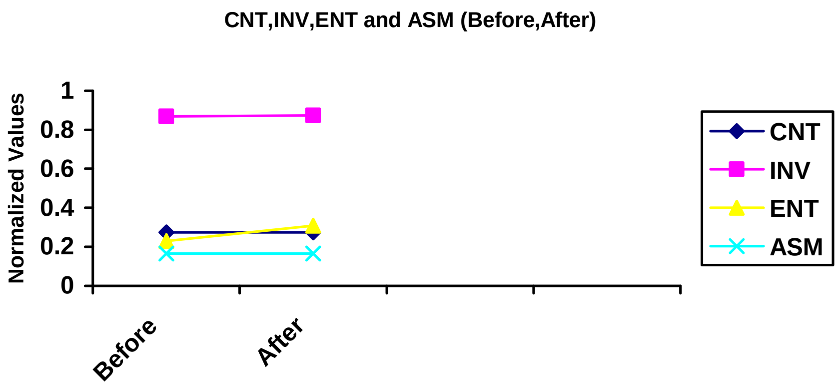
Table 3-13: The value of statistical features for textured image D84 with quantization level =32

	32 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	2.1527	0.6280	4.5306	0.0243	0.0708	0.6556	63189	2674571
After	2.1527	0.6306	6.1161	0.0244	0.0711	0.6583	63438	2685117

It is clear from these tables and from figure (3-17) that most of the selected features except the entropy feature are stable in the two cases before

and after since the values of entropy feature have perceptible slope in the two cases before and after.

Figure (3-18) shows the behavior of the selected features with different quantization level. It is clear from the figure that some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.



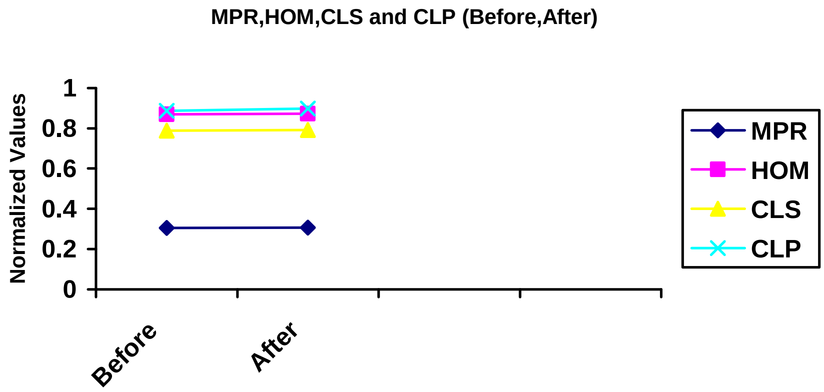


Figure (3-17): The behavior of the selected features in the two cases of before and after.

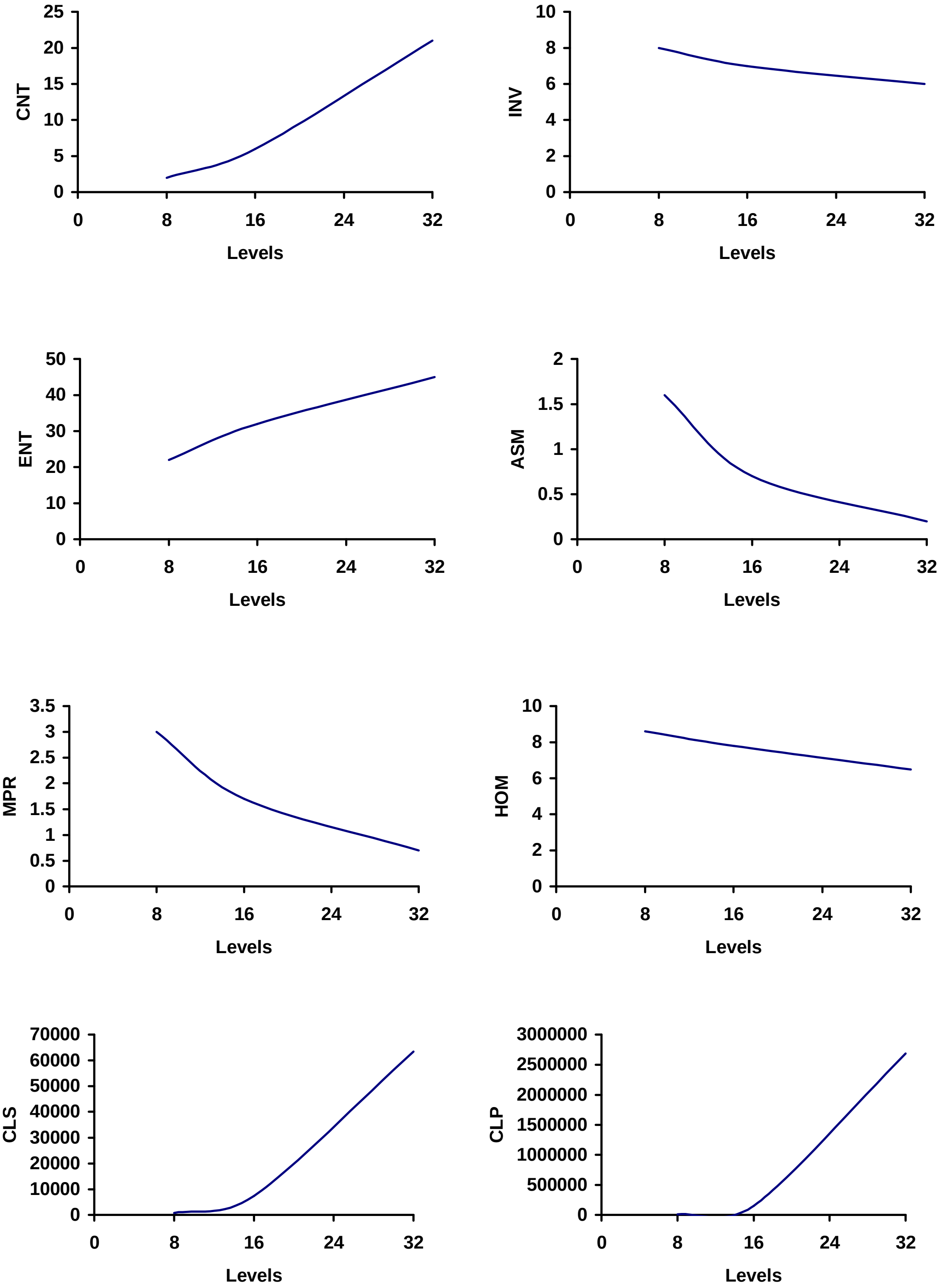


Figure (3-18): The behavior of the selected features with different quantization level (8, 16, and 32)

Table (3-14) shows the extracted features from D84 image with different block size 64×64 and with different quantization level (16, and 32).

Table (3-14): Extracted features for each block (block size 64×64) of the D84 image with quantization level 16 and 32 in the two cases before and after

		Level - 16		Level -32	
		Before	After	Before	After
CNT	Block1	0.1322	0.1327	0.4087	0.4101
	Block2	0.1629	0.1634	0.5159	0.5177
	Block3	0.1588	0.1593	0.4769	0.4785
	Block4	0.1722	0.1727	0.4487	0.4501
INV	Block1	0.1968	0.1975	0.1613	0.1619
	Block2	0.1907	0.1951	0.1572	0.1579
	Block3	0.1881	0.1889	0.1561	0.1568
	Block4	0.2368	0.2375	0.2013	0.2019
ENT	Block1	1.0774	1.4477	1.3768	1.8504
	Block2	1.1477	1.5421	1.4375	1.9374
	Block3	1.1686	1.5683	1.4436	1.9374
	Block4	1.1174	1.4877	1.4168	1.8904
ASM	Block1	0.0067	0.0068	0.0025	0.0025
	Block2	0.0050	0.0050	0.0019	0.0019
	Block3	0.0039	0.0040	0.0016	0.0016
	Block4	0.0467	0.0468	0.0042	0.0042

To be continue

Table (3-14): Extracted features for each block (block size 64×64) of the D84 image with quantization level 16 and 32 in the two cases before and after

		Level - 16		Level -32	
		Before	After	Before	After
MPR	Block1	0.0618	0.0621	0.0340	0.0341
	Block2	0.0485	0.0487	0.0296	0.0230
	Block3	0.0309	0.0310	0.0172	0.0171
	Block4	0.1018	0.1021	0.0743	0.0741
HOM	Block1	0.1981	0.1989	0.1666	0.1673
	Block2	0.1927	0.1935	0.1638	0.1645
	Block3	0.1898	0.1905	0.1626	0.1633
	Block4	0.2381	0.2389	0.2066	0.2073
CLS	Block1	2289.6	2298.6	19428.0	19504.8
	Block2	1913.2	1920.8	16363.3	16428.0
	Block3	1688.2	1694.9	14540.1	14597.2
	Block4	2289.6	2298.7	19428.0	19504.9
CLP	Block1	50150	50349	865893	869318
	Block2	40066	40135	645876	699728
	Block3	34120	34265	560135	602701
	Block4	50150	50349	865893	869318

The results of the previous tables of Experiment 3 would be presented in the same way that experiment 2 . Figure (3-19) and figure (3-20) presents the behavior of the selected features for each block in the D84 image. Since the block size in this case is 64×64 with quantization level 16 and 32 respectively. It should be mentioned that the values of the features are normalized to the value one. The results shows that there is no clearly difference in the extracted feature value in the two cases before and after except the entropy feature, where the changes is perceptible in the two cases before and after.

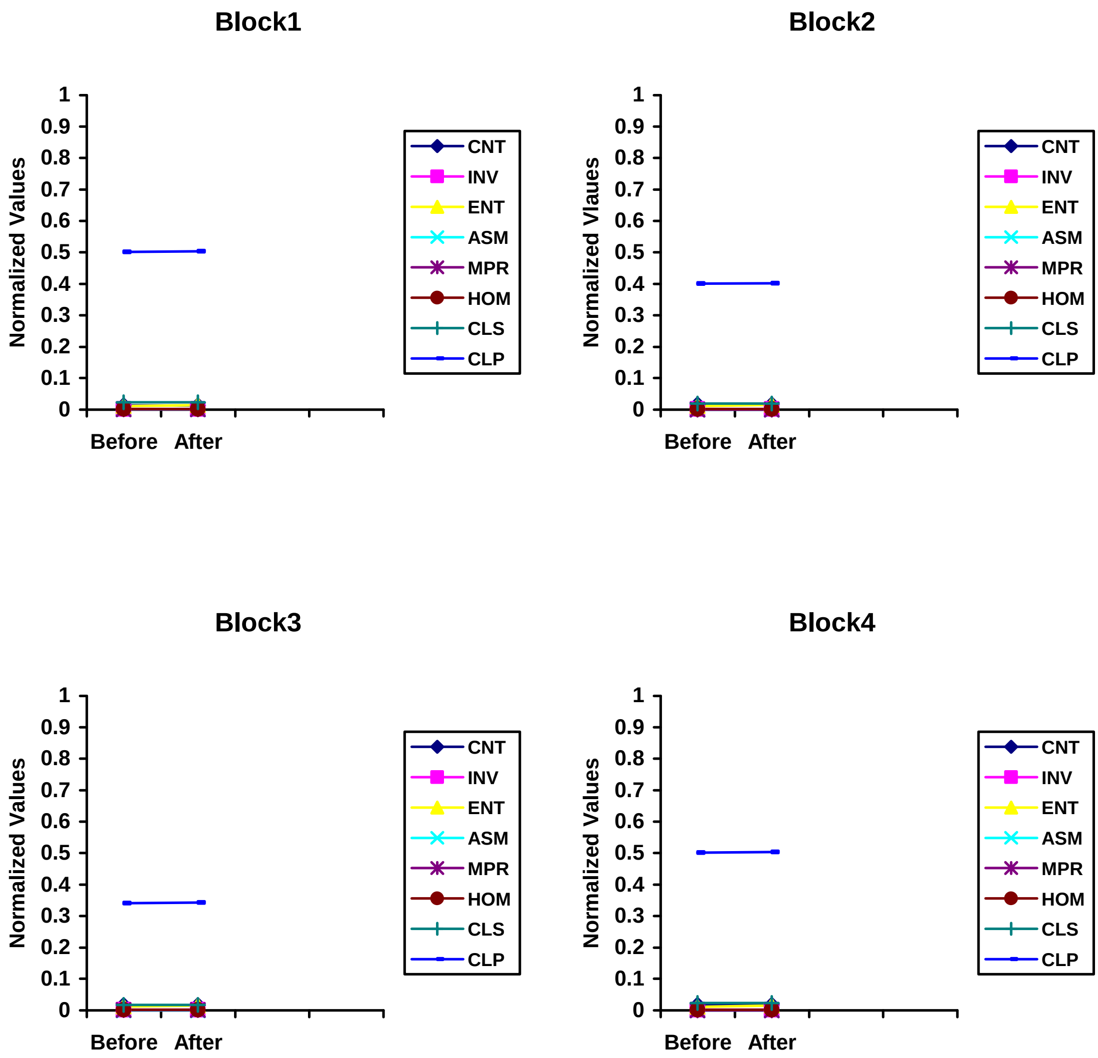


Figure (3-19): The behavior of blocks with selected features of the D84 image, with block size 64×64 and quantization level 16 in the two cases of before and after.

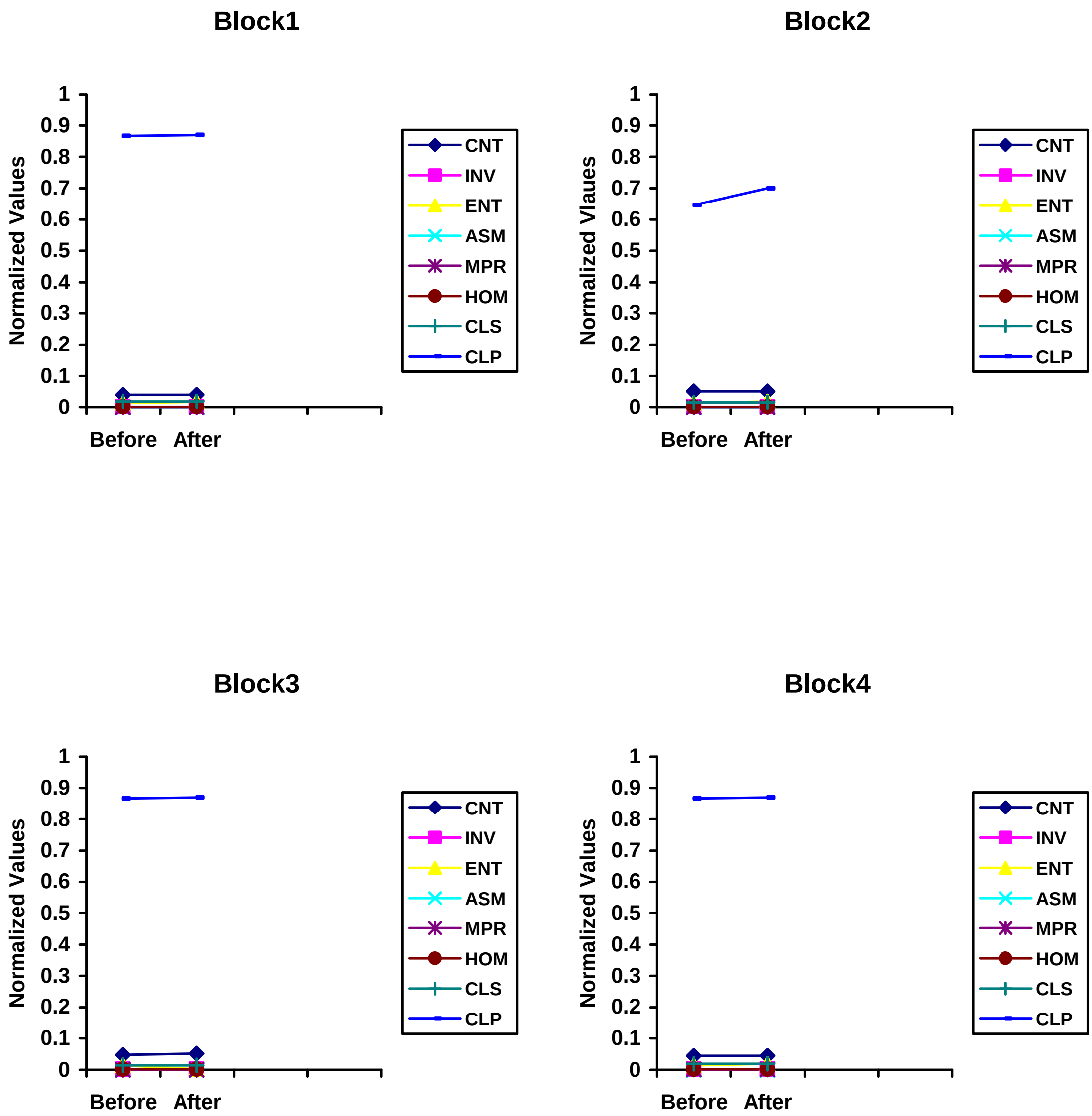


Figure (3-20): The behavior of blocks with selected features of the D84 image, with block size 64×64 and quantization level 32 in the two cases of before and after.

Chapter Three

System Development and Implementation

3.1 Introduction

The theoretical concepts of texture analysis and image classification were discussed in the previous chapter. This chapter is devoted to describe the computer programs design and implementation to offer the facilities, which may be required to perform the classification process.

To perform the texture classification process, three textured images from Brodatz album are chosen and implemented for this purpose. These are (D17, D18, and D84) as shown in figure (3-1). Each of these images has been digitized into 128×128 pixels of 256 gray-level. The screen images are of bit-map (BMP) type. A detailed description of the BMP file format is presented in Appendix (A).

D17 D18 D84

Figure (3-1): The three textured images used as test material

The system was implemented and written using visual Basic version 6.0 on a personal computer (Pentium IV processor with 256 RAM and 20 GB hard disk that works under windows XP).

3.2 Features Set

The goal in image analysis is to extract information useful for solving application based problem. This is done by intelligently reducing the amount of image data with the tools we have explored. A feature vector is one method to represent an image, or part of an image object, by finding measurements on a set of features. Therefore, finding a specific features-vector that has the best discrimination power has been one of the most important problems in the field of pattern analysis and texture classification. The statistical features is one of the most important features that is used to evaluate the performance of Co-occurrence matrices for solving texture classification problem, thus, the statistical feature is adopted in our work.

- **Statistical Feature Set**

The statistical texture features are known to contain significant discriminatory information for image classification. Some of the commonly used statistical features are based on gray-level Co-occurrence matrix. In this work the statistical feature is extracted for different window size (sub-image of size M×M) with different quantization level. The head line of the presented work can be summarized by the following two sets:

Set-1: For each image, the Co-occurrence matrix P is extracted with different quantization level 8, 16 and 32; eight statistical texture features are calculated depending on the extracted Co-occurrence matrix P. These eight statistical texture features which are chosen and adopted in this work are:

1. Maximum probability 2.Entropy 3. Homogeneity
4. Cluster-Shade 5. Cluster-Prominence 6. Contrast
7. Angular Second Moment. 8. Inverse Difference Moment

These statistical features are defined in eq's (2.2), (2.4), (2.5), (2.7), (2.8), (2. 9), (2.10), and (2.11) respectively.

<u>Set-2:</u> In this set the same procedure presented in set -1 is applied but with different block size M×M of the original image (the original image is divided into sub images with block size 32X 32 and 64 X 64), then the Co-occurrence matrix P is extracted for each block size, then the selected feature (presented in ***set-1***) is calculated depending on the extracted Co-occurrence matrix P.

3.3 System Structure

The features extraction is performed through the user interface. The user interface includes two choices, through which the user can perform the following operations (see figure (3-2)):

•Apply Co-occurrence matrix on original image.

•Apply Co-occurrence matrix on sub images.

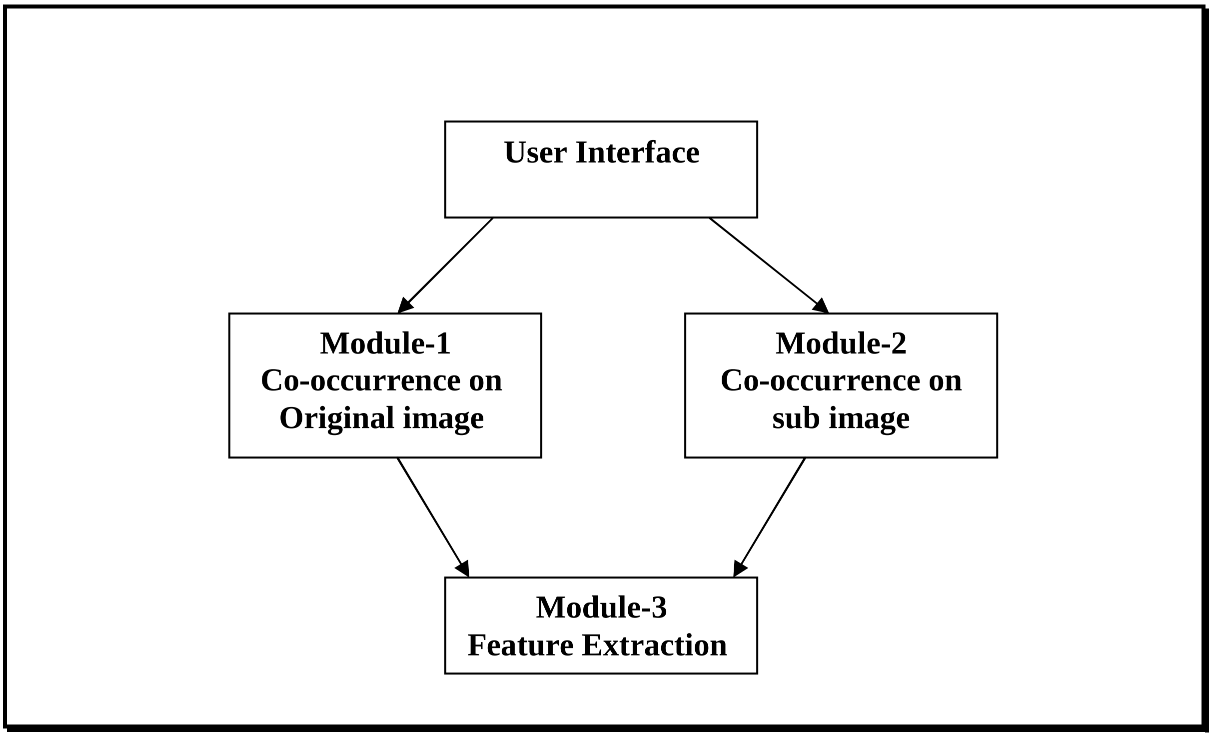


Figure (3-2): The System Modules

When the features extracted from Module-1 and Module-2, one can make a comparison and the analysis between the results.

3.4 The Design Approach

For a typical texture classification system, the determination of the class is one of the aspects of overall task. Texture classification system generally contains several stages.

In this work, a Texture-Image Classification System "TICS" was implemented by using Co-occurrence matrices algorithm. During the early stages of the system design, the designer needs to specify the input image format (to analyze the input image and extract the image-data), determine the feature set that should be calculated (from image data). Finally, specify the Co-occurrence matrices (using new way to calculate the features set and comparing the results).

Considering the above argument, TICS was constructed using number of modules, each module performs specific task. Collectively, these modules combine to perform the overall texture classification task (using the selected features). From the functional point of view, TICS consists of seven modules (see figure (3-3)).

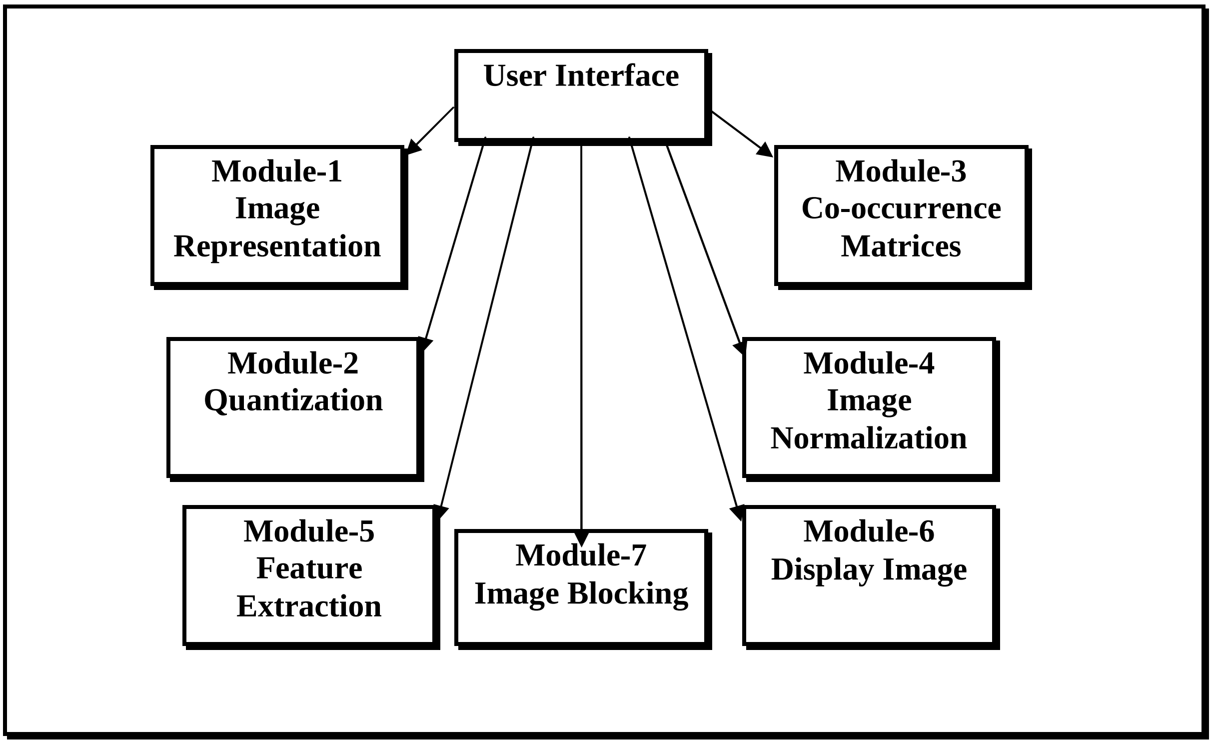


Figure (3-3): Texture Image Classification System (TICS) Modules

The Flow Control of TICS is presented in Figure (3-4).

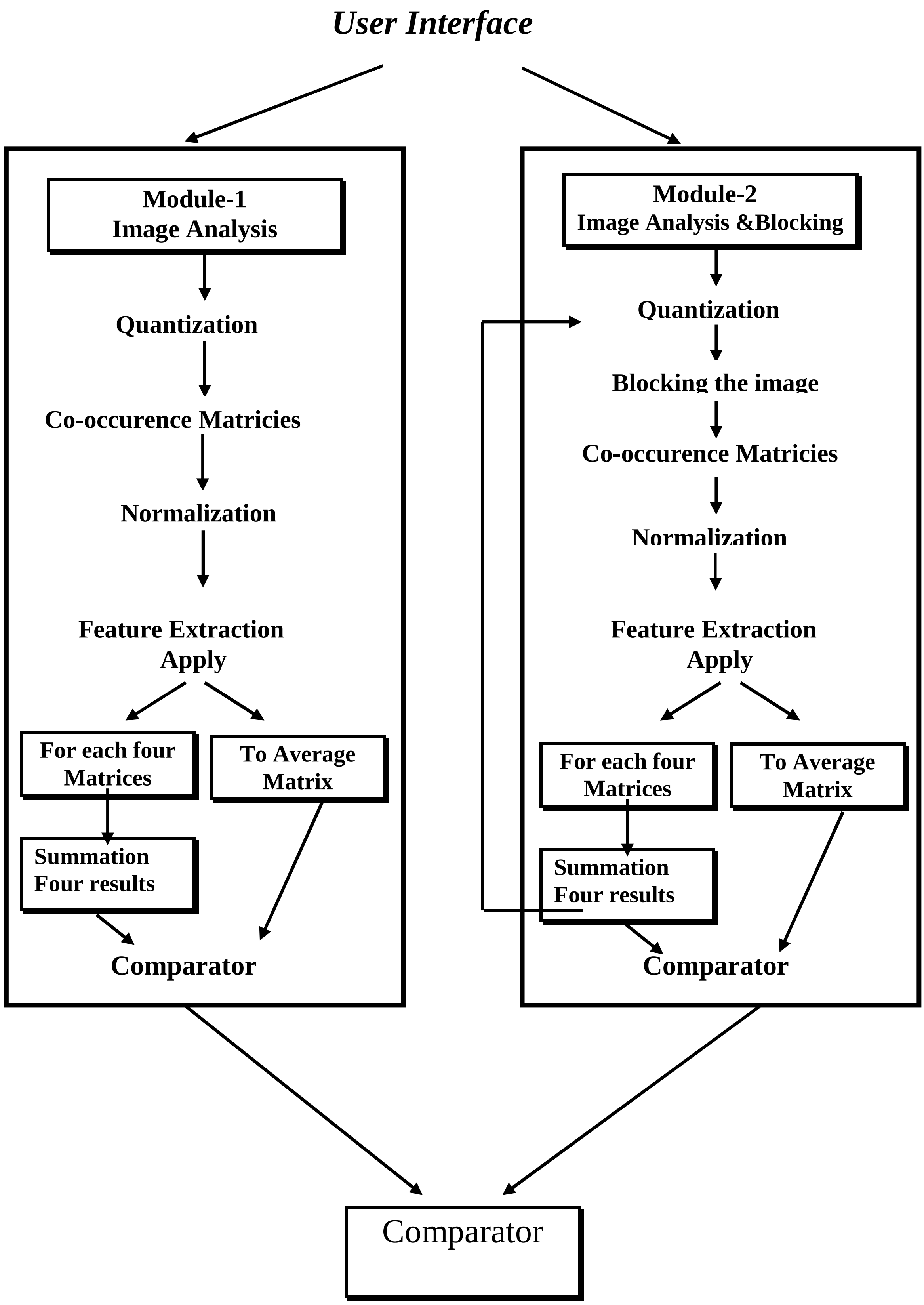


Figure (3-4):Flow Control of TICS

3.4.1 Module-1: Image Representation

Scanners are capable of producing image representation in a variety of formats. One of the most popular of these formats is the bit-map (BMP) format. BMP files consist of three parts (the detailed structure of the BMP files is shown in appendix A). These three parts are header (provides essential information about the image such as image-width, image-height, number of bit/pixel, and a pointer to the beginning of the image-data), color palette (represent the intensities in red, blue, and green (RGB)), and image-data (represents the pixel values). In the present work only the gray images are adopted .

Image representation module concerned with analyzing the image file to get information about the input image (image-width, image-height, and the image-data), and pass this information to the next modules.

3.4.2 Module-2: Image Quantization

The main draw back in using the spatial gray level dependence method is the large memory requirement for storing the Co-occurrence matrices. Sometimes the Co-occurrence matrices used for texture characterization are more voluminous than the original images from which they are derived. Quantization process overcomes this problem. For this reason image quantization process is adopted in this work.

Image quantization is the process of reducing the image data by removing some of detail information by mapping groups of data points to a single point. This can be done to the pixel values themselves. In the present work the gray level reduction is achieved by taking the data and reducing the number of bits per pixel.

3.4.3 Module-3: Co-occurrence Matrices

Algorithm (3.1) Co-occurrence Matrices

As be mentioned before, the gray level Co-occurrence matrix is the two dimensional matrix of joint probability P (I, J) between pairs of pixel separated by a distance d in a given direction.

This algorithm is executed on a two matrices the first one is the input BMP file image (original image) and the second one is the matrix indices that is depend on quantization and blocking size input.

Step 0: Read BMP file.

Step 1: ***For K = 0 to width-image - 1***

For L = 0 to height-image - 1

For I = 0 to width-image-index - 1

For J = 0 to height –image-index - 1

If (Bmp image (K, L) = I) Then Go To **Step2**

{Check all array contents with the each index I if it is equal to it then now enter in four different angles (0°, 45°, 90°, and 135°)} for specific pixel value check the neighbors in 4 angles if it found equal to J index, increment the counter when complete search for specific value store the value of counter in new array of (i, j)}.

Next L

Next K

Initialize again all counters of four angles to search to next indices

Next J

Next I

Step 2: Calculate the Average of the Co-occurrence matrix (since the result from step 1 is four matrices according to four angles 0°, 45°, 90°, and 135°) by applying the following equation :

$$p_{ave}(i,j)=\frac{1}{4}\sum_{j=0}^{hight-1}\sum_{i=0}^{width-1}p_{\vartheta=0}(i,j)+p_{\vartheta=45}(i,j)+p_{\vartheta=90}(i,j)+p_{\vartheta=135}(i,j)$$

Step 3: End.

3.4.4 Module-4: Normalization of the Co-occurrence Matrix

This step is accomplished by dividing each entry in the Co-occurrence matrix by the total number of paired occurrences (equation 2-1).

3.4.5 Module-5: Feature Extraction

Features extraction abstracts high-level information about individual patterns to facilitate texture classification. Therefore, to discriminate images with different textural characteristics, it is essential to extract texture features. Feature set (presented in section 3.2.1) were extracted from selected textured images.

3.4.6 Module-6: Display-Image

This module used for displaying the processed image at the end of any executing module when the user desire that.

3.4.7 Module-7: Image Blocking

In this module the image can be divided into array of blocks (sub-images), usually of size $2^k \times 2^k$ (where *k* is integer input value).

Algorithm (3.2): Image Blocking

Step 0: Block size (*k*).

Let M=256 div 2^k : Let N be number of blocks (N=M^2)

Step 1: Read image blocks.

For Y = 0 to height \ 2^k - 1

For X = 0 to width \ 2^k - 1

For y2 = 0 to 2^k - 1

For x2 = 0 to 2^k - 1

Store-image(X, Y, x2, y2) = image(X * 2^k + x2, Y * 2^k + y2)

Next x2

Next y2

Next X

Next Y

Step 2: End.

3.5 The Implementation Approach

This section (implementation approach) explains the details of implementation of this work. Algorithm (3.3) explain the followed steps of the image analysis based on texture feature.

Algorithm (3.3): Image Analysis Based on Texture features

Step 0: Read BMP file (image).

Step 1: Apply Quantization method on the data of BMP file.

Step 2: Apply Co-occurrence matrices method (see Algorithm 3.1).

Step 3: Calculate the average of the Co-occurrence matrix and normalize it. by applying the related equations (see chapter 2).

Step 4: Extract features for the average Co-occurrence matrix.

Step 5: Calculate the Co-occurrence matrix for each angle and normalize it. In this process four matrices are extracted.

Step 6: Extract features for the four matrices.

Step 7: Select the block size needed for dividing the original image (see Algorithm 3.2) and select the number of level needed for quantization process.

Step 8: For each sub-image go to step 2 until finishing the process of the last sub-image.

Step 9: Compare the result of features of original image with each sub image and analysis it.

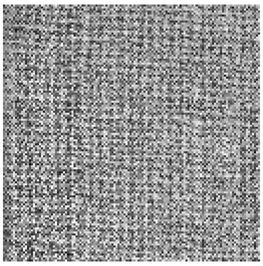
Step 10: End.

3.5.1 Experiment 1 :

The first selected textured image used as a test material is D17 image. The D17 is of a size of (128 × 128) with 256 gray levels (quantization level = 8). The eight selected features (maximum probability, entropy, homogeneity, cluster-Shade, cluster-Prominence, contrast, angular second moment, and inverse difference moment) are calculated for the original image and for the sub image for different block size 32 x 32 and 64 x 64 as be shown in figure (3-5) with different quantization level 5, 4, and 3.

It should be mentioned that the features are calculated in two ways, the first one for the average Co-occurrence matrix (first case named before) and the second one for the Co-occurrence matrix of angle 0°, 45°, 90°, and 135°(second case named after). Four values for the same feature is extracted (one for each angle) for the second case, and then the average value for the four features is calculated .

The calculated values for the eight features for D17 image for the two cases with 8, 32, and 64 level is presented in tables (3-1), (3-2), and (3-3) respectively.



(A)

(B)

(C)

Figure (3-5): Experiment 1
(A) Original Image D17,
(B) Extracted Features with window size 64×64.
(C) Extracted Features with window size 32×32.

Table 3-1: The value of statistical features for textured image D17 with quantization level =3

	8 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	6.0865	0.3700	4.1253	2.4458	0.0390	0.0447	679.67	6798.2
After	6.0865	0.3713	5.5127	2.4272	0.0388	0.0446	682.27	6823.7

Table 3-2: The value of statistical features for textured image D17 with quantization level =4

	16 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	23.881	0.2159	5.5649	0.0063	0.0109	0.3099	6333.1	131753
After	23.881	0.2167	7.4654	0.0062	0.0103	0.3000	6357.3	132249

Table 3-3: The value of statistical features for textured image D17 with quantization level =5

	32 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	95.4240	0.1177	7.0477	0.0016	0.0033	0.2035	54601	231892
After	95.4240	0.1181	9.4552	0.0015	0.0030	0.2033	54813	232765

It is clear from these tables that most of the selected features are stable in the two cases before and after except the feature of the entropy since the difference in the feature value of the two cases (before and after) is perceptible. This property can be utilized in the process of the discrimination pattern.

Figure (3-6) shows the behavior of the selected features in the case of before and after. As be mentioned before that the entropy feature gives perceptible slope in the case of before and after.

Figure (3-7) shows the behavior of the selected features with different quantization level. It is clear from the figure the some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.

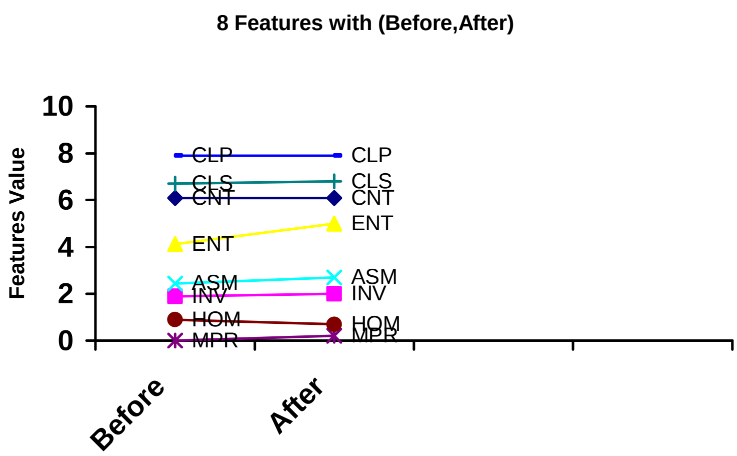


Figure (3-6): The behavior of the selected features in the case of before and after.

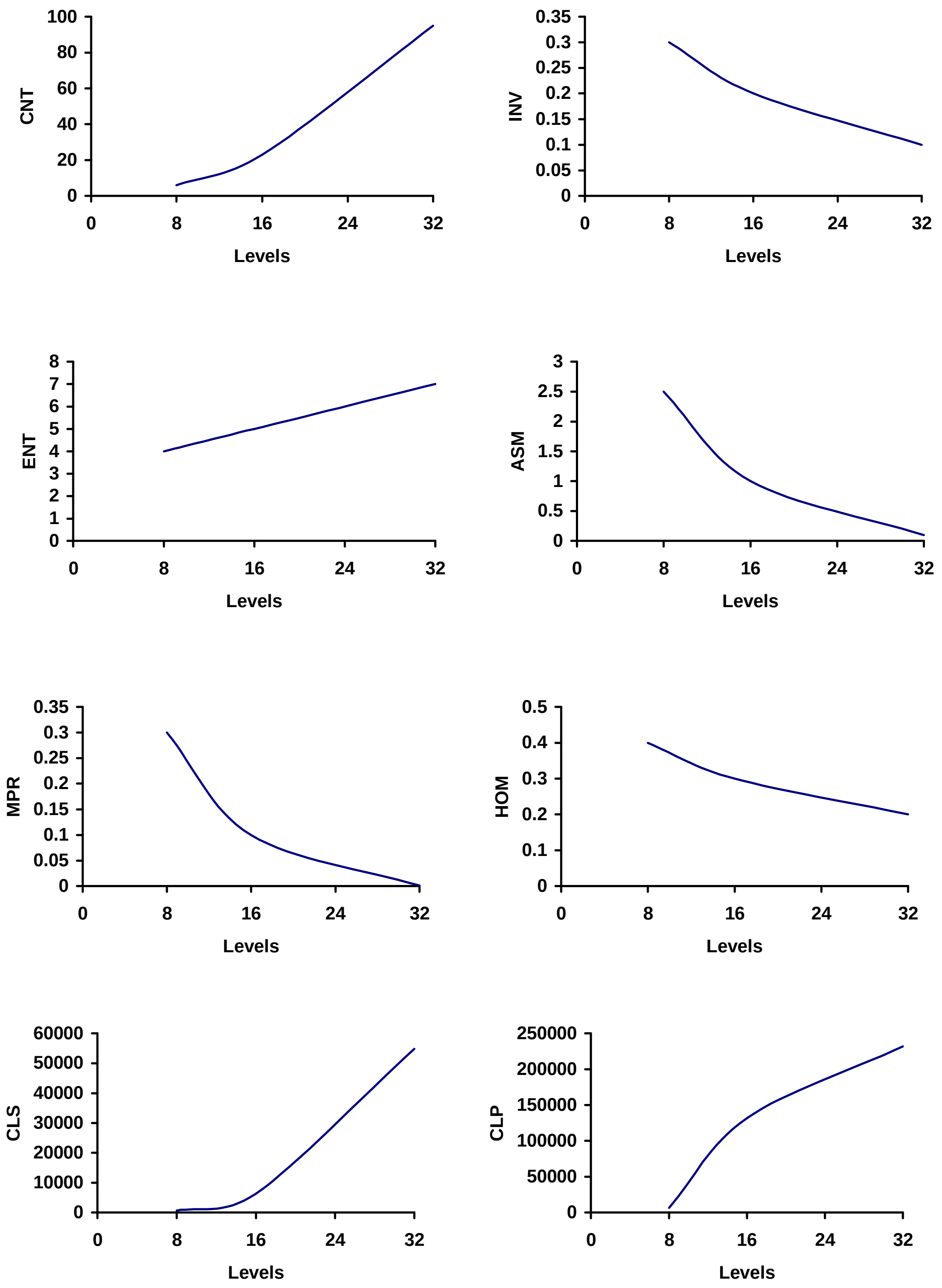


Figure (3-7): The behavior of the selected features with different quantization level (8, 16, and 32).

Table (3-4) shows the extracted features from D17 image with different block size (64 x 64) and with different quantization level (8, and 16).

Table (3-4): Extracted features for each block (block size 64×64) of the D17 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
CNT	Block1	5.9644	6.0185	23.426	23.640
	Block2	5.5802	5.5803	21.746	21.943
	Block3	6.7693	6.8294	26.906	27.147
	Block4	6.0044	6.0585	23.466	23.680
INV	Block1	0.3716	0.3743	0.2175	0.2190
	Block2	0.3822	0.3825	0.2266	0.2238
	Block3	0.3510	0.3536	0.2003	0.2017
	Block4	0.4116	0.4143	0.2575	0.2500
ENT	Block1	4.1089	5.5185	5.5501	7.4709
	Block2	4.0030	5.3787	5.4251	7.3083
	Block3	4.1919	5.6119	5.6328	7.5808
	Block4	4.1489	5.5585	5.5901	7.5109
ASM	Block1	0.0242	0.0241	0.0063	0.0062
	Block2	0.0278	0.0278	0.0074	0.0073
	Block3	0.0217	0.0217	0.0056	0.0056
	Block4	0.0242	0.0241	0.0046	0.0046

To be continue

Table (3-4): Extracted features for each block (block size 64×64) of the D17 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
MPR	Block1	0.0366	0.0366	0.0113	0.0104
	Block2	0.0501	0.0526	0.0158	0.0141
	Block3	0.0332	0.0293	0.0095	0.0078
	Block4	0.0766	0.0766	0.0051	0.0050
HOM	Block1	0.4479	0.4513	0.3110	0.3133
	Block2	0.4569	0.4603	0.3194	0.3218
	Block3	0.4310	0.4342	0.2952	0.2974
	Block4	0.4879	0.4913	0.3510	0.3530
CLS	Block1	631.71	636.575	5913.7	5959.3
	Block2	660.34	665.461	6161.3	6209.2
	Block3	701.24	706.64	6537.1	6587.5
	Block4	631.75	636.61	5913.7	5959.3
CLP	Block1	6209.5	6265.1	121004	121916
	Block2	6500.1	6528.9	125705	126741
	Block3	27230.1	7235.8	214033	140411
	Block4	6259.9	6256.2	121618	121916

Table (3-5) shows the extracted features from D17 image with different block size (32 x 32) and with quantization level 16.

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 16 in the two cases before and after

		Level -16	
		Before	After
CNT	Block1	5.6940	5.7987
	Block2	5.9577	6.0708
	Block3	5.5607	5.6625
	Block4	5.4083	5.5076
	Block5	5.9259	6.0325
	Block6	5.9456	6.0546
	Block7	5.8314	5.9379
	Block8	5.4378	5.5374
	Block9	6.5039	6.6255
	Block10	6.3089	6.4192
	Block11	6.0802	6.0930
	Block12	5.4403	5.5400
	Block13	6.9222	7.0503
	Block14	7.0390	7.1667
	Block15	6.5002	6.6238
	Block16	5.6940	5.7987

		Level -16	
		Before	After
INV	Block1	0.3783	0.3839
	Block2	0.3652	0.3705
	Block3	0.3823	0.3881
	Block4	0.4215	0.4272
	Block5	0.3669	0.3725
	Block6	0.3630	0.3684
	Block7	0.3693	0.3747
	Block8	0.3852	0.3910
	Block9	0.3553	0.3605
	Block10	0.3562	0.3616
	Block11	0.3599	0.3600
	Block12	0.3752	0.3807
	Block13	0.3436	0.3438
	Block14	0.3423	0.3474
	Block15	0.3626	0.3678
	Block16	0.3783	0.3839

To be continue

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 16 in the two cases before and after

		Level -16	
		Before	After
ENT	Block1	4.0420	5.4855
	Block2	4.0402	5.4300
	Block3	3.9605	5.3688
	Block4	3.9566	5.3634
	Block5	4.0348	5.4576
	Block6	4.0193	5.4421
	Block7	3.9948	5.4171
	Block8	3.9749	5.3879
	Block9	4.0882	5.5015
	Block10	4.1076	5.5468
	Block11	4.0613	5.4944
	Block12	3.9519	5.3515
	Block13	4.1710	5.6330
	Block14	4.2032	5.6714
	Block15	4.1563	5.6174
	Block16	4.0420	5.4855

		Level -16	
		Before	After
ASM	Block1	0.0255	0.0255
	Block2	0.0253	0.0260
	Block3	0.0279	0.0282
	Block4	0.0696	0.0698
	Block5	0.0259	0.0260
	Block6	0.0262	0.0264
	Block7	0.0264	0.0265
	Block8	0.0278	0.0280
	Block9	0.0242	0.0244
	Block10	0.0234	0.0234
	Block11	0.0251	0.0251
	Block12	0.0277	0.0279
	Block13	0.0213	0.0213
	Block14	0.0210	0.0212
	Block15	0.0223	0.0227
	Block16	0.0255	0.0256

To be continue

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 16 in the two cases before and after

		Level -16	
		Before	After
MPR	Block1	0.0501	0.0463
	Block2	0.0482	0.0469
	Block3	0.0525	0.0521
	Block4	0.0502	0.0498
	Block5	0.0458	0.0450
	Block6	0.0485	0.0470
	Block7	0.0493	0.0486
	Block8	0.0525	0.0523
	Block9	0.0443	0.0439
	Block10	0.0385	0.0380
	Block11	0.0474	0.0434
	Block12	0.0454	0.0434
	Block13	0.0340	0.0310
	Block14	0.0338	0.0317
	Block15	0.0357	0.0356
	Block16	0.0501	0.0463

		Level -16	
		Before	After
HOM	Block1	0.4537	0.4607
	Block2	0.4410	0.4477
	Block3	0.5556	0.5626
	Block4	0.4945	0.5015
	Block5	0.4443	0.4512
	Block6	0.4413	0.4480
	Block7	0.4454	0.4521
	Block8	0.4579	0.4650
	Block9	0.4336	0.4462
	Block10	0.4354	0.4422
	Block11	0.4366	0.4433
	Block12	0.4497	0.4566
	Block13	0.4225	0.4290
	Block14	0.4232	0.4298
	Block15	0.4396	0.4462
	Block16	0.4537	0.4607

To be continue

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 16 in the two cases before and after

		Level -16	
		Before	After
CLS	Block1	584.29	589.47
	Block2	708.42	719.54
	Block3	648.96	659.26
	Block4	652.87	663.22
	Block5	725.81	737.35
	Block6	733.29	744.87
	Block7	666.35	676.84
	Block8	639.91	650.01
	Block9	776.66	788.37
	Block10	702.11	710.25
	Block11	648.48	658.66
	Block12	622.93	632.69
	Block13	656.66	666.87
	Block14	676.00	686.58
	Block15	666.39	676.69
	Block16	584.29	593.74

		Level -16	
		Before	After
CLP	Block1	5613.4	5699.8
	Block2	7254.4	7260.4
	Block3	6432.9	6440.6
	Block4	6463.9	6472.8
	Block5	7469.9	7472.8
	Block6	7552.9	7554.4
	Block7	6692.9	6695.8
	Block8	6318.9	6321.4
	Block9	8239.5	8248.1
	Block10	7238.9	7240.2
	Block11	6515.9	6524.2
	Block12	6118.9	6128.1
	Block13	6775.3	6785.9
	Block14	6096.9	6105.0
	Block15	6824.6	6834.6
	Block16	5688.8	5699.8

It is clear from the values of the calculated features, which are presented in table (3-4) that most of the selected features not affected by the size of the block; these results led us to the following remarks:

- The definition of the texture is verified, sine it represent the repetition of fundamental image elements.
- It is preferable to select the sample of the texture with minimum size of block to extract the statistical texture features.

Same thing noticed in the previous tables can be notice from the results of table (3-5), since that most of the selected features are stable in the two cases before and after except the feature of the entropy since the difference in the feature value of the two cases (before and after) is perceptible.

Figure (3-8) reflects the behavior of the selected features in the case of before and after. It is clear from this figure that the entropy feature gives perceptible slope in the case of before and after, and this result is similar to the result obtained from figure (3-9).

Figure (3-10) reflects the behavior of the selected features with 16 levels. Same thing can be seen, some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.

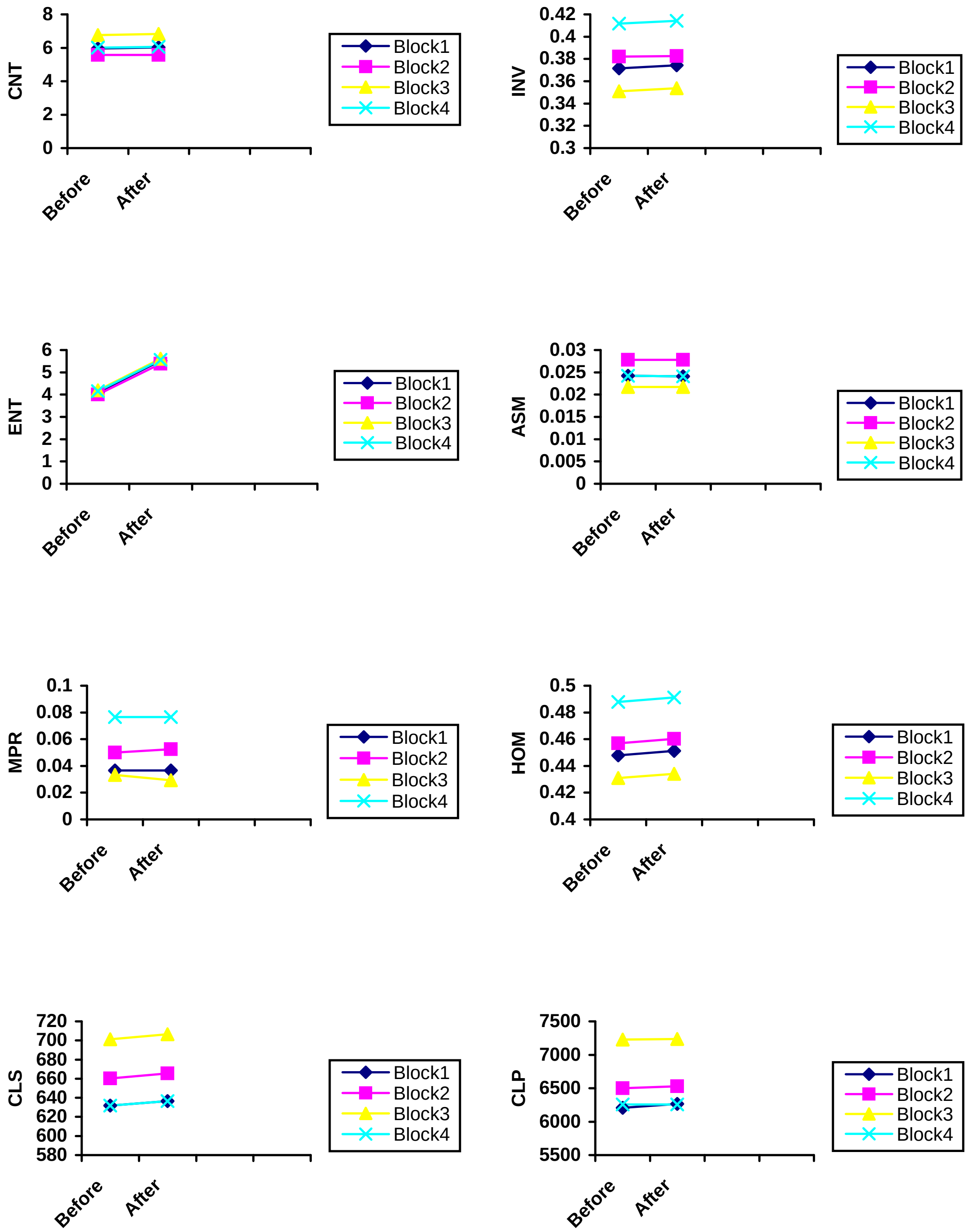


Figure (3-8): The behavior of the selected features in each block (block size 64×64) of the D17 image with quantization level 8 in the two cases of before.

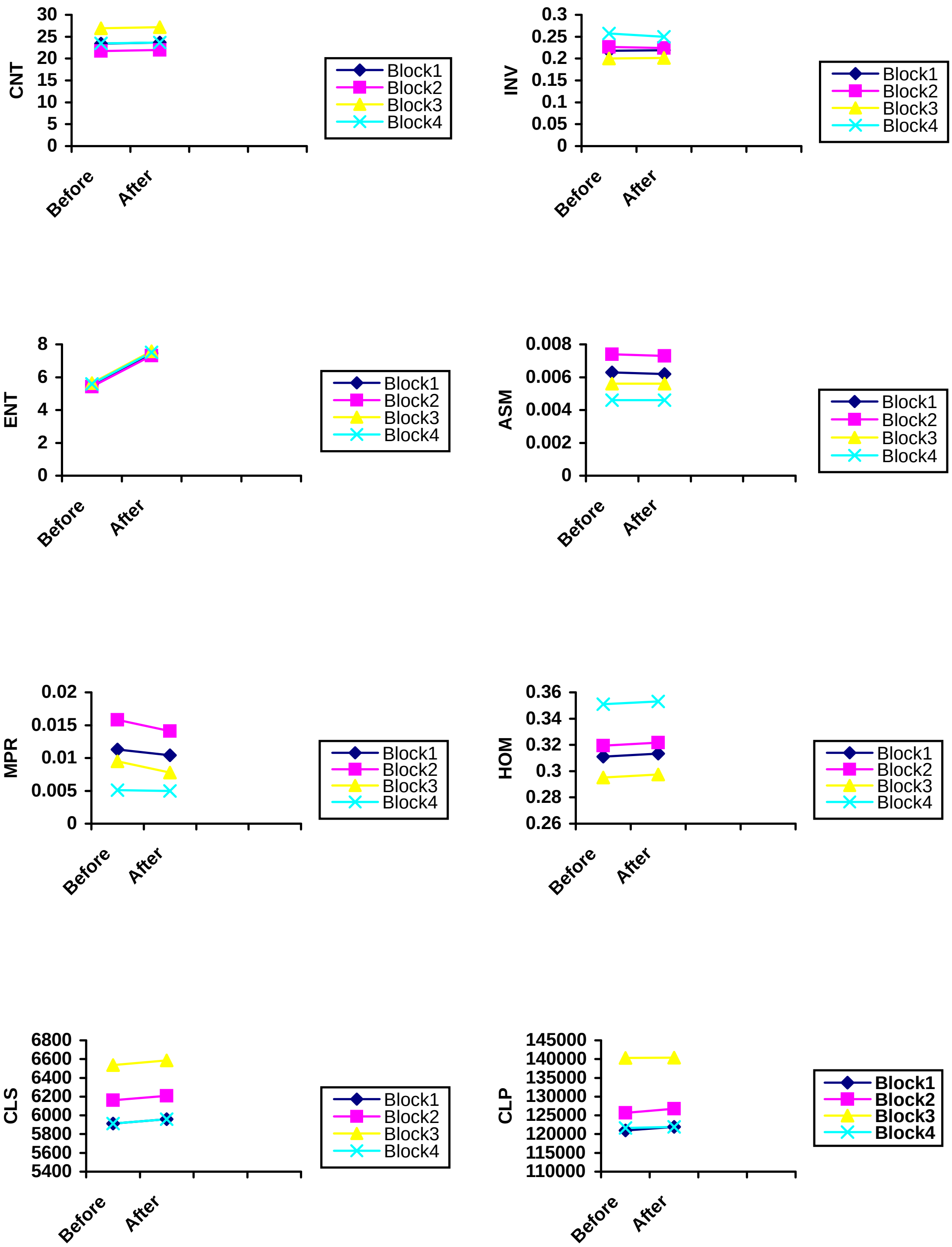


Figure (3-9): The behavior of the selected features in each block (block size 64×64) of the D17 image with quantization level 16 in the two cases of before.

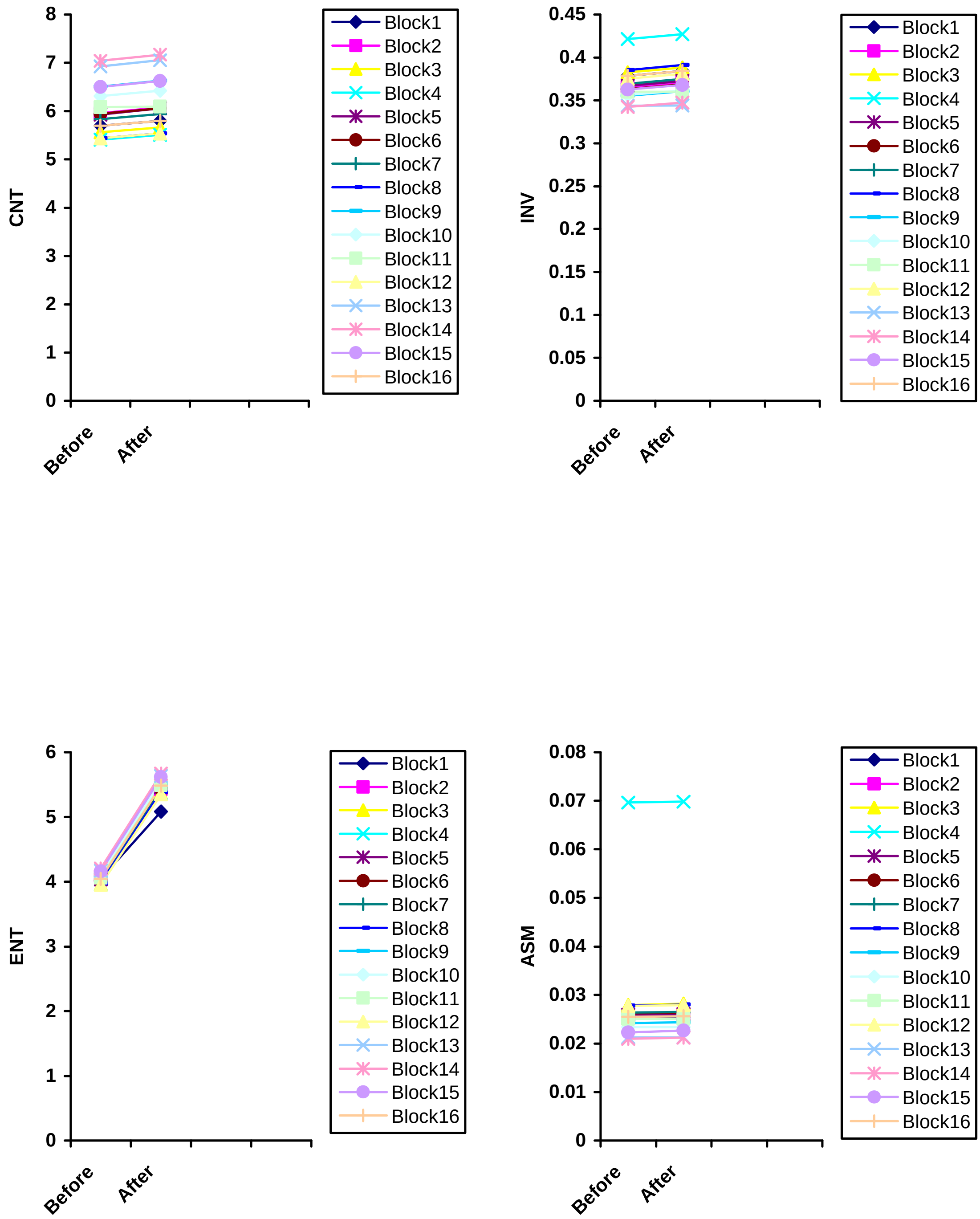


Figure (3-10): The behavior of the selected features in each block (block size 32×32) of theD17 image with quantization level 16 in the two cases of before and after.

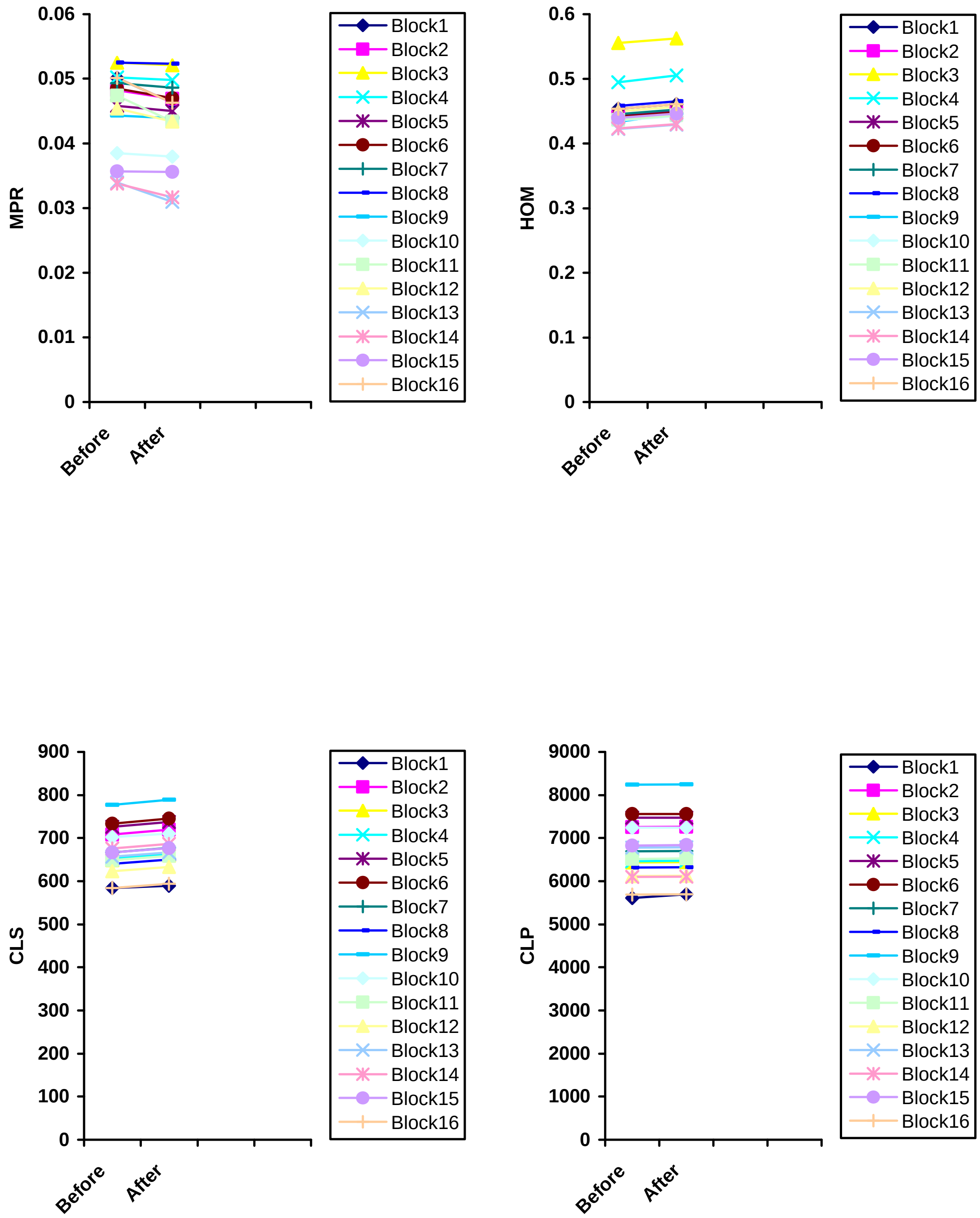
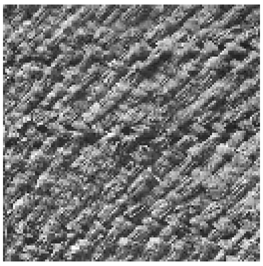


Figure (3-10): The behavior of the selected features in each block (block size 32×32) of theD17 image with quantization level 16 in the two cases of before and after.

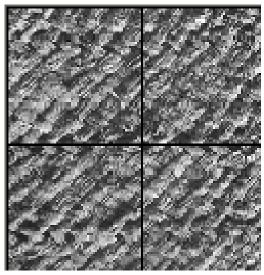
3.5.2 Experiment 2 :

The second selected textured image used as a test material is D18 image. The D18 is of a size of (128 × 128) with 256 gray levels (quantization level = 8). The eight selected features (maximum probability, entropy, homogeneity, cluster-Shade, cluster-Prominence, contrast, angular second moment, and inverse difference moment) are calculated for the original image and for the sub image for different block size 32 x 32 and 64 x 64 as be shown in figure (3-11) with different quantization level 5, 4, and 3.

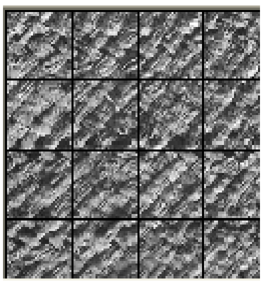
The features are calculated in two ways, the first one for the average Co-occurrence matrix and the second one for the Co-occurrence matrix of angle 0°, 45°, 90°, and 135° as be mentioned before that the two ways named before and after respectively. Four values for the same feature is extracted (one for each angle) for the second case, and then the average value for the four features is calculated.



(A)



(B)



(C)

Figure 3-11: Experiment 2
(A) Original Image D18,
(B) Extracted Features with window size 64×64.
(C) Extracted Features with window size 32×32.

Table 3-6: The value of statistical features for textured image D18 with quantization level =3

	8 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	2.9560	0.5212	3.7328	3.8060	0.0798	0.5681	375.31	3354.9
After	2.9560	0.5233	3.0284	3.8070	0.0801	0.5704	376.80	3368.3

Table 3-7: The value of statistical features for textured image D18 with quantization level =4

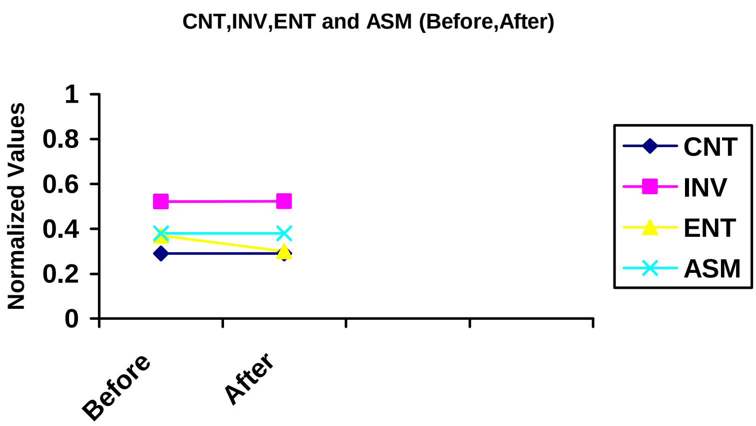
	16 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	11.343	0.3430	5.1631	0.0104	0.0305	0.4207	3572.7	66315
After	11.343	0.3444	6.9524	0.0104	0.0306	0.4224	3586.9	66578

Table 3-8: The value of statistical features for textured image D18 with quantization level =5

	32 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	44.774	0.2024	6.6243	0.0027	0.0084	0.2921	31141	1179058
After	44.774	0.2051	8.9182	0.0027	0.0083	0.2932	31265	1183749

It is clearly from these tables and from figure (3-12) that most of the selected features except the entropy feature are stable in the two cases before and after since the values of entropy feature have perceptible slope in the two cases before and after.

Figure (3-13) shows the behavior of the selected features with different quantization level. It is clear from the figure the some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.



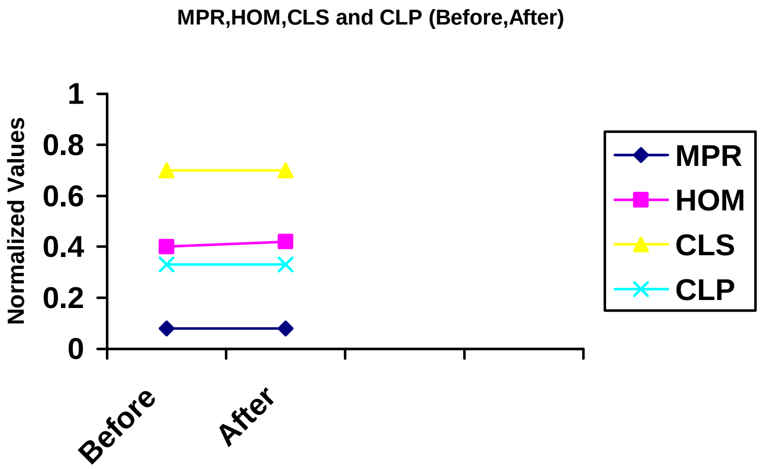


Figure (3-12): The behavior of the selected features in the two cases of before and after.

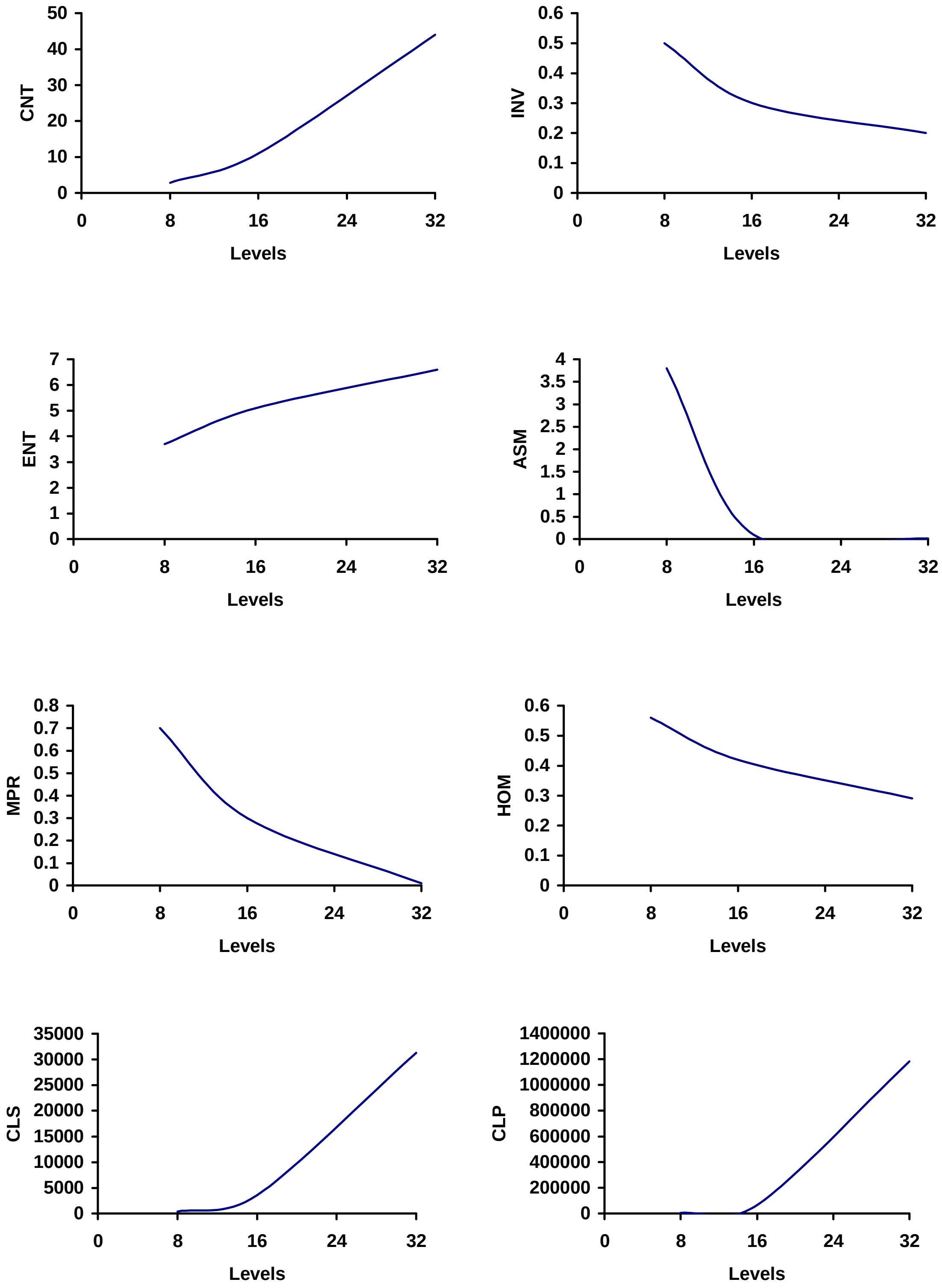


Figure (3-13): The behavior of the selected features with different quantization level (8, 16, and 32)

Table (3-9) shows the extracted features from D18 image with different block size (64×64) and with different quantization level (8, and 16).

Table (3-9): Extracted features for each block (block size 64×64) of the D18 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	**After**	**Before**	**After**
CNT	**Block1**	**2.9018**	**2.9242**	**11.149**	**11,234**
	Block2	**2.6433**	**2.6636**	**10.174**	**10.252**
	Block3	**3.1608**	**3.1847**	**12.153**	**12.244**
	Block4	**2.9418**	**2.9642**	**11.894**	**11.274**
INV	**Block1**	**0.5154**	**0.5196**	**0.3368**	**0.3395**
	Block2	**0.5417**	**0.5461**	**0.3611**	**0.3640**
	Block3	**0.5056**	**0.5097**	**0.3301**	**0.3328**
	Block4	**0.5554**	**0.5559**	**0.3768**	**0.3790**
ENT	**Block1**	**3.1778**	**5.0305**	**5.1501**	**6.9633**
	Block2	**3.6190**	**4.9619**	**5.0348**	**6.8132**
	Block3	**3.7465**	**5.0663**	**5.1632**	**6.9783**
	Block4	**3.7578**	**5.0705**	**5.1901**	**7.0033**
ASM	**Block1**	**0.0374**	**0.0377**	**0.0101**	**0.0100**
	Block2	**0.0418**	**0.0420**	**0.0118**	**0.0117**
	Block3	**0.0376**	**0.0380**	**0.0106**	**0.0107**
	Block4	**0.0774**	**0.0772**	**0.0501**	**0.0500**

To be continue

Table (3-9): Extracted features for each block (block size 64×64) of the D18 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
MPR	Block1	0.0814	0.0821	0.0252	0.0254
	Block2	0.0864	0.0871	0.0387	0.0390
	Block3	0.0812	0.0819	0.0326	0.0329
	Block4	0.0812	0.0813	0.0652	0.0654
HOM	Block1	0.5627	0.5672	0.4154	0.4188
	Block2	0.5841	0.5888	0.4351	0.4386
	Block3	0.5552	0.5597	0.4097	0.4130
	Block4	0.6070	0.6076	0.4554	0.4588
CLS	Block1	389.49	392.61	3699.7	3729.3
	Block2	344.56	347.31	3300.7	3446.9
	Block3	363.44	366.35	3446.9	3474.6
	Block4	389.53	392.65	3699.8	3729.8
CLP	Block1	3492.3	3520.3	68907	69460
	Block2	3000.5	3008.2	59720	59908
	Block3	3290.4	3296.3	64730	64746
	Block4	3516.5	3520.3	69455	69460

The results of the previous tables would be presented in a way differ as be presented in Experiment (1), Figure (3-13) presents the behavior of the selected features for each block in the D18 image. Since block size in this case 64×64. It should be mentioned that the values of the features are normalized to the value one. The results shows that there is not clearly in the extracted feature value in the two cases before and after expect the entropy feature, where the changes is perceptible in the two cases before and after.

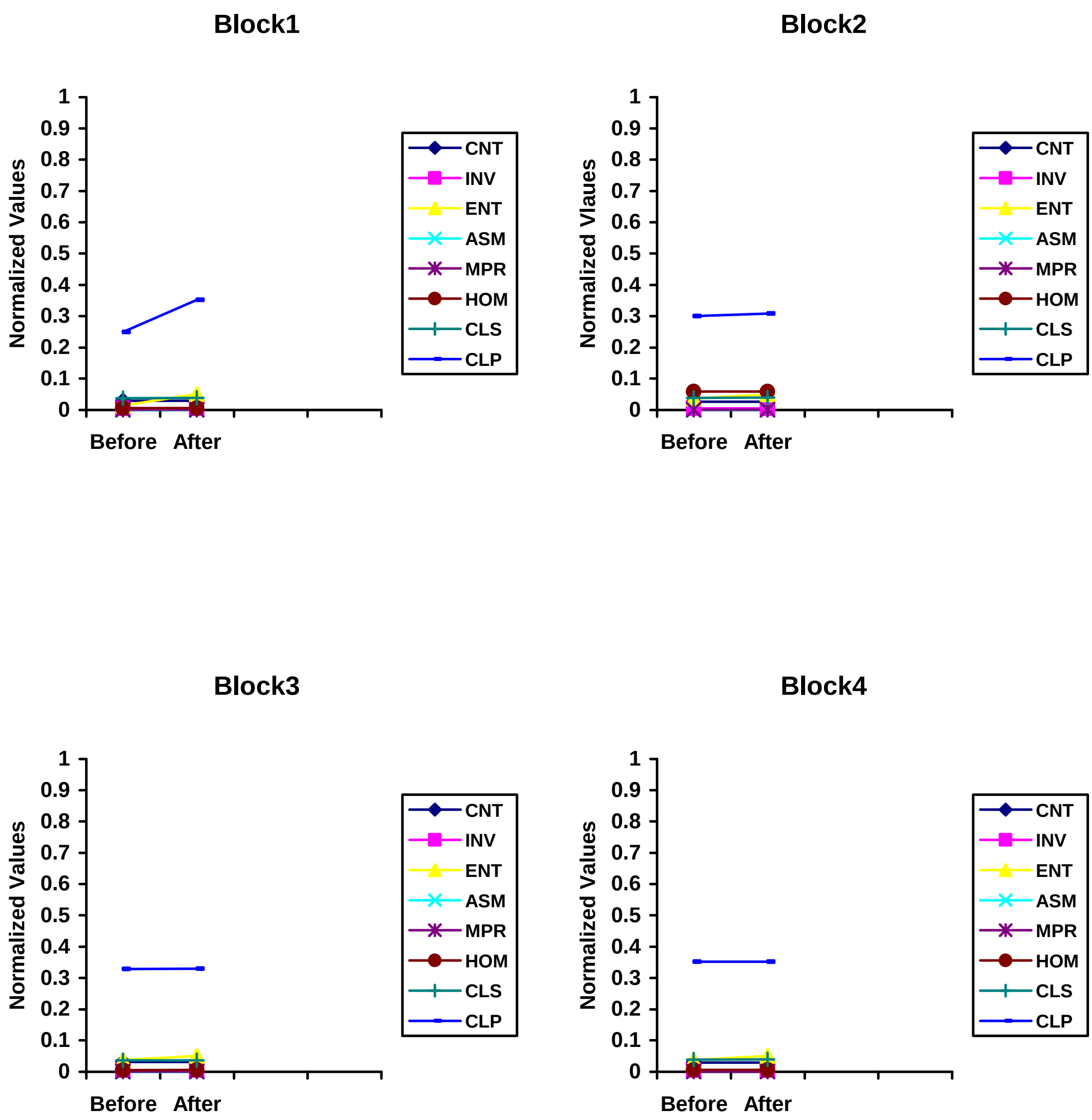


Figure (3-13): The behavior of blocks with selected features of the D18 image, with block size 64×64 and quantization level 8 in the two cases of before and after.

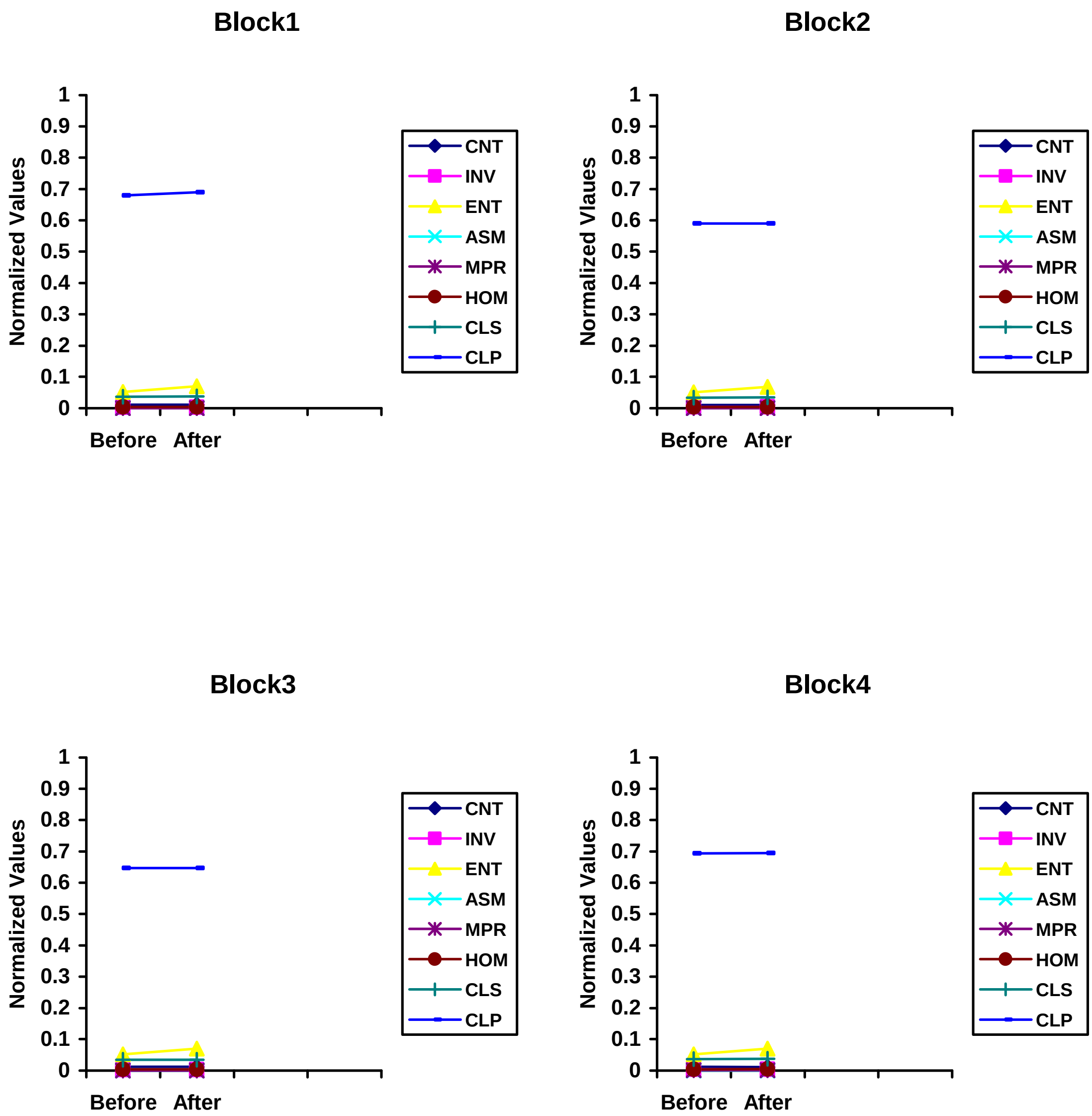


Figure (3-14): The behavior of blocks with selected features of the D18 image, with block size 64×64 and quantization level 16 in the two cases of before and after.

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 16 in the two cases before and after

		Level -16	
		Before	After
CNT	Block1	2.9030	2.9475
	Block2	2.7702	2.8138
	Block3	2.7235	2.7665
	Block4	2.9455	2.9901
	Block5	3.1217	3.1706
	Block6	2.7870	2.8309
	Block7	2.4627	2.5023
	Block8	2.4416	2.4793
	Block9	3.1460	3.1945
	Block10	2.8919	2.9373
	Block11	2.9092	2.9556
	Block12	2.3283	2.3651
	Block13	3.4984	3.5529
	Block14	2.9946	3.0398
	Block15	3.4098	3.4630
	Block16	2.9031	2.9475

		Level -16	
		Before	After
INV	Block1	0.5071	0.5154
	Block2	0.5279	0.5376
	Block3	0.5304	0.5390
	Block4	0.5644	0.5732
	Block5	0.5082	0.5166
	Block6	0.5345	0.5432
	Block7	0.5354	0.5442
	Block8	0.5615	0.5708
	Block9	0.5073	0.5156
	Block10	0.5086	0.5170
	Block11	0.5061	0.5144
	Block12	0.5433	0.5522
	Block13	0.4935	0.5016
	Block14	0.5035	0.5119
	Block15	0.4917	0.4998
	Block16	0.5071	0.5154

To be continue

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 16 in the two cases before and after

		Level -16	
		Before	After
ENT	Block1	3.6875	5.0307
	Block2	3.7022	5.0540
	Block3	3.5649	4.8682
	Block4	3.7026	5.0563
	Block5	3.6778	5.0185
	Block6	3.5518	4.8474
	Block7	3.5244	4.7997
	Block8	3.5372	4.8573
	Block9	3.7268	5.0882
	Block10	3.6454	4.9605
	Block11	3.7381	5.0873
	Block12	3.4960	4.7657
	Block13	3.7785	5.1306
	Block14	3.7018	5.0530
	Block15	3.7753	5.1410
	Block16	3.3687	5.0307

		Level -16	
		Before	After
ASM	Block1	0.0373	0.0381
	Block2	0.0357	0.0363
	Block3	0.0437	0.0452
	Block4	0.0796	0.0801
	Block5	0.0401	0.0409
	Block6	0.0466	0.0474
	Block7	0.0427	0.0437
	Block8	0.0434	0.0439
	Block9	0.0376	0.0380
	Block10	0.0392	0.0401
	Block11	0.0348	0.0353
	Block12	0.0461	0.0469
	Block13	0.0360	0.0369
	Block14	0.0383	0.0391
	Block15	0.0350	0.0356
	Block16	0.0373	0.0381

To be continue

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 16 in the two cases before and after

		Level -16	
		Before	After
MPR	Block1	0.0716	0.0720
	Block2	0.0615	0.0612
	Block3	0.1036	0.1053
	Block4	0.1373	0.1389
	Block5	0.0989	0.1006
	Block6	0.1158	0.1177
	Block7	0.0887	0.0901
	Block8	0.0924	0.0931
	Block9	0.0868	0.0818
	Block10	0.0843	0.0857
	Block11	0.0730	0.0715
	Block12	0.0989	0.1005
	Block13	0.0787	0.0776
	Block14	0.0761	0.0771
	Block15	0.0815	0.0828
	Block16	0.0716	0.0728

		Level -16	
		Before	After
HOM	Block1	0.5547	0.5638
	Block2	0.5714	0.5808
	Block3	0.5742	0.5836
	Block4	0.6095	0.6190
	Block5	0.5567	0.5659
	Block6	0.5789	0.5883
	Block7	0.5768	0.5862
	Block8	0.5998	0.6097
	Block9	0.5540	0.5631
	Block10	0.5564	0.5656
	Block11	0.5539	0.5630
	Block12	0.5843	0.5938
	Block13	0.5463	0.5552
	Block14	0.5522	0.5614
	Block15	0.5431	0.5522
	Block16	0.5547	0.5638

To be continue

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 16 in the two cases before and after

		Level -16	
		Before	After
CLS	Block1	370.32	376.38
	Block2	485.07	492.92
	Block3	306.07	311.05
	Block4	362.45	368.33
	Block5	349.31	354.98
	Block6	303.85	308.79
	Block7	330.08	335.43
	Block8	374.44	380.55
	Block9	389.66	396.03
	Block10	337.54	343.05
	Block11	439.90	447.53
	Block12	317.70	322.88
	Block13	361.17	367.04
	Block14	358.59	364.45
	Block15	413.39	420.14
	Block16	370.32	376.38

		Level -16	
		Before	After
CLP	Block1	3321.4	3376.3
	Block2	4550.3	4606.4
	Block3	2510.4	2626.2
	Block4	3210.7	3264.2
	Block5	3125.3	3171.6
	Block6	2579.4	2625.3
	Block7	2760.4	2816.4
	Block8	3354.4	3389.5
	Block9	3590.4	3637.9
	Block10	2935.4	2988.4
	Block11	4085.6	4130.6
	Block12	2634.2	2686.3
	Block13	3282.4	3333.5
	Block14	3242.0	3294.0
	Block15	3710.9	3844.0
	Block16	3334.5	3376.3

Figure (3-15) shows the results of selected features for each block normalization to the value one, with 16 block, it is clearly from the graph the similarity and satiability of feature values, between all blocks that see it in figure (3-13) and (3-14).

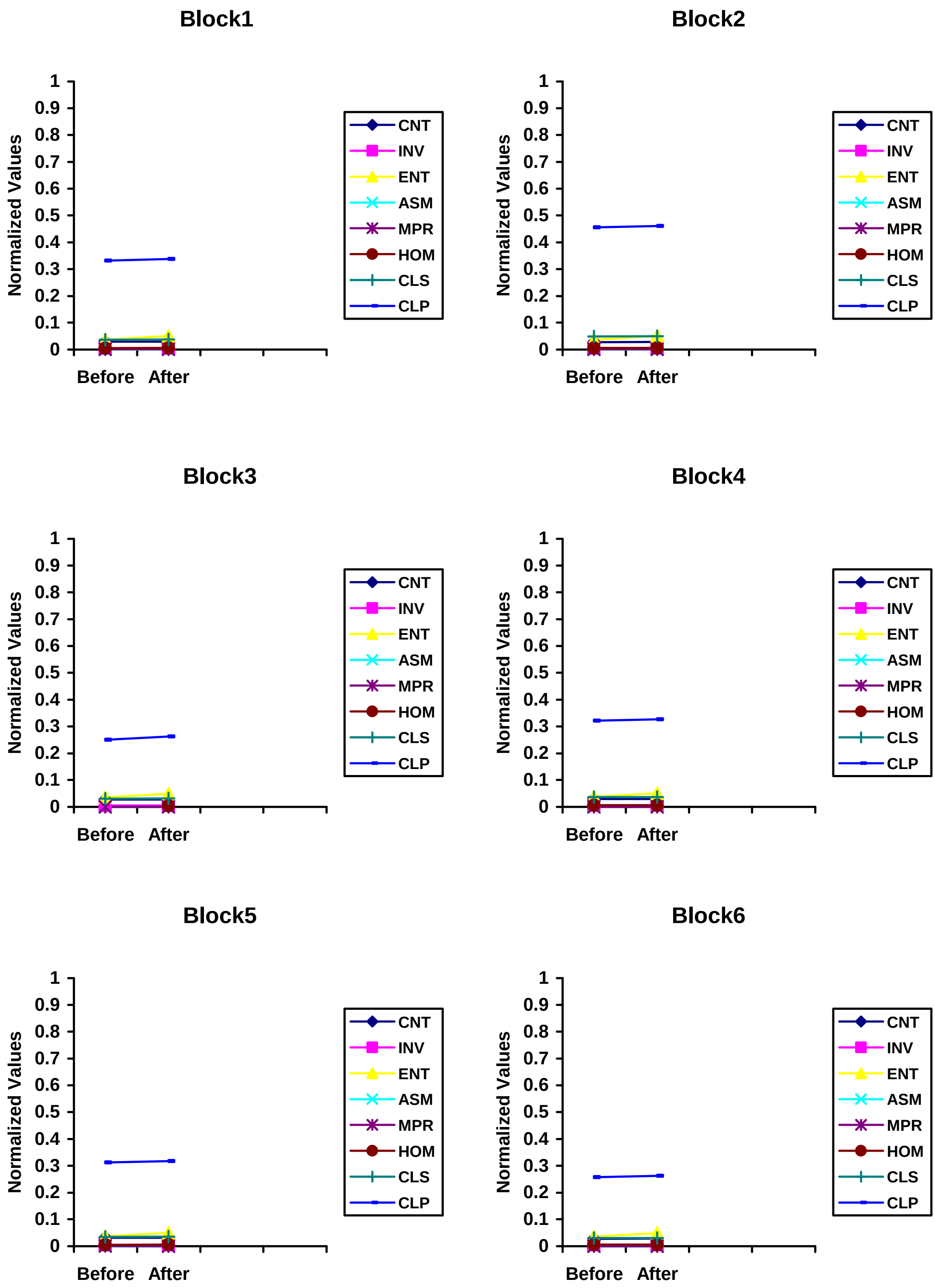


Figure (3-15): The behavior of blocks with selected features of the D18 image, with block size 32×32 and quantization level 16 in the two cases of before and after.

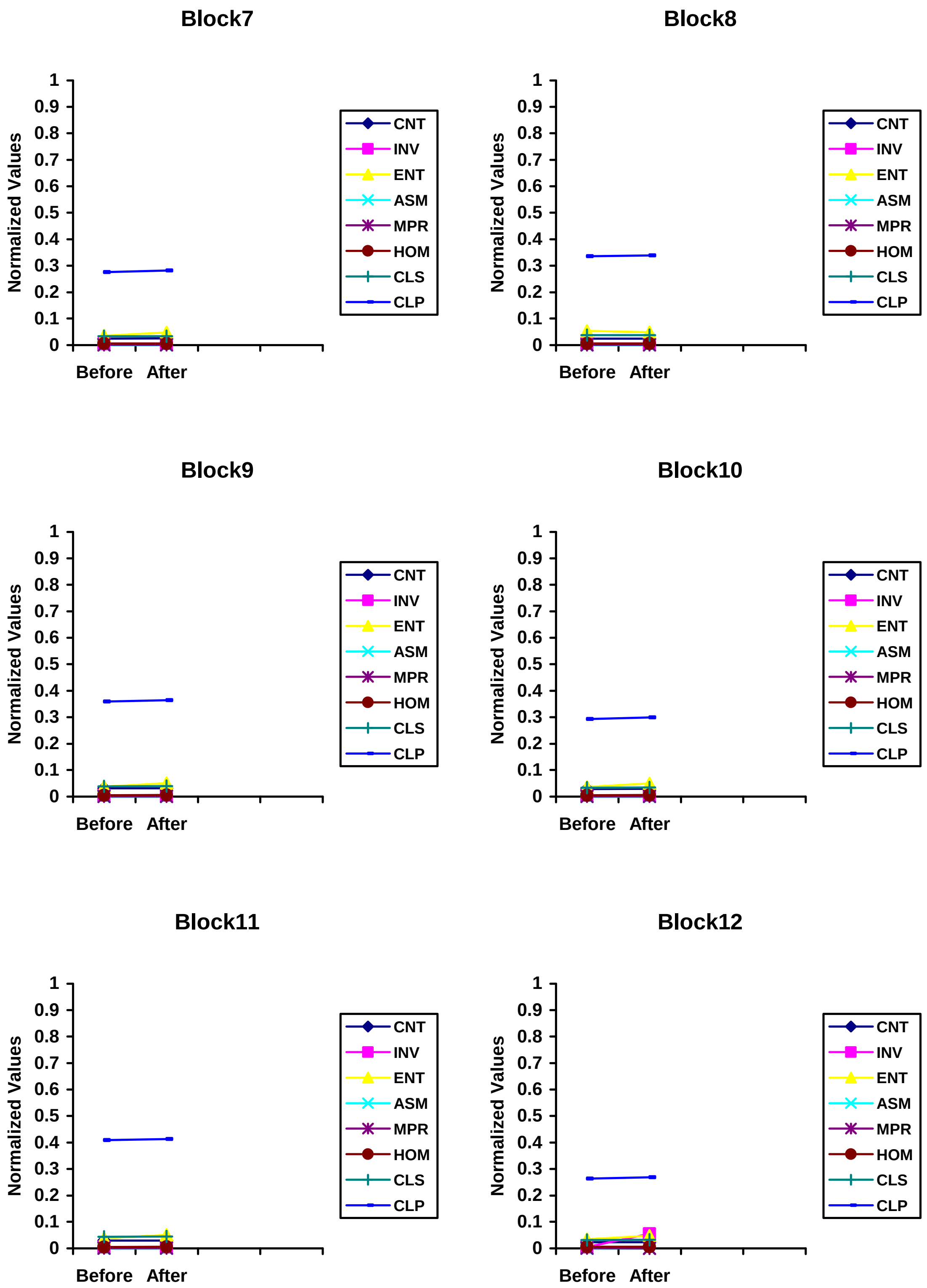


Figure (3-15): The behavior of blocks with selected features of the D18 image, with block size 32×32 and quantization level 16 in the two cases of before and after.

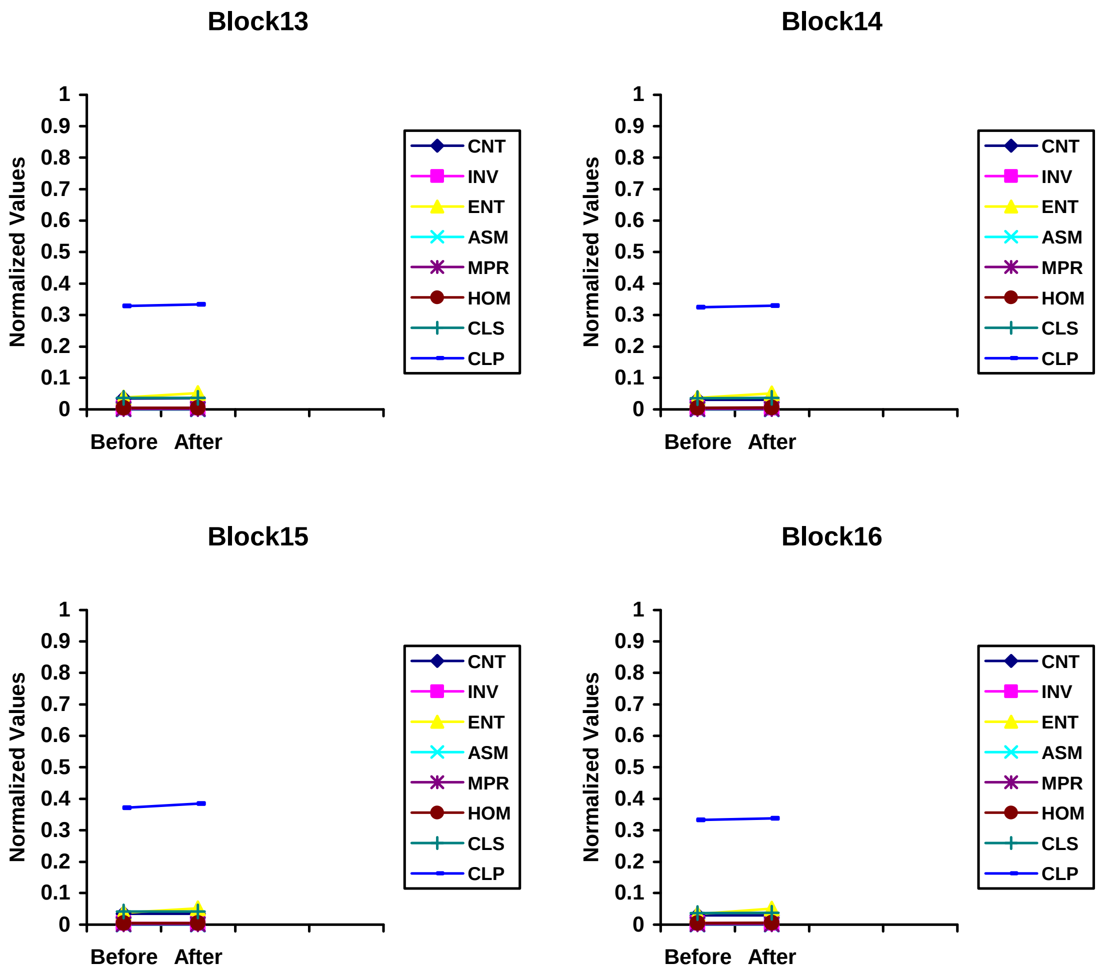
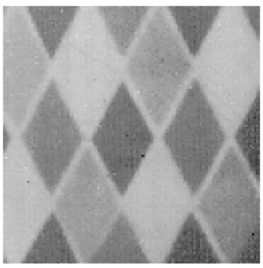


Figure (3-15): The behavior of blocks with selected features of the D18 image, with block size 32×32 and quantization level 16 in the two cases of before and after.

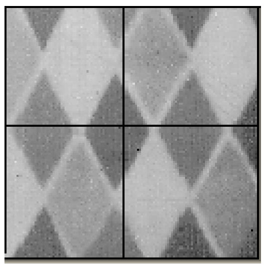
3.5.3 Experiment 3 :

The second selected textured image used as a test material is D84 image. The D84 is of a size of (128 × 128) with 256 gray levels (quantization level = 8). The eight selected features (maximum probability, entropy, homogeneity, cluster-Shade, cluster-Prominence, contrast, angular second moment, and inverse difference moment) are calculated for the original image and for the sub image for different block size 32 x 32 and 64 x 64 as be shown in figure (3-16) with different quantization level 5, 4, and 3.

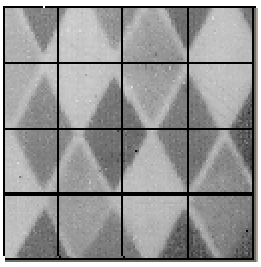
The features are calculated in two ways, the first one for the average Co-occurrence matrix and the second one for the Co-occurrence matrix of angle 0°, 45°, 90°, and 135° as be mentioned before that the two ways named before and after respectively. Four values for the same feature is extracted (one for each angle) for the second case, and then the average value for the four features is calculated.



(A)



(B)



(C)

Figure 3-16: Experiment 3
(A) Original Image D84,
(B) Extracted Features with window size 64×64.
(C) Extracted Features with window size 32×32.

Table 3-11: The value of statistical features for textured image D84 with quantization level =3

	8 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	0.2741	0.8688	2.2929	0.1651	0.3044	0.8697	789.42	7879.9
After	0.2741	0.8732	3.0804	0.1663	0.3056	0.8731	792.53	7911.0

Table 3-12: The value of statistical features for textured image D84 with quantization level =4

	16 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	0.6691	0.7723	3.2014	0.0707	0.1720	0.7802	7376.1	153101
After	0.6691	0.7754	4.4260	0.0711	0.1727	0. 7833	7405.2	153704

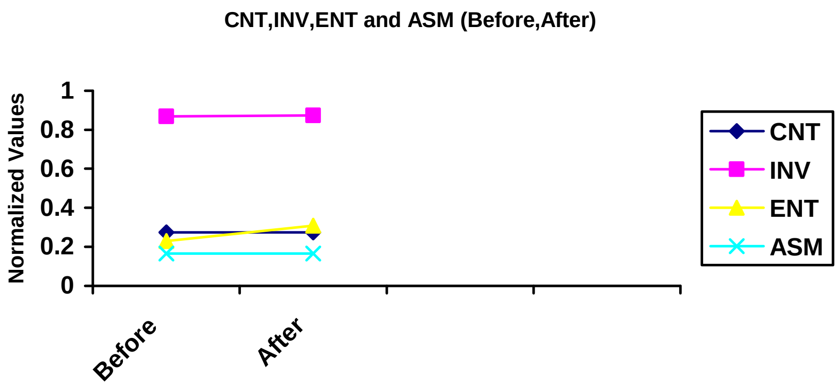
Table 3-13: The value of statistical features for textured image D84 with quantization level =5

	32 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	2.1527	0.6280	4.5306	0.0243	0.0708	0.6556	63189	2674571
After	2.1527	0.6306	6.1161	0.0244	0.0711	0.6583	63438	2685117

It is clear from these tables and from figure (3-17) that most of the selected features except the entropy feature are stable in the two cases before

and after since the values of entropy feature have perceptible slope in the two cases before and after.

Figure (3-18) shows the behavior of the selected features with different quantization level. It is clear from the figure the some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.



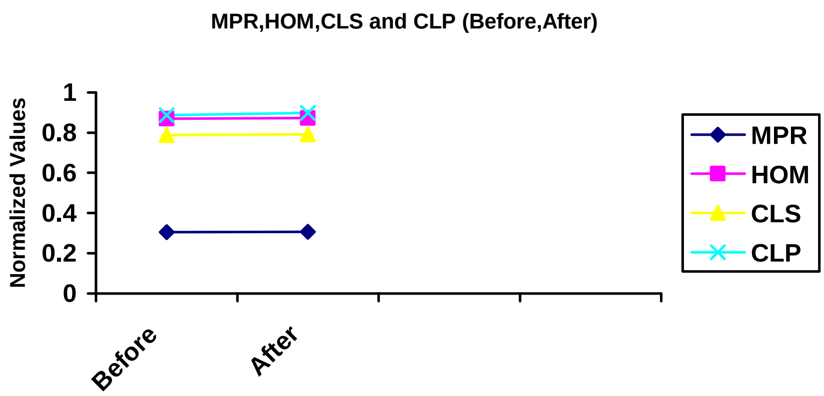


Figure (3-17): The behavior of the selected features in the two cases of before and after.

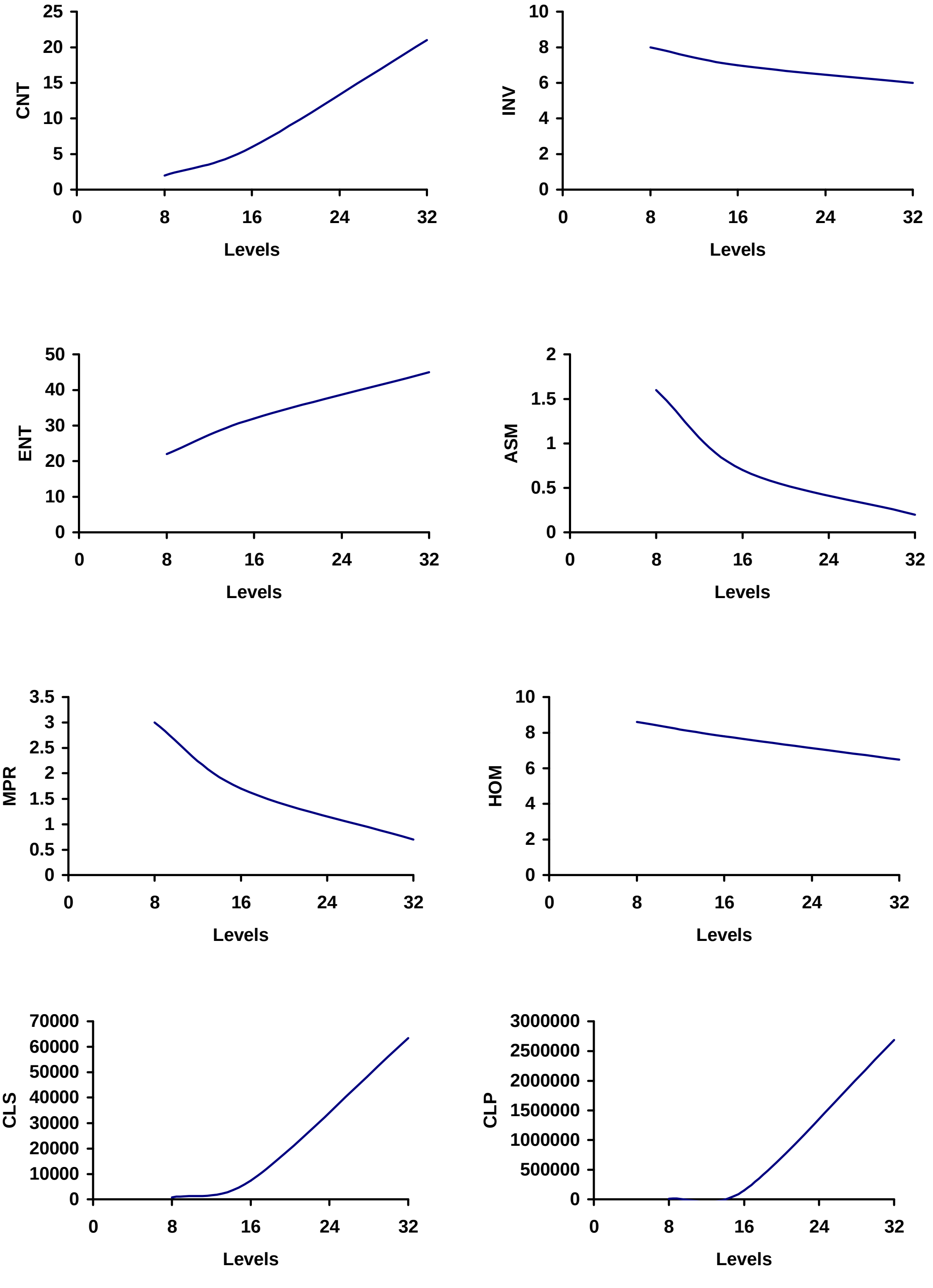


Figure (3-18): The behavior of the selected features with different quantization level (8, 16, and 32)

Table (3-14) shows the extracted features from D84 image with different block size 64×64 and with different quantization level (16, and 32).

Table (3-14): Extracted features for each block (block size 64×64) of the D18 image with quantization level 16 and 32 in the two cases before and after

		Level - 16		Level -32	
		Before	**After**	**Before**	**After**
CNT	**Block1**	**0.1322**	**0.1327**	**0.4087**	**0.4101**
	Block2	**0.1629**	**0.1634**	**0.5159**	**0.5177**
	Block3	**0.1588**	**0.1593**	**0.4769**	**0.4785**
	Block4	**0.1722**	**0.1727**	**0.4487**	**0.4501**
INV	**Block1**	**0.1968**	**0.1975**	**0.1613**	**0.1619**
	Block2	**0.1907**	**0.1951**	**0.1572**	**0.1579**
	Block3	**0.1881**	**0.1889**	**0.1561**	**0.1568**
	Block4	**0.2368**	**0.2375**	**0.2013**	**0.2019**
ENT	**Block1**	**1.0774**	**1.4477**	**1.3768**	**1.8504**
	Block2	**1.1477**	**1.5421**	**1.4375**	**1.9374**
	Block3	**1.1686**	**1.5683**	**1.4436**	**1.9374**
	Block4	**1.1174**	**1.4877**	**1.4168**	**1.8904**
ASM	**Block1**	**0.0067**	**0.0068**	**0.0025**	**0.0025**
	Block2	**0.0050**	**0.0050**	**0.0019**	**0.0019**
	Block3	**0.0039**	**0.0040**	**0.0016**	**0.0016**
	Block4	**0.0467**	**0.0468**	**0.0042**	**0.0042**

To be continue

Table (3-14): Extracted features for each block (block size 64×64) of the D18 image with quantization level 16 and 32 in the two cases before and after

		Level - 16		Level -32	
		Before	After	Before	After
MPR	Block1	0.0618	0.0621	0.0340	0.0341
	Block2	0.0485	0.0487	0.0296	0.0230
	Block3	0.0309	0.0310	0.0172	0.0171
	Block4	0.1018	0.1021	0.0743	0.0741
HOM	Block1	0.1981	0.1989	0.1666	0.1673
	Block2	0.1927	0.1935	0.1638	0.1645
	Block3	0.1898	0.1905	0.1626	0.1633
	Block4	0.2381	0.2389	0.2066	0.2073
CLS	Block1	2289.6	2298.6	19428.0	19504.8
	Block2	1913.2	1920.8	16363.3	16428.0
	Block3	1688.2	1694.9	14540.1	14597.2
	Block4	2289.6	2298.7	19428.0	19504.9
CLP	Block1	50150	50349	865893	869318
	Block2	40066	40135	645876	699728
	Block3	34120	34265	560135	602701
	Block4	50150	50349	865893	869318

The results of the previous tables of Experiment 3would be presented in the same way that experiment 2 showed. Figure (3-19) presents the behavior of the selected features for each block in the D84 image. Since the block size in this case is 64×64. It should be mentioned that the values of the features are normalized to the value one.

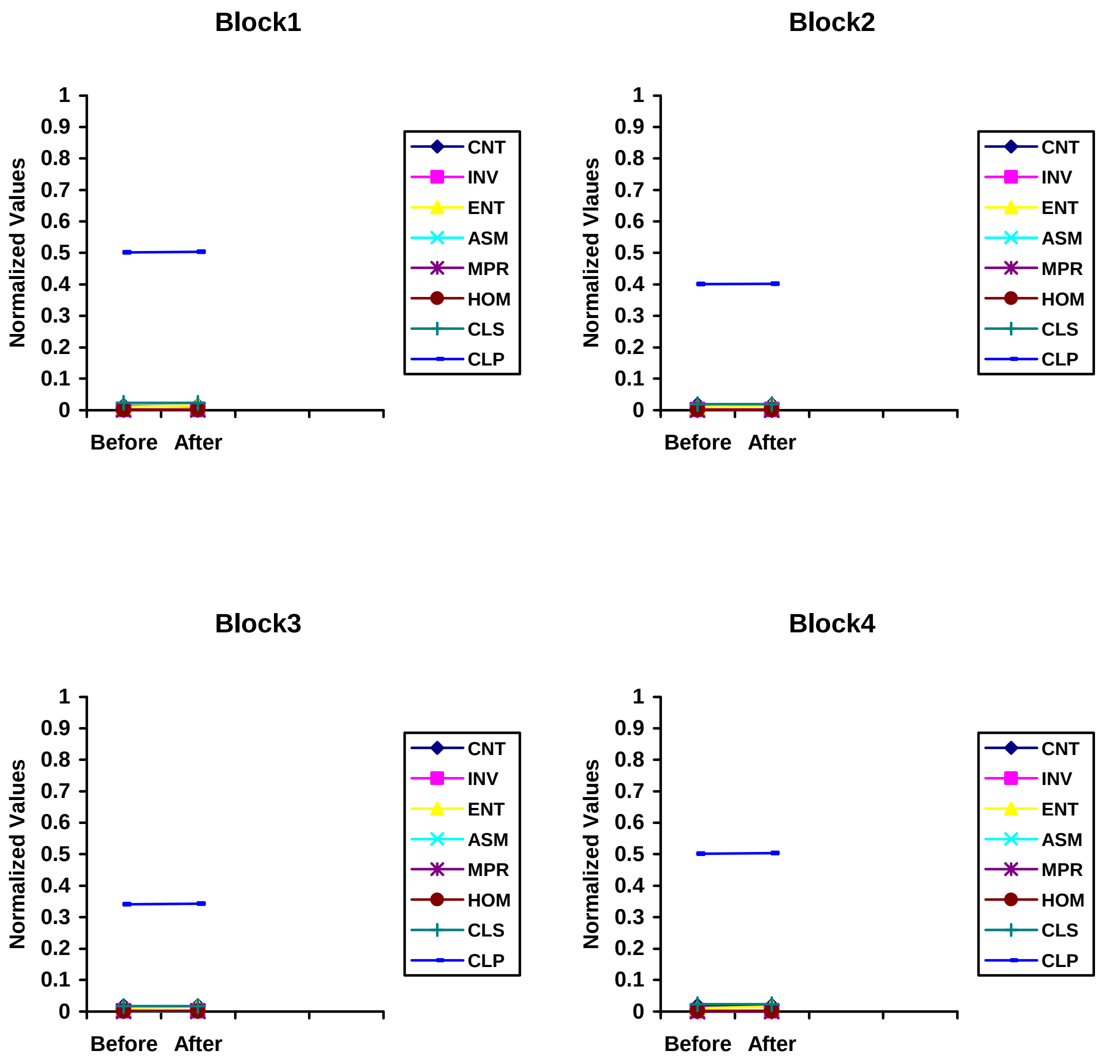


Figure (3-19): The behavior of blocks with selected features of the D84 image, with block size 64×64 and quantization level 16 in the two cases of before and after.

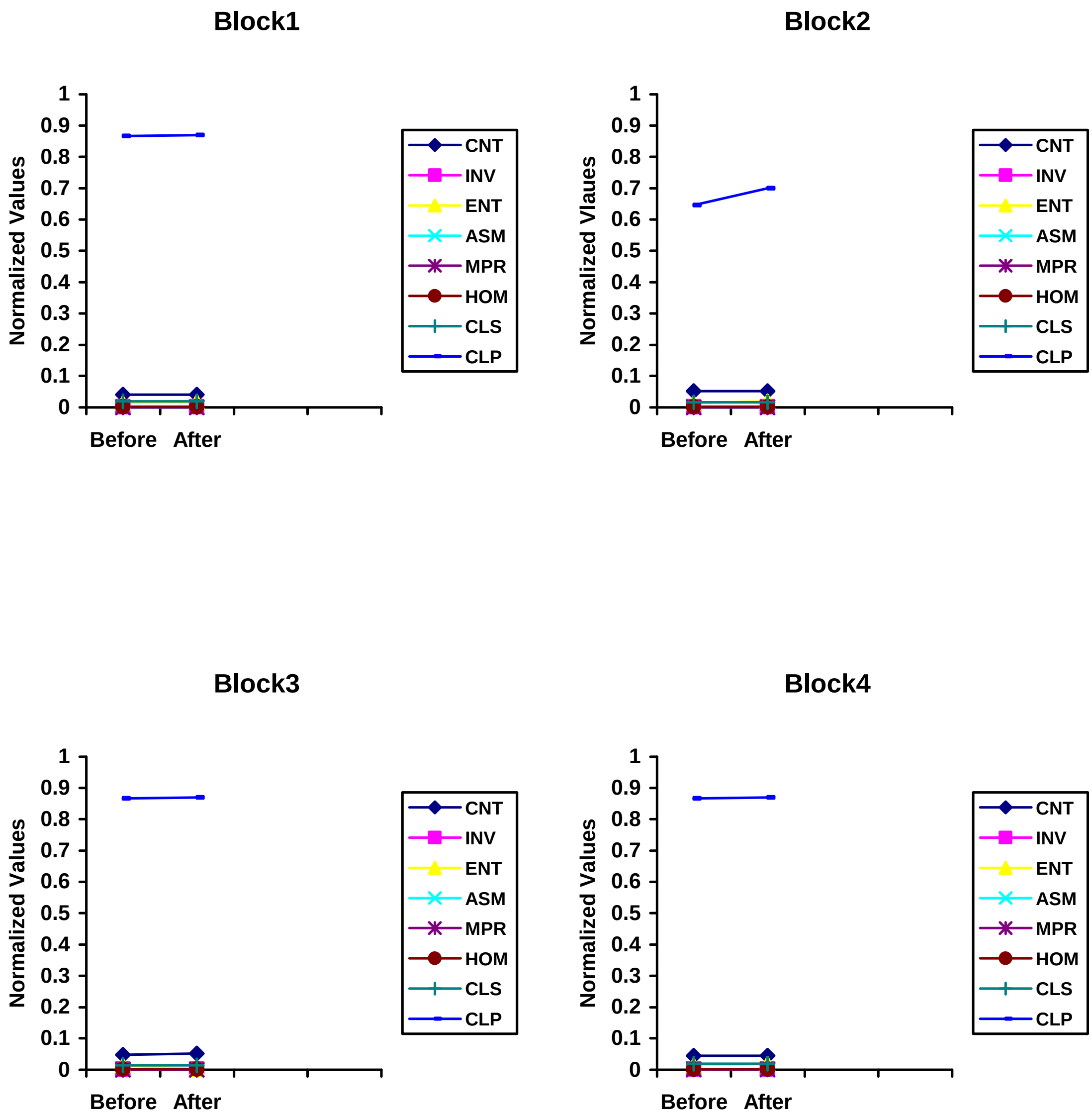


Figure (3-20): The behavior of blocks with selected features of the D84 image, with block size 64×64 and quantization level 32 in the two cases of before and after.

Chapter Three

System Development and Implementation

3.1 Introduction

The theoretical concepts of texture analysis and image classification were discussed in the previous chapter. This chapter is devoted to describe the computer programs design and implementation to offer the facilities, which may be required to perform the classification process.

To perform the texture classification process, three textured images from Brodatz album are chosen and implemented for this purpose. These are (D17, D18, and D84) as shown in figure (3-1). Each of these images has been digitized into 128×128 pixels of 256 gray-level. The screen images are of bit-map (BMP) type. A detailed description of the BMP file format is presented in the Appendix (A).

D17 D18 D84

Figure (3-1): The three textured images used as test material

The system was implemented and written using visual Basic version 6.0 on a personal computer (Pentium IV processor with 256 RAM and 20 GB hard disk that works under windows XP).

3.2 Features Set

The goal in image analysis is to extract data useful for solving application based problem. This is done by intelligently reducing the amount of image data with the tools have explored. A feature vector is one method to represent an image, or part of an image object, by finding measurements on a set of features. Therefore, finding a specific features-vector that has the best discrimination power has been one of the most important problems in the field of texture analysis and image classification. The statistical features is one of the most important features that is used to evaluate the performance of Co-occurrence matrices for solving texture classification problem, thus, the statistical feature is adopted in work.

- **Statistical Feature Set**

The texture statistical features are known to contain significant discriminatory information for image classification. Some of the commonly used statistical features are based on gray-level Co-occurrence matrix. In this work the statistical feature is extracted for different window sizes (sub-image of size M×M) with different quantization level. The head line of the presented work can be summarized by the following two modules:

Module-1: For each image, the Co-occurrence matrix P is extracted with different quantization levels 8, 16 and 32; eight statistical texture features are calculated depending on the extracted Co-occurrence matrix P. These eight statistical texture features which are chosen and adopted in this work are:

1. MPR	2.ENT	3. HOM
4. CLS	5. CLP	6. CNT
7. ASM	8. INV	

These statistical features are defined in eq's (2.2), (2.4), (2.5), (2.7), (2.8), (2. 9), (2.10), and (2.11) respectively.

<u>Module-2:</u> In this module the same procedure presented in set -1 is applied but with different block size M×M of the original image (the original image is divided into sub images with block size 32X 32 and 64 X 64), then the Co-occurrence matrix P is extracted for each block size, then the selected features (presented in ***module-1***) is calculated depending on the extracted Co-occurrence matrix P.

3.3 TICS System Structure

In this work, a Texture-Image Classification System "TICS" was implemented by using Co-occurrence matrices algorithm.

The features extraction is performed through the user interface. The user interface includes two choices, through which the user can perform the following operations (see figure (3-2)):

•Apply Co-occurrence matrix on original image.

•Apply Co-occurrence matrix on sub images.

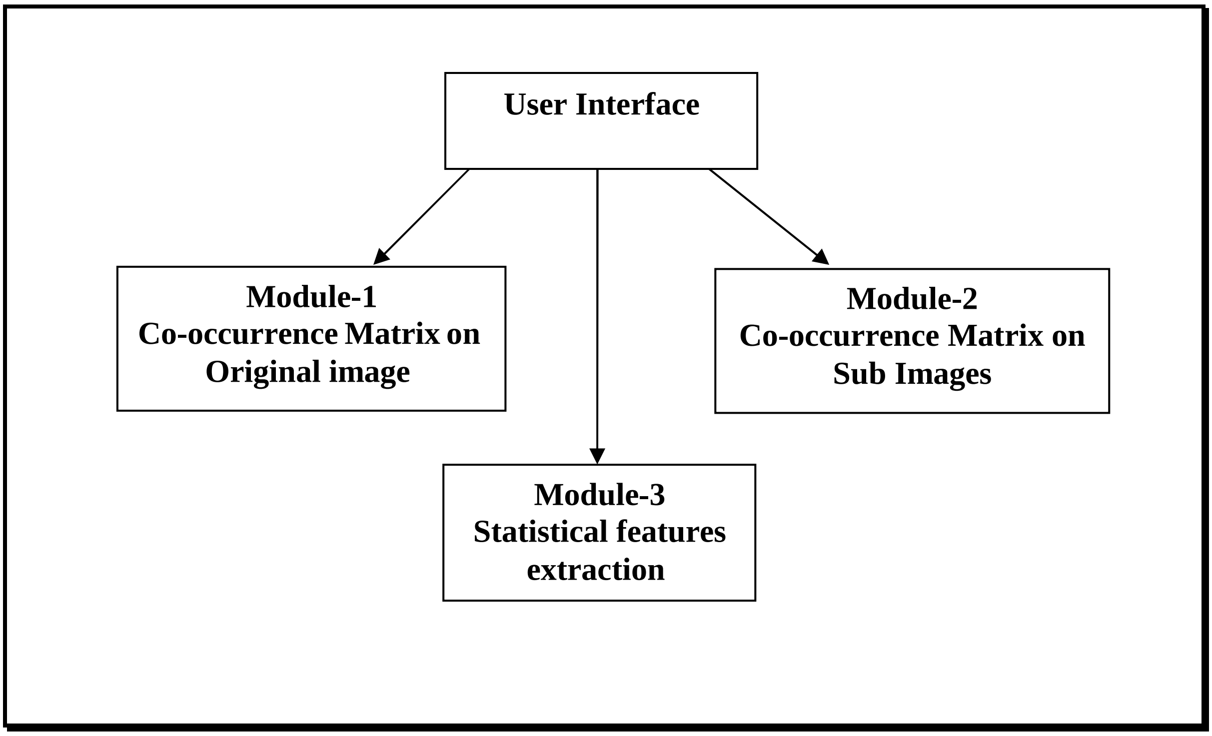


Figure (3-2): The Main Modules

When applying Module-1 and Module-2, one can make a comparison and the analysis between the results by extract features from module-3.

3.4 The Design Approach

For a typical texture classification system, the determination of the class is one of the aspects of overall task. Texture classification system generally contains several modules.

During the early stages of the system design, the designer needs to specify the input image format (to analyze the input image and extract the image-data), determine the feature set that should be calculated (from image data). Finally, specify the Co-occurrence matrices (using new way to calculate the features set and comparing the results).

Considering the above argument, TICS was constructed using number of modules, each module performs specific task. Collectively, these modules combine to perform the overall texture classification task (using the selected features). From the functional point of view, TICS consists of seven modules (see figure (3-3)).

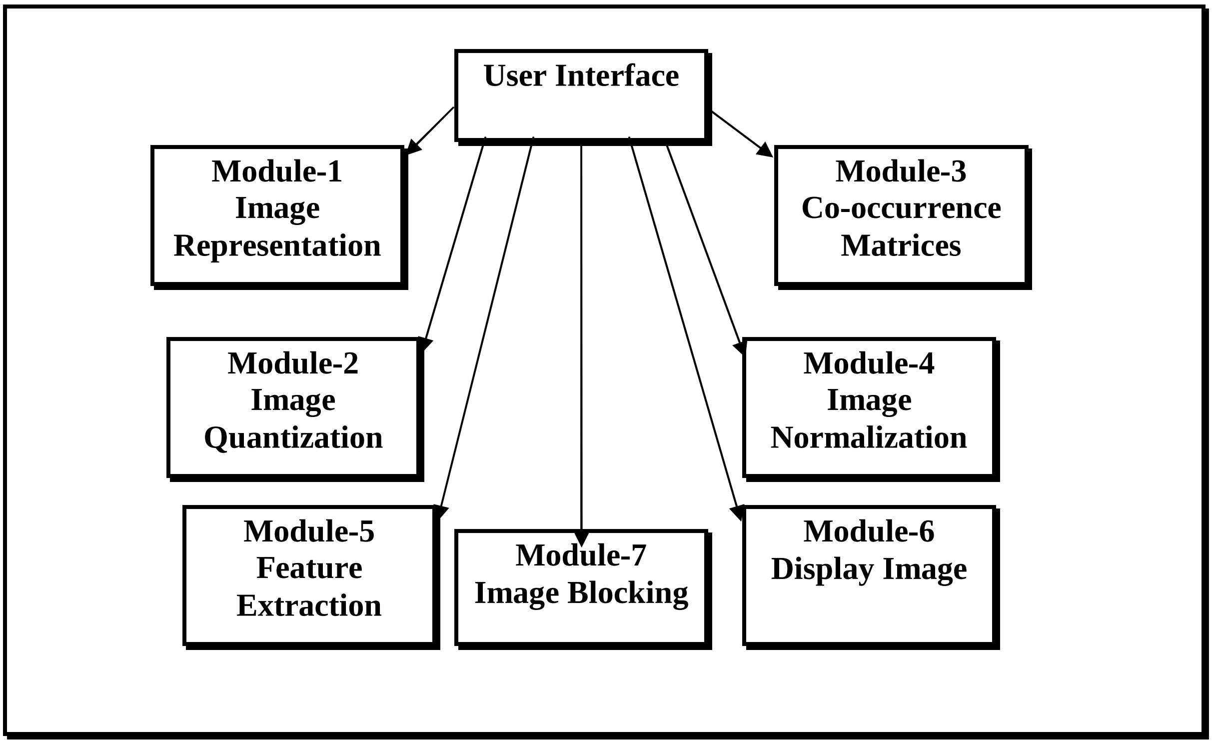


Figure (3-3): Texture Image Classification System (TICS) Sub Modules.

The Flow Control of TICS is presented in Figure (3-4).

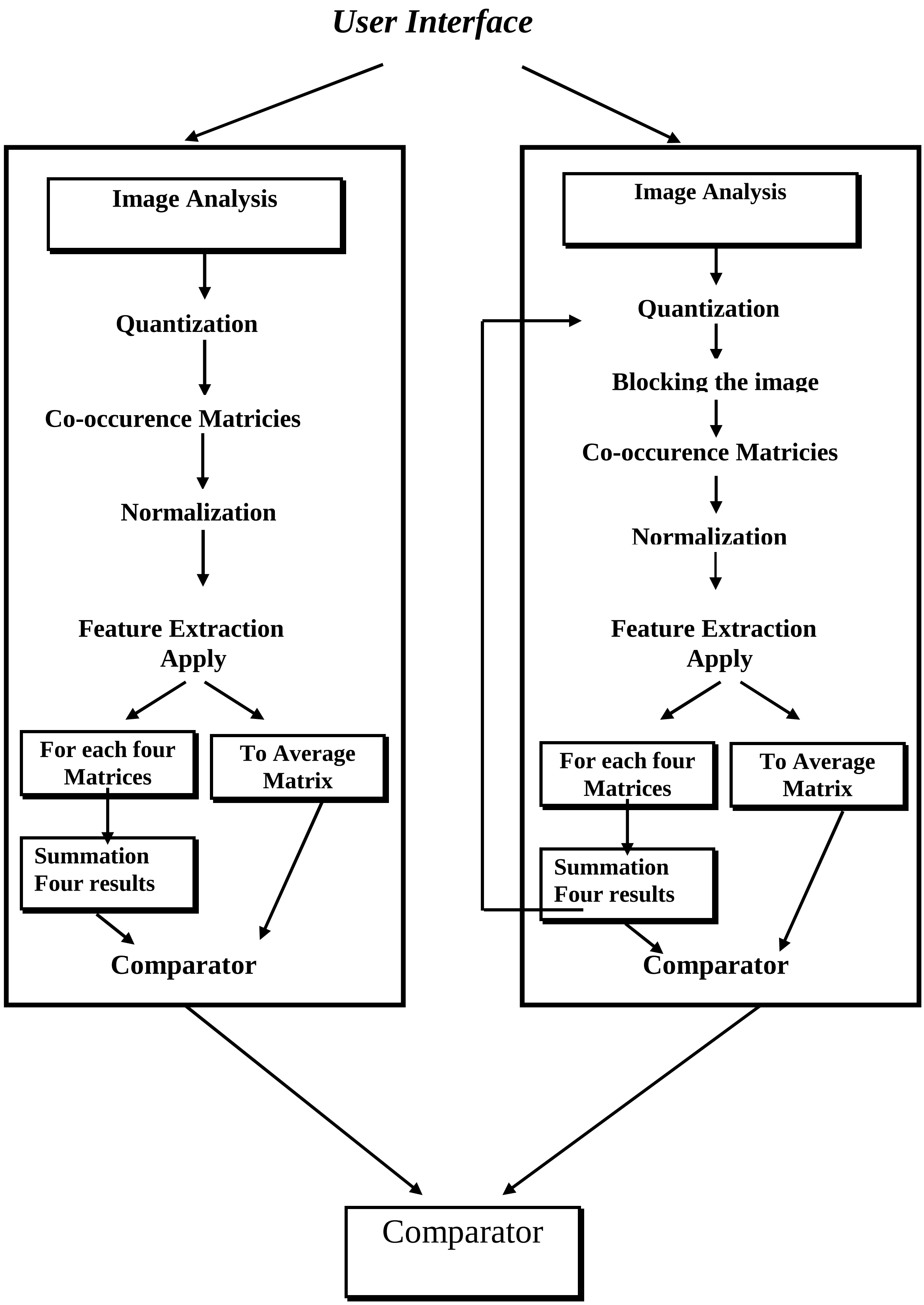


Figure (3-4):Flow Control of TICS

3.4.1 Module-1: Image Representation

Scanners are capable of producing image representation in a variety of formats. One of the most popular of these formats is the bit-map (BMP) format. BMP files consist of three parts (the detailed structure of the BMP files is shown in appendix A). These three parts are header (provides essential information about the image such as image-width, image-height, number of bit/pixel, and a pointer to the beginning of the image-data), color palette (represent the intensities in red, green, and blue (RGB)), and image-data (represents the pixel values). In the present work only the gray images are adopted .

Image representation module concerned with analyzing the image file to get information about the input image (image-width, image-height, and the image-data), and pass this information to the next modules.

3.4.2 Module-2: Image Quantization

The main draw back in using the spatial gray level dependence method is the large memory requirement for storing the Co-occurrence matrices. Sometimes the Co-occurrence matrices used for texture characterization are more voluminous than the original images from which they are derived. Quantization process overcomes this problem. For this reason image quantization process is adopted in this work.

Image quantization is the process of reducing the image data by removing some of detail information by mapping groups of data points to a single point. This can be done to the pixel values themselves. In the present work the gray level reduction is achieved by taking the data and reducing the number of bits per pixel.

3.4.3 Module-3: Co-occurrence Matrices

As be mentioned before, the gray level Co-occurrence matrix is the two dimensional matrix of joint probability P (I, J) between pairs of pixel separated by a distance d in a given direction.

Algorithm 3.1 (Co-occurrence Algorithm)

```
Input:Img_data[img_size,img_size]
Output:th_0[quantize_lvl,quantize_lvl],th_45[quantize_lvl,quantize_lvl],th_90[quant
ize_lvl,quantize_lvl], th_135[quantize_lvl,quantize_lvl].
Begin
  Let  C_0=comput_0((,Img_data,k,l,j,img_size)
  Let  C_45=comput_0((,Img_data,k,l,j,img_size)
  Let  C_90=comput_0((,Img_data,k,l,j_img_size)
  Let  C_135=comput_0((,Img_data,k,l,j,img_size)

   For i=0 to img_size -1
     For j=0 to img_size-1  begin
        For k=0 to quantiz_lvl-1
          For l=0 to quantize_lvl-1
             If(Img_data[i,j]=k) then begin
               Count_0=count_0+C_0
               Count_45=count_45+C_45
               Count_90=count_90+C_90
               Count_135=count_135+C_135
            End if
       Th_0(i,j)=count_0
       Count_0=0
       Th_45(i,j)=count_45
       Count_45=0
       Th_90(i,j)=count_90
```

To be Continue

```
        Count_90=0
        Th_135(i,j)=count_135
        Count_135=0
End.
```

Algorithm 3.2 (comput_0 angle)

```
Input: Input:img_data(img_size,img_size),k,l,j,x=0
Output:x
Begin
    if(j<Img_size) then
          if(img_data(i,j+1)=l) then
            x=x+1
            if (j>0) then
              if (img_data(i,j-1)=j) then
              x=x+1
   return x
End.
```

Algorithm 3.3 (comput_45 angle)

```
Input:Img_data,(img_size,img_size),k,l,j,img_size,y=0
Output:y
 Begin
    If (j<(img_size-1) & (i>0)) then
      If (img_data(i-1,j+1)=l) then
        y=y+1
    if ((j>0) & (i(img_size-2))) then
      if(img_data(i+1,j-1))then
      y=y+1
  return y
End.
```

Algorithm 3.4 (comput_90 angle)

```
Input:Img_data,(img_size,img_size),k,l,j,img_size,z=0
Output:z
 Begin
      If(i<img_size-2))  then
         If(img_data(i+1,j)=l) then
           z=z+1
       if(i>0) then
         if(img_data(i-1,j)=l) then
            z=z+1
   return z
End.
```

Algorithm 3.5 (comput_135 angle)

```
Input:Img_data,(img_size,img_size),k,l,j,img_size,w=0
Output:w
 Begin
      If((i>0)&(j>0)) then
         If(img_data(i-1,j-1)= l) then
           w=w+1
      if((i<img_size-2)&(j<img_size-1)) then
        if(img_size(i+1,j+1)=l) then
           w=w+1
End.
```

3.4.4 Module-4: Normalization of the Co-occurrence Matrix

This step is accomplished by dividing each entry in the Co-occurrence matrix by the total number of paired occurrences (equation 2-1).

3.4.5 Module-5: Feature Extraction

Features extraction abstracts high-level information about individual patterns to facilitate texture classification. Therefore, to discriminate images with different textural characteristics, it is essential to extract texture features. Feature set (presented in section 3.2.1) were extracted from selected textured images.

3.4.6 Module-6: Display-Image

This module used for displaying the processed image at the end of any executing module when the user desire that.

3.4.7 Module-7: Image Blocking

In this module the image can be divided into array of blocks (sub-images)

Algorithm 3.6 (Blocking Image)

Input Block size(k) usually size $2^k * 2^k$

Begin Let M= 128 div 2^k

For y=0 to height 2^k **-1**

For x=0 to width 2^k **-1**

For y2=0 to 2^k **-1**

For x2= 0 to 2^k **-1**

Store_imge(x,y,x2,y2)=imge(x* 2^k **+x2,y*** 2^k **+y2)**

End.

3.5 TICS Implementation

This section explains the details of implementation of this work. Algorithm (3.7) explain the followed steps of the image analysis based on texture feature.

Algorithm (3.7): Statistical Textural Features Analysis for Gray Images

Step 0: Read BMP file (image).

Step 1: Apply Quantization method on the data of BMP file.

Step 2: Apply Co-occurrence matrices method (see Algorithm 3.1,3.2,3.3,3.4.3.5).

Step 3: Calculate the average of the Co-occurrence matrix and normalize it. by applying the related equation:

$$p_{ave}(i,j) = \frac{1}{4}\sum_{j=0}^{hight-1}\sum_{i=0}^{width-1} p_{\vartheta=0}(i,j) + p_{\vartheta=45}(i,j) + p_{\vartheta=90}(i,j) + p_{\vartheta=135}(i,j) \qquad 3.1$$

Step 4: Extract features for the average Co-occurrence matrix.

Step 5: Calculate the Co-occurrence matrix for each angle and normalize it. In this process four matrices are extracted.

Step 6: Extract features for the four matrices.

Step 7: Select the block size needed for dividing the original image (see Algorithm 3.6) and select the number of level needed for quantization process.

Step 8: For each sub-image go to step 2 until finishing the process of the last sub-image.

Step 9: Compare the result of features of original image with each sub image and analysis it.

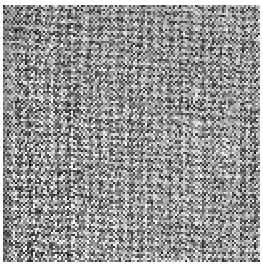
Step 10: End.

3.5.1 Experiment1 (D17) :

The first selected textured image used as a test material is D17 image. The D17 is of a size of (128 × 128) with 256 gray levels. The eight selected features (MPR, ENT, HOM, CLS, CLP, CNT, ASM, and INV) are calculated for the original image and for the sub image for different block sizes 32 x 32 and 64 x 64 as be shown in figure (3-5) with different quantization levels 8, 16, and 32.

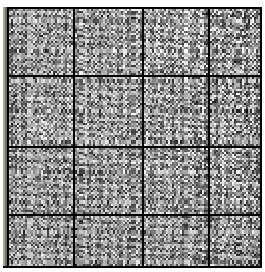
It should be mentioned that the features are calculated in two ways, the first one for the average Co-occurrence matrix (first case named before) and the second one for the Co-occurrence matrix of angle 0°, 45°, 90°, and 135°(second case named after). Four values for the same feature is extracted (one for each angle) for the second case, and then the average value for the four features is calculated .

The calculated values for the eight features for D17 image for the two cases with 8, 32, and 64 level is presented in tables (3-1), (3-2), and (3-3) respectively.



(A)

(B)



(C)

Figure (3-5): Experiment 1
(A) Original Image D17,
(B) Extracted Features with block size 64×64.
(C) Extracted Features with block size 32×32.

Table 3-1: The value of statistical features for textured image D17 with quantization level =8

	8 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	6.0865	0.3700	4.1253	2.4458	0.0390	0.0447	679.67	6798.2
After	6.0865	0.3713	5.5127	2.4272	0.0388	0.0446	682.27	6823.7

Table 3-2: The value of statistical features for textured image D17 with quantization level =16

	16 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	23.881	0.2159	5.5649	0.0063	0.0109	0.3099	6333.1	131753
After	23.881	0.2167	7.4654	0.0062	0.0103	0.3000	6357.3	132249

Table 3-3: The value of statistical features for textured image D17 with quantization level =32

	32 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	95.4240	0.1177	7.0477	0.0016	0.0033	0.2035	54601	231892
After	95.4240	0.1181	9.4552	0.0015	0.0030	0.2033	54813	232765

It is clear from these tables that most of the selected features are stable in the two cases before and after except the feature of the entropy since the difference in the feature value of the two cases (before and after) is perceptible. This property can be utilized in the process of the discrimination pattern.

Figure (3-6) shows the behavior of the selected features in the case of before and after. As be mentioned before that the entropy feature gives perceptible slope in the case of before and after.

Figure (3-7) shows the behavior of the selected features with different quantization levels. It is clear from the figure that some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.

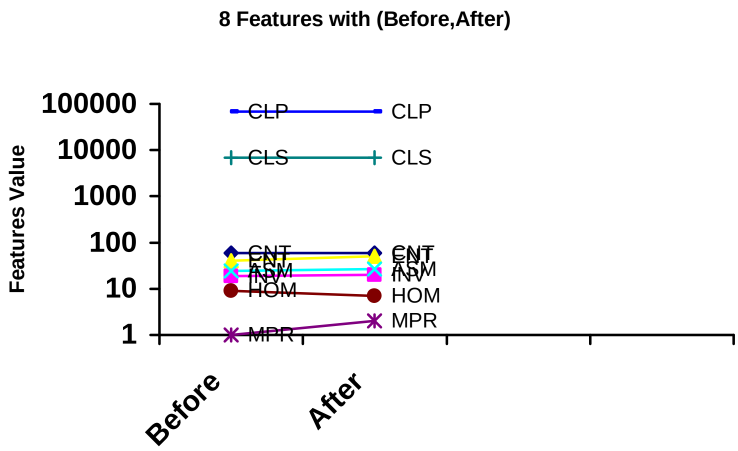


Figure (3-6): The behavior of the selected features in the case of before and after.

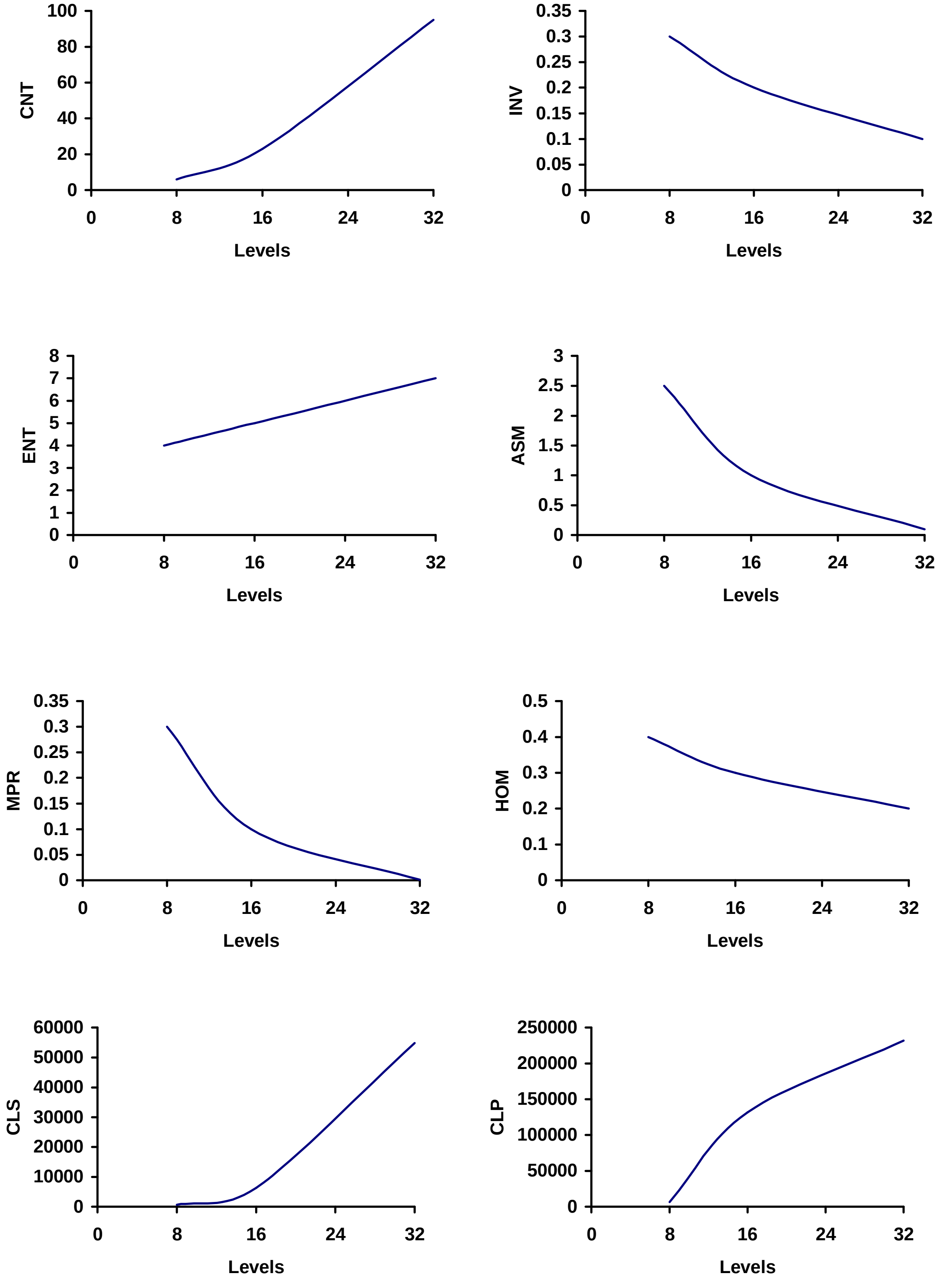


Figure (3-7): The behavior of the selected features with different quantization level (8, 16, and 32).

Table (3-4) shows the extracted features from D17 image with block size (64 x 64) and with different quantization level (8, and 16).

Table (3-4): Extracted features for each block (block size 64×64) of the D17 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
CNT	Block1	5.9644	6.0185	23.426	23.640
	Block2	5.5802	5.5803	21.746	21.943
	Block3	6.7693	6.8294	26.906	27.147
	Block4	6.0044	6.0585	23.466	23.680
INV	Block1	0.3716	0.3743	0.2175	0.2190
	Block2	0.3822	0.3825	0.2266	0.2238
	Block3	0.3510	0.3536	0.2003	0.2017
	Block4	0.4116	0.4143	0.2575	0.2500
ENT	Block1	4.1089	5.5185	5.5501	7.4709
	Block2	4.0030	5.3787	5.4251	7.3083
	Block3	4.1919	5.6119	5.6328	7.5808
	Block4	4.1489	5.5585	5.5901	7.5109
ASM	Block1	0.0242	0.0241	0.0063	0.0062
	Block2	0.0278	0.0278	0.0074	0.0073
	Block3	0.0217	0.0217	0.0056	0.0056
	Block4	0.0242	0.0241	0.0046	0.0046

To be continue

Table (3-4): Extracted features for each block (block size 64×64) of the D17 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
MPR	Block1	0.0366	0.0366	0.0113	0.0104
	Block2	0.0501	0.0526	0.0158	0.0141
	Block3	0.0332	0.0293	0.0095	0.0078
	Block4	0.0766	0.0766	0.0051	0.0050
HOM	Block1	0.4479	0.4513	0.3110	0.3133
	Block2	0.4569	0.4603	0.3194	0.3218
	Block3	0.4310	0.4342	0.2952	0.2974
	Block4	0.4879	0.4913	0.3510	0.3530
CLS	Block1	631.71	636.575	5913.7	5959.3
	Block2	660.34	665.461	6161.3	6209.2
	Block3	701.24	706.64	6537.1	6587.5
	Block4	631.75	636.61	5913.7	5959.3
CLP	Block1	6209.5	6265.1	121004	121916
	Block2	6500.1	6528.9	125705	126741
	Block3	27230.1	7235.8	214033	140411
	Block4	6259.9	6256.2	121618	121916

Table (3-5) shows the extracted features from D17 image with block size (32 x 32) and with quantization level 8.

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
CNT	Block1	5.6940	5.7987
	Block2	5.9577	6.0708
	Block3	5.5607	5.6625
	Block4	5.4083	5.5076
	Block5	5.9259	6.0325
	Block6	5.9456	6.0546
	Block7	5.8314	5.9379
	Block8	5.4378	5.5374
	Block9	6.5039	6.6255
	Block10	6.3089	6.4192
	Block11	6.0802	6.0930
	Block12	5.4403	5.5400
	Block13	6.9222	7.0503
	Block14	7.0390	7.1667
	Block15	6.5002	6.6238
	Block16	5.6940	5.7987

		Level -8	
		Before	After
INV	Block1	0.3783	0.3839
	Block2	0.3652	0.3705
	Block3	0.3823	0.3881
	Block4	0.4215	0.4272
	Block5	0.3669	0.3725
	Block6	0.3630	0.3684
	Block7	0.3693	0.3747
	Block8	0.3852	0.3910
	Block9	0.3553	0.3605
	Block10	0.3562	0.3616
	Block11	0.3599	0.3600
	Block12	0.3752	0.3807
	Block13	0.3436	0.3438
	Block14	0.3423	0.3474
	Block15	0.3626	0.3678
	Block16	0.3783	0.3839

To be continue

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
ENT	Block1	4.0420	5.4855
	Block2	4.0402	5.4300
	Block3	3.9605	5.3688
	Block4	3.9566	5.3634
	Block5	4.0348	5.4576
	Block6	4.0193	5.4421
	Block7	3.9948	5.4171
	Block8	3.9749	5.3879
	Block9	4.0882	5.5015
	Block10	4.1076	5.5468
	Block11	4.0613	5.4944
	Block12	3.9519	5.3515
	Block13	4.1710	5.6330
	Block14	4.2032	5.6714
	Block15	4.1563	5.6174
	Block16	4.0420	5.4855

		Level -8	
		Before	After
ASM	Block1	0.0255	0.0255
	Block2	0.0253	0.0260
	Block3	0.0279	0.0282
	Block4	0.0696	0.0698
	Block5	0.0259	0.0260
	Block6	0.0262	0.0264
	Block7	0.0264	0.0265
	Block8	0.0278	0.0280
	Block9	0.0242	0.0244
	Block10	0.0234	0.0234
	Block11	0.0251	0.0251
	Block12	0.0277	0.0279
	Block13	0.0213	0.0213
	Block14	0.0210	0.0212
	Block15	0.0223	0.0227
	Block16	0.0255	0.0256

To be continue

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
MPR	Block1	0.0501	0.0463
	Block2	0.0482	0.0469
	Block3	0.0525	0.0521
	Block4	0.0502	0.0498
	Block5	0.0458	0.0450
	Block6	0.0485	0.0470
	Block7	0.0493	0.0486
	Block8	0.0525	0.0523
	Block9	0.0443	0.0439
	Block10	0.0385	0.0380
	Block11	0.0474	0.0434
	Block12	0.0454	0.0434
	Block13	0.0340	0.0310
	Block14	0.0338	0.0317
	Block15	0.0357	0.0356
	Block16	0.0501	0.0463

		Level -8	
		Before	After
HOM	Block1	0.4537	0.4607
	Block2	0.4410	0.4477
	Block3	0.5556	0.5626
	Block4	0.4945	0.5015
	Block5	0.4443	0.4512
	Block6	0.4413	0.4480
	Block7	0.4454	0.4521
	Block8	0.4579	0.4650
	Block9	0.4336	0.4462
	Block10	0.4354	0.4422
	Block11	0.4366	0.4433
	Block12	0.4497	0.4566
	Block13	0.4225	0.4290
	Block14	0.4232	0.4298
	Block15	0.4396	0.4462
	Block16	0.4537	0.4607

To be continue

Table (3-5): Extracted features for each block (block size 32×32) of the D17 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
CLS	Block1	584.29	589.47
	Block2	708.42	719.54
	Block3	648.96	659.26
	Block4	652.87	663.22
	Block5	725.81	737.35
	Block6	733.29	744.87
	Block7	666.35	676.84
	Block8	639.91	650.01
	Block9	776.66	788.37
	Block10	702.11	710.25
	Block11	648.48	658.66
	Block12	622.93	632.69
	Block13	656.66	666.87
	Block14	676.00	686.58
	Block15	666.39	676.69
	Block16	584.29	593.74

		Level -8	
		Before	After
CLP	Block1	5613.4	5699.8
	Block2	7254.4	7260.4
	Block3	6432.9	6440.6
	Block4	6463.9	6472.8
	Block5	7469.9	7472.8
	Block6	7552.9	7554.4
	Block7	6692.9	6695.8
	Block8	6318.9	6321.4
	Block9	8239.5	8248.1
	Block10	7238.9	7240.2
	Block11	6515.9	6524.2
	Block12	6118.9	6128.1
	Block13	6775.3	6785.9
	Block14	6096.9	6105.0
	Block15	6824.6	6834.6
	Block16	5688.8	5699.8

It is clear from the values of the calculated features, which are presented in table (3-4) that most of the selected features not affected by the size of the block; these results led us to the following remarks:

- The definition of the texture is verified, sine it represent the repetition of fundamental image elements.
- It is preferable to select the sample of the texture with minimum size of block to extract the statistical texture features.

Same thing noticed in the previous tables can be notice from the results of table (3-5), since that most of the selected features are stable in the two cases before and after except the feature of the entropy since the difference in the feature value of the two cases (before and after) is perceptible.

Figure (3-8) reflects the behavior of the selected features in the case of before and after. It is clear from this figure that the entropy feature gives perceptible slope in the case of before and after, and this result is similar to the result obtained from figure (3-9).

Figure (3-10) reflects the behavior of the selected features with 16 levels. Same thing can be seen, some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.

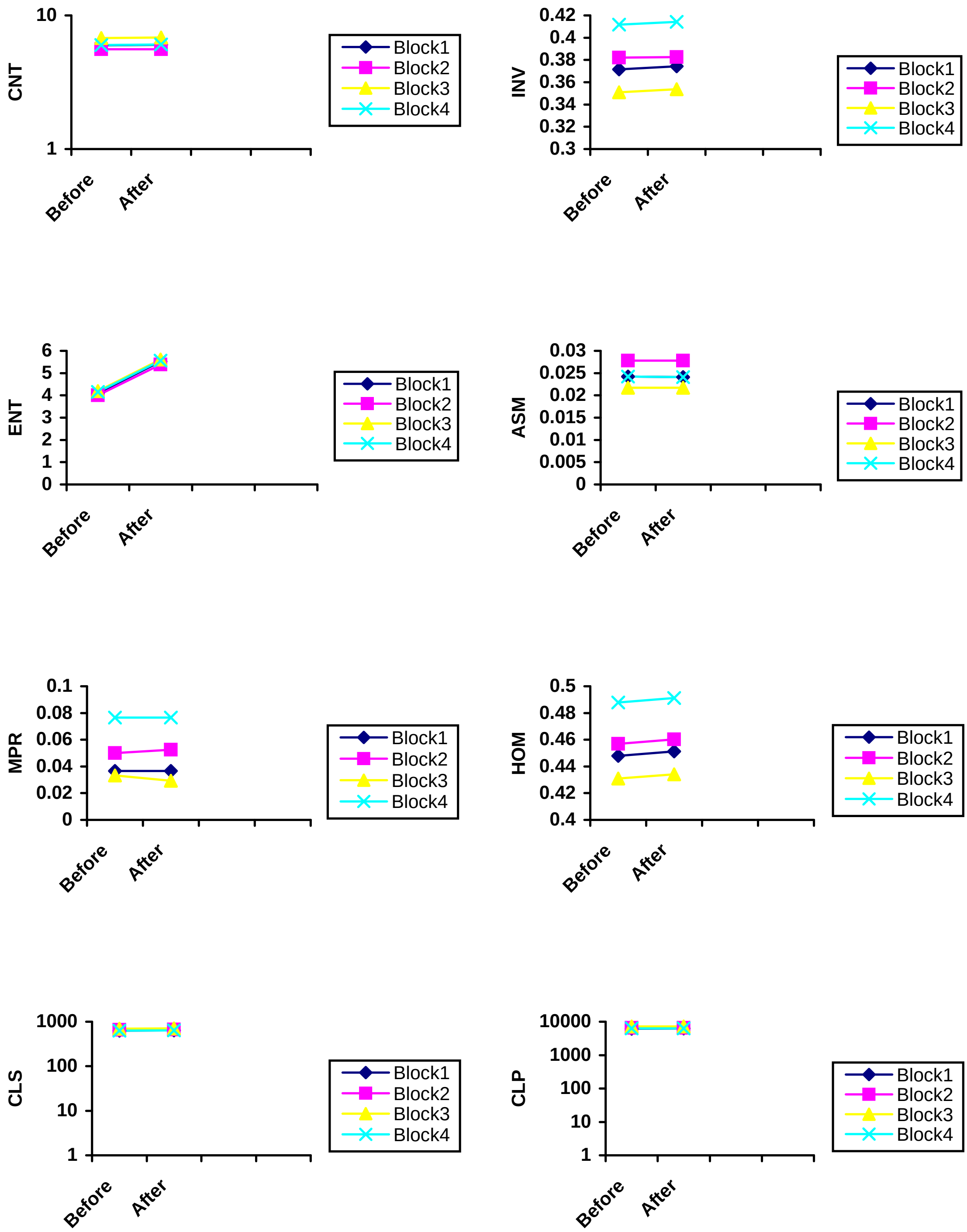


Figure (3-8): The behavior of the selected features in each block (block size 64×64) of the D17 image with quantization level 8 in the two cases of before.

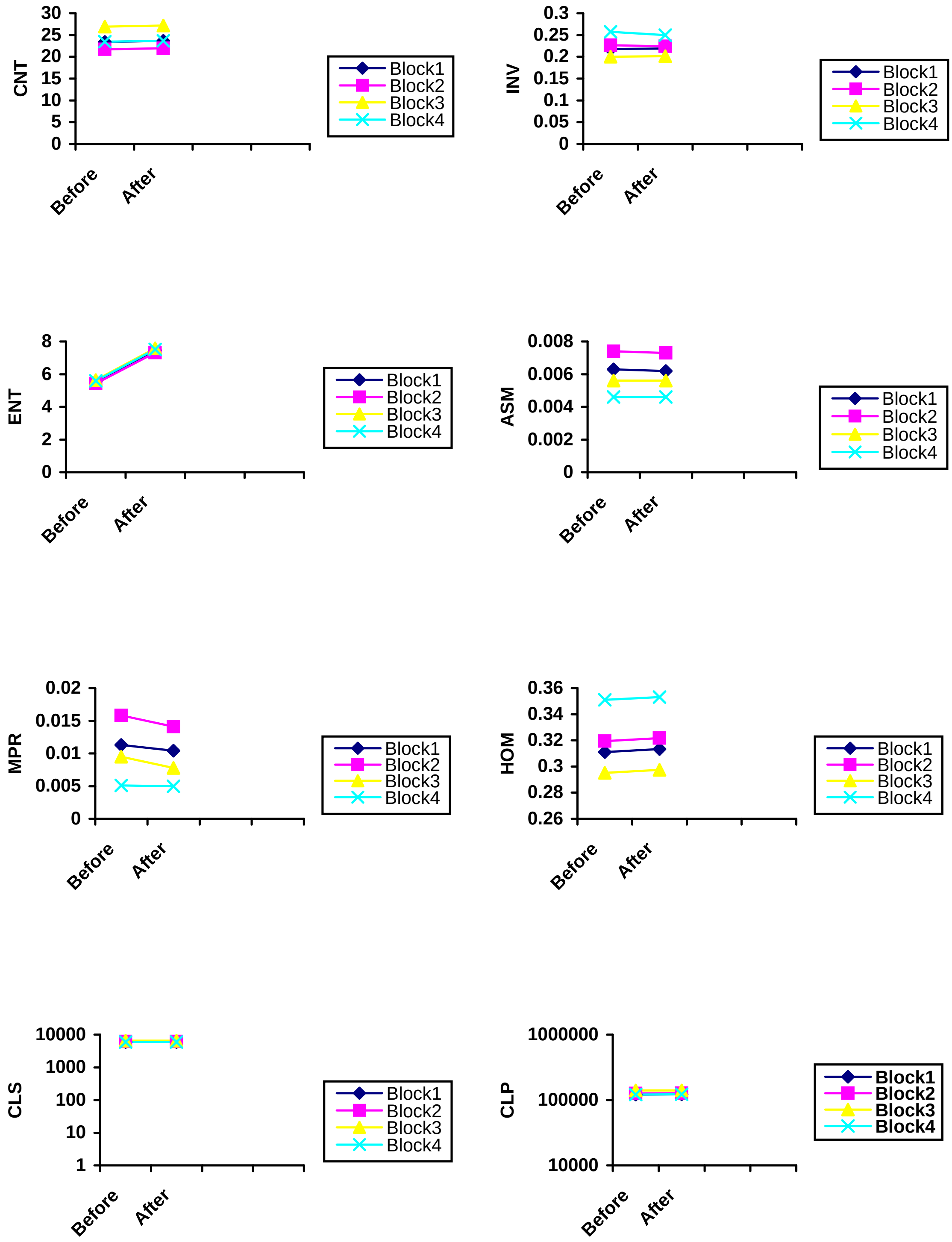


Figure (3-9): The behavior of the selected features in each block (block size 64×64) of the D17 image with quantization level 16 in the two cases of before.

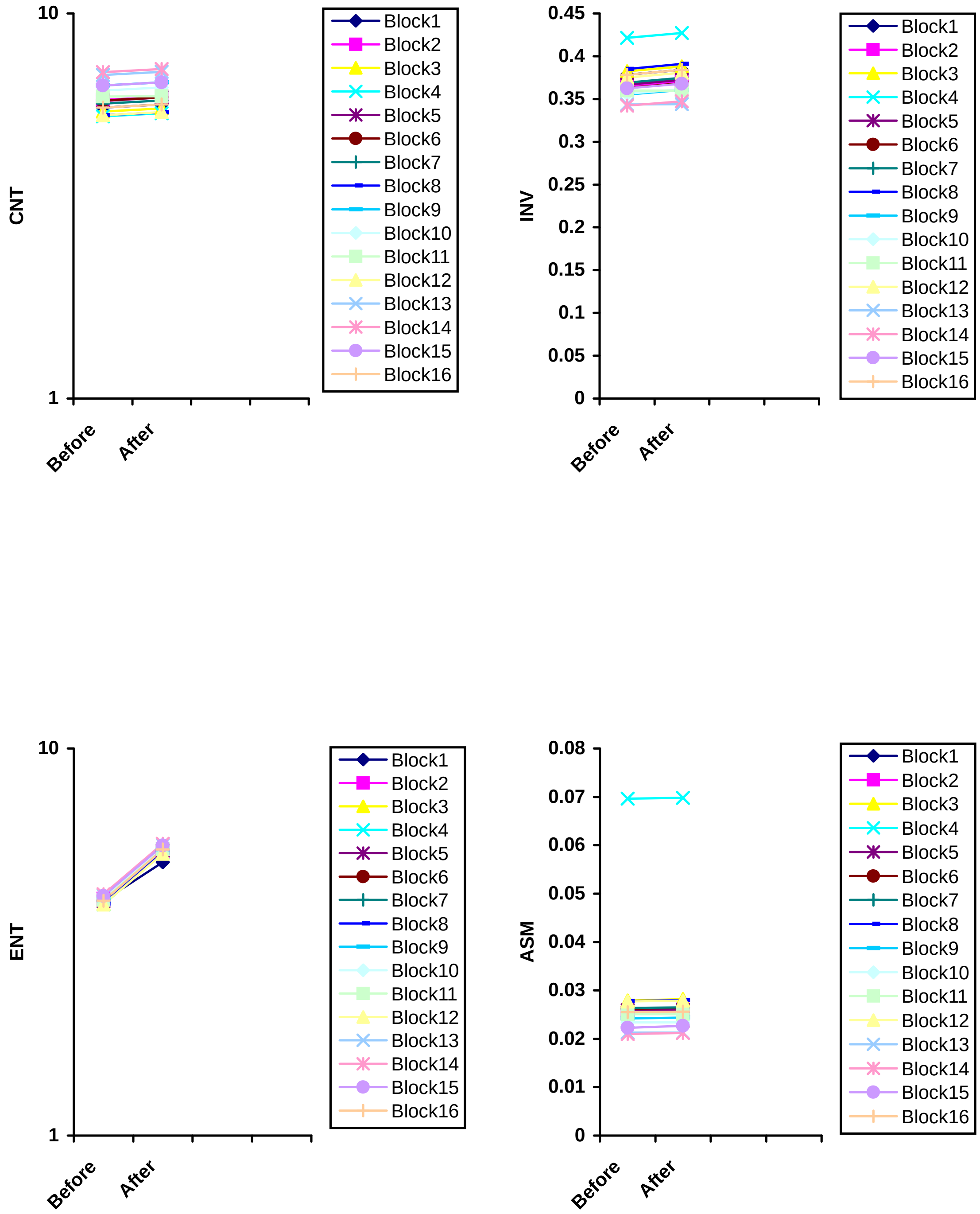


Figure (3-10): The behavior of the selected features in each block (block size 32×32) of theD17 image with quantization level 8 in the two cases of before and after.

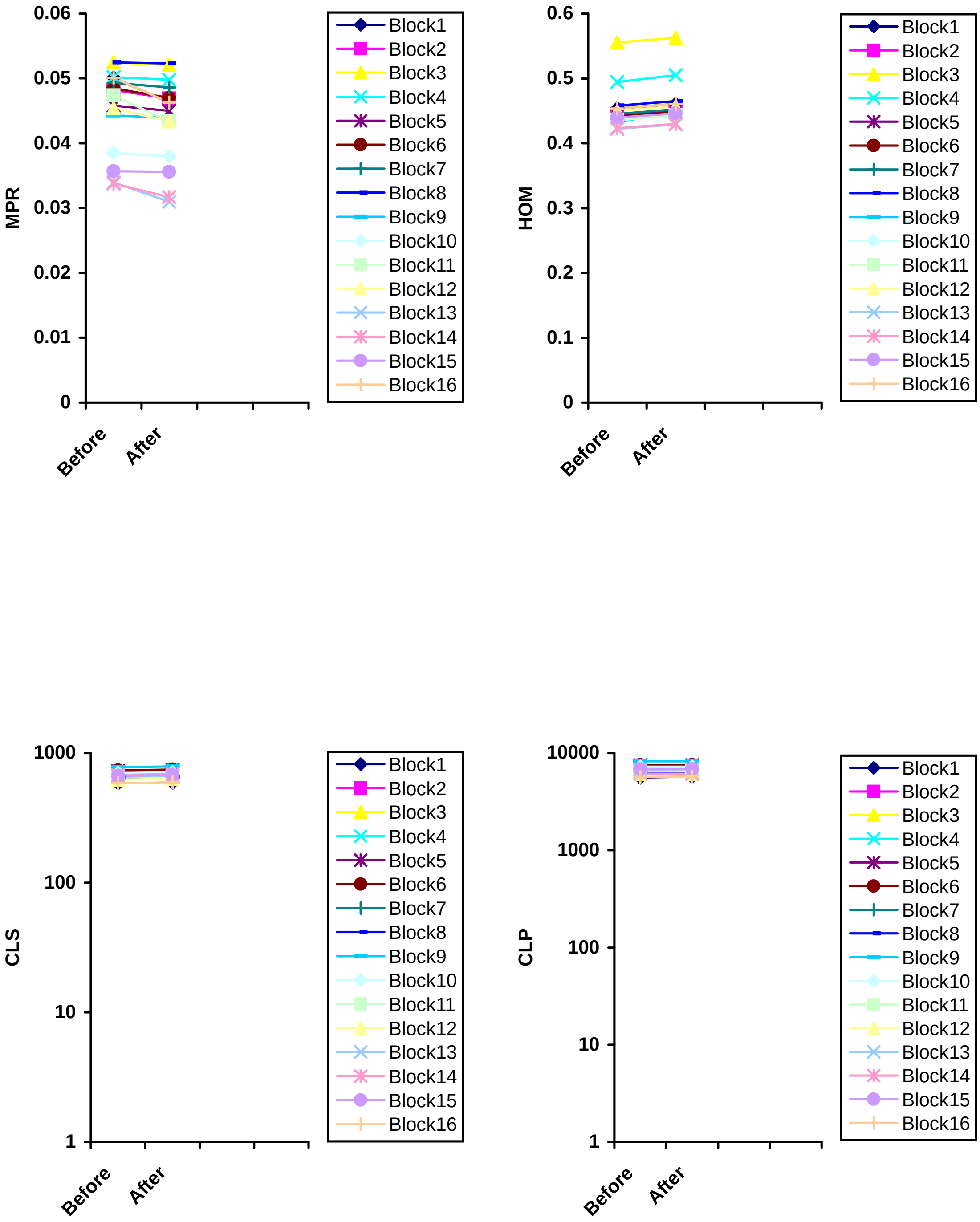
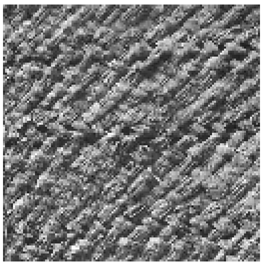


Figure (3-10): The behavior of the selected features in each block (block size 32×32) of theD17 image with quantization level 8 in the two cases of before and after.

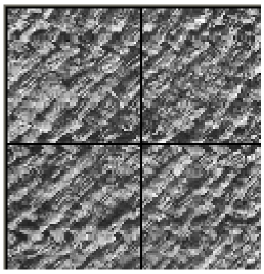
3.5.2 Experiment 2 (D18):

The second selected textured image used as a test material is D18 image. The D18 is of a size of (128 × 128) with 256 gray levels. The eight selected features are calculated for the original image and for the sub image for different block size 32 x 32 and 64 x 64 as be shown in figure (3-11) with different quantization level 8, 16, and 32.

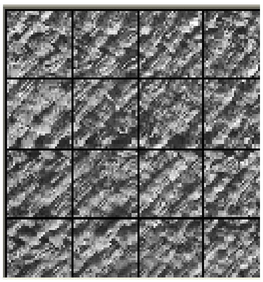
The features are calculated in two ways, the first one for the average Co-occurrence matrix and the second one for the Co-occurrence matrix of angle 0°, 45°, 90°, and 135° as be mentioned before that the two ways named before and after respectively. Four values for the same feature is extracted (one for each angle) for the second case, and then the average value for the four features is calculated.



(A)



(B)



(C)

Figure 3-11: Experiment 2
(A) Original Image D18,
(B) Extracted Features with block size 64×64.
(C) Extracted Features with block size 32×32.

Table 3-6: The value of statistical features for textured image D18 with quantization level =8

	8 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	2.9560	0.5212	3.7328	3.8060	0.0798	0.5681	375.31	3354.9
After	2.9560	0.5233	3.0284	3.8070	0.0801	0.5704	376.80	3368.3

Table 3-7: The value of statistical features for textured image D18 with quantization level =16

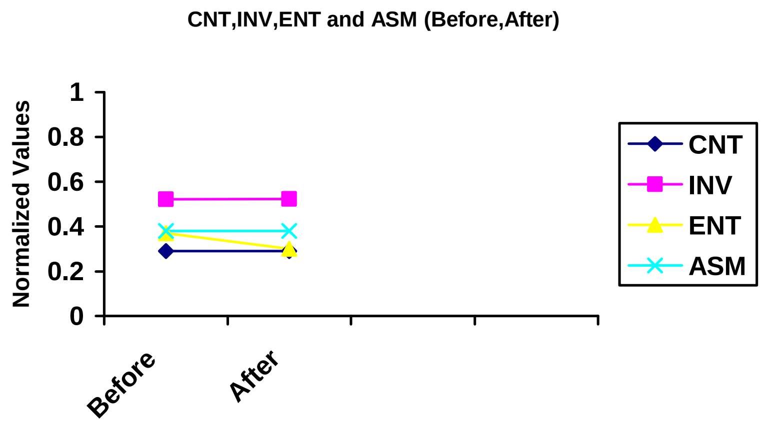
	16 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	11.343	0.3430	5.1631	0.0104	0.0305	0.4207	3572.7	66315
After	11.343	0.3444	6.9524	0.0104	0.0306	0.4224	3586.9	66578

Table 3-8: The value of statistical features for textured image D84 with quantization level =32

	32 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	44.774	0.2024	6.6243	0.0027	0.0084	0.2921	31141	1179058
After	44.774	0.2051	8.9182	0.0027	0.0083	0.2932	31265	1183749

It is clear from these tables and from figure (3-12) that most of the selected features except the entropy feature are stable in the two cases before and after since the values of entropy feature have perceptible slope in the two cases before and after.

Figure (3-13) shows the behavior of the selected features with different quantization level. It is clear from the figure that some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.



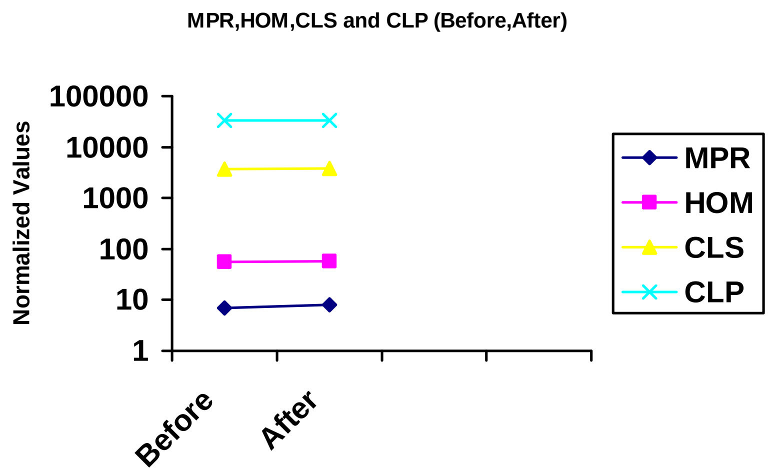


Figure (3-12): The behavior of the selected features in the two cases of before and after.

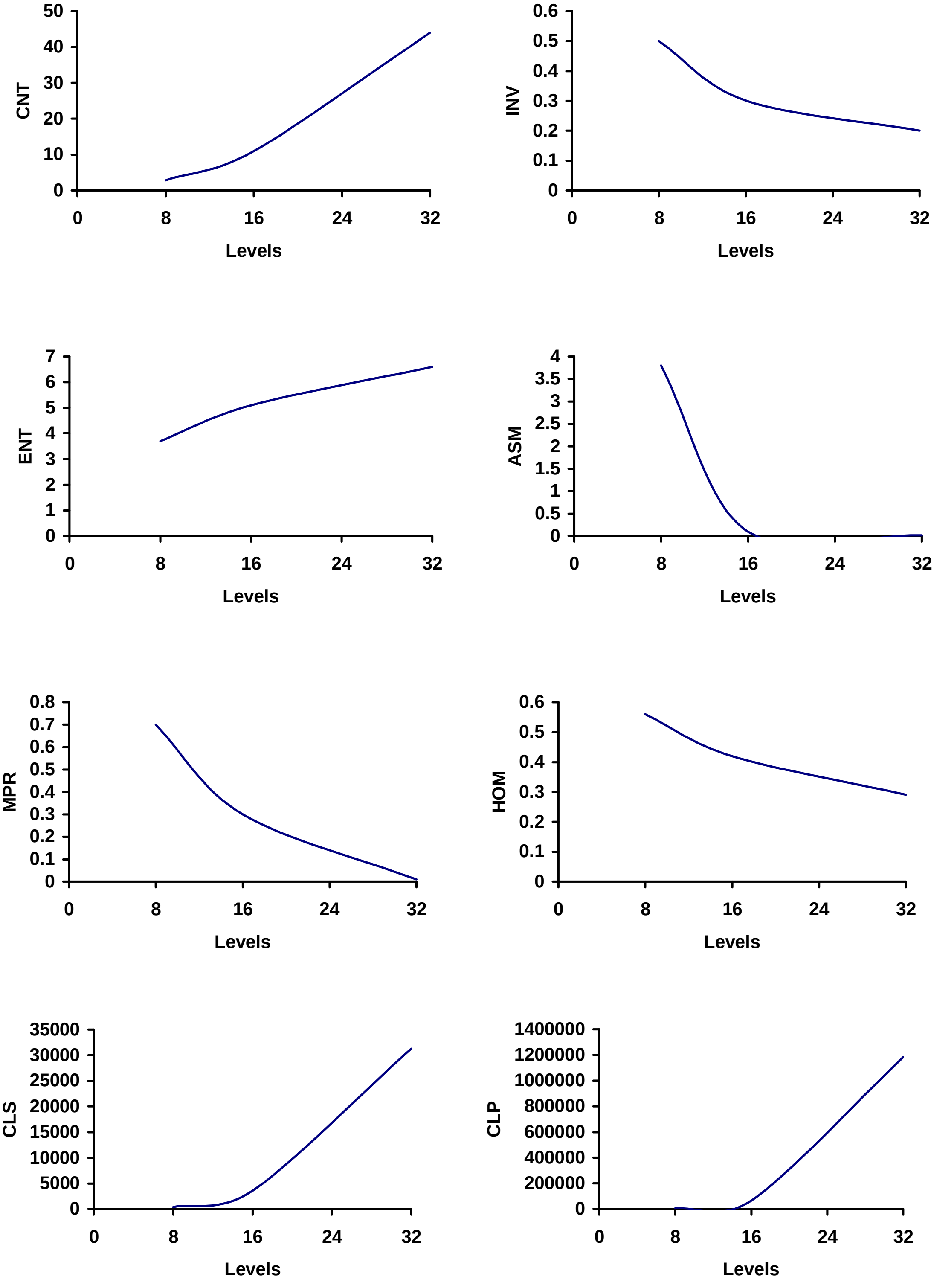


Figure (3-13): The behavior of the selected features with different quantization level (8, 16, and 32)

Table (3-9) shows the extracted features from D18 image with block size (64×64) and with different quantization level (8, and 16).

Table (3-9): Extracted features for each block (block size 64×64) of the D18 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
CNT	Block1	2.9018	2.9242	11.149	11,234
	Block2	2.6433	2.6636	10.174	10.252
	Block3	3.1608	3.1847	12.153	12.244
	Block4	2.9418	2.9642	11.894	11.274
INV	Block1	0.5154	0.5196	0.3368	0.3395
	Block2	0.5417	0.5461	0.3611	0.3640
	Block3	0.5056	0.5097	0.3301	0.3328
	Block4	0.5554	0.5559	0.3768	0.3790
ENT	Block1	3.1778	5.0305	5.1501	6.9633
	Block2	3.6190	4.9619	5.0348	6.8132
	Block3	3.7465	5.0663	5.1632	6.9783
	Block4	3.7578	5.0705	5.1901	7.0033
ASM	Block1	0.0374	0.0377	0.0101	0.0100
	Block2	0.0418	0.0420	0.0118	0.0117
	Block3	0.0376	0.0380	0.0106	0.0107
	Block4	0.0774	0.0772	0.0501	0.0500

To be continue

Table (3-9): Extracted features for each block (block size 64×64) of the D18 image with quantization level 8 and 16 in the two cases before and after

		Level - 8		Level -16	
		Before	After	Before	After
MPR	Block1	0.0814	0.0821	0.0252	0.0254
	Block2	0.0864	0.0871	0.0387	0.0390
	Block3	0.0812	0.0819	0.0326	0.0329
	Block4	0.0812	0.0813	0.0652	0.0654
HOM	Block1	0.5627	0.5672	0.4154	0.4188
	Block2	0.5841	0.5888	0.4351	0.4386
	Block3	0.5552	0.5597	0.4097	0.4130
	Block4	0.6070	0.6076	0.4554	0.4588
CLS	Block1	389.49	392.61	3699.7	3729.3
	Block2	344.56	347.31	3300.7	3446.9
	Block3	363.44	366.35	3446.9	3474.6
	Block4	389.53	392.65	3699.8	3729.8
CLP	Block1	3492.3	3520.3	68907	69460
	Block2	3000.5	3008.2	59720	59908
	Block3	3290.4	3296.3	64730	64746
	Block4	3516.5	3520.3	69455	69460

The results of the previous tables would be presented in a different way as be presented in Experiment (1), Figure (3-13) and figure (3-14) presents the behavior of the selected features for each block in the D18 image, since block size in this case 64×64 with quantization level 8 and 16 respectively. It should be mentioned that the values of the features are normalized to the value one. The results shows that there is no clearly difference in the extracted feature value in the two cases before and after expect the entropy feature, where the changes is perceptible in the two cases before and after.

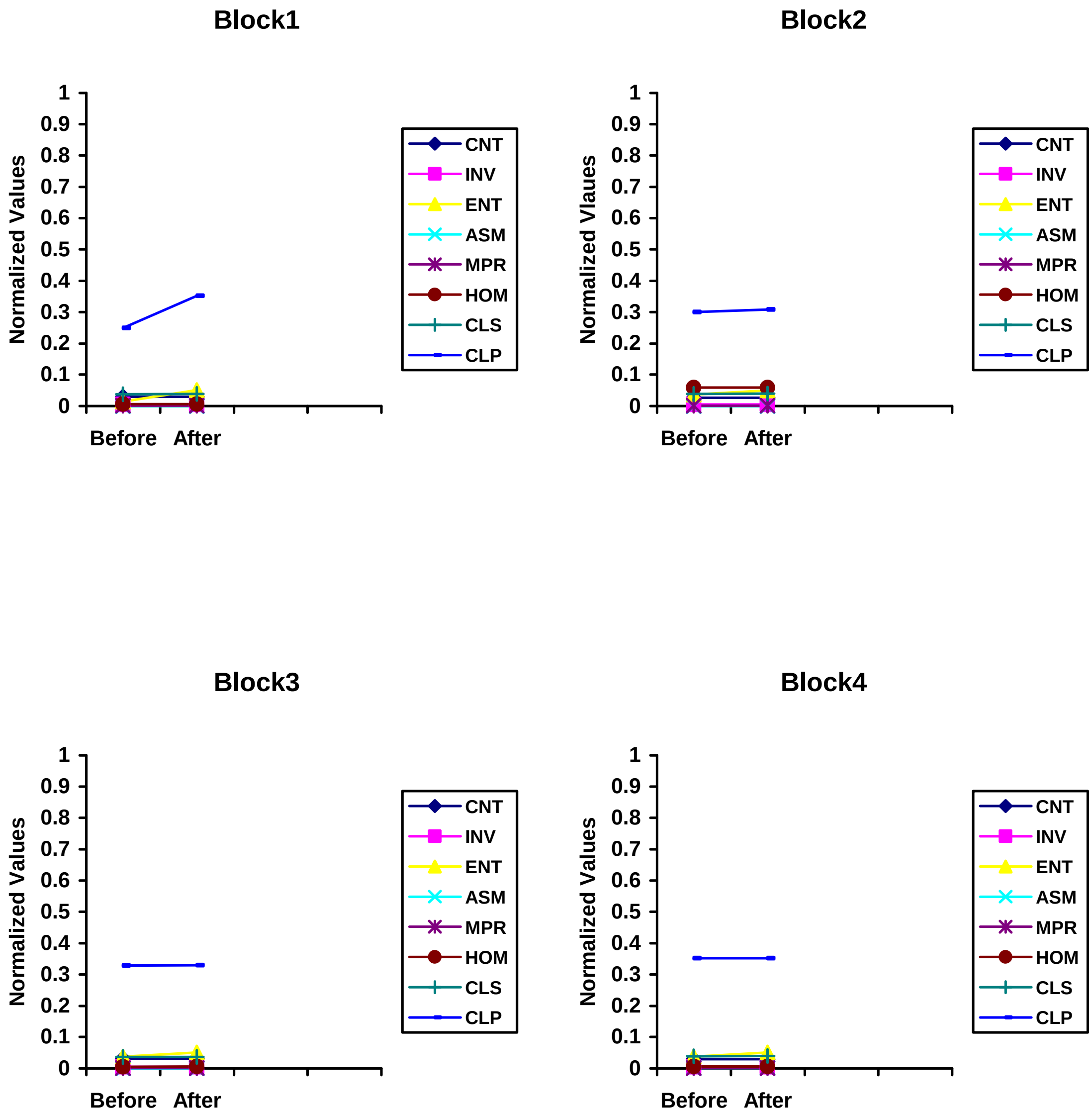


Figure (3-13): The behavior of blocks with selected features of the D18 image, with block size 64×64 and quantization level 8 in the two cases of before and after.

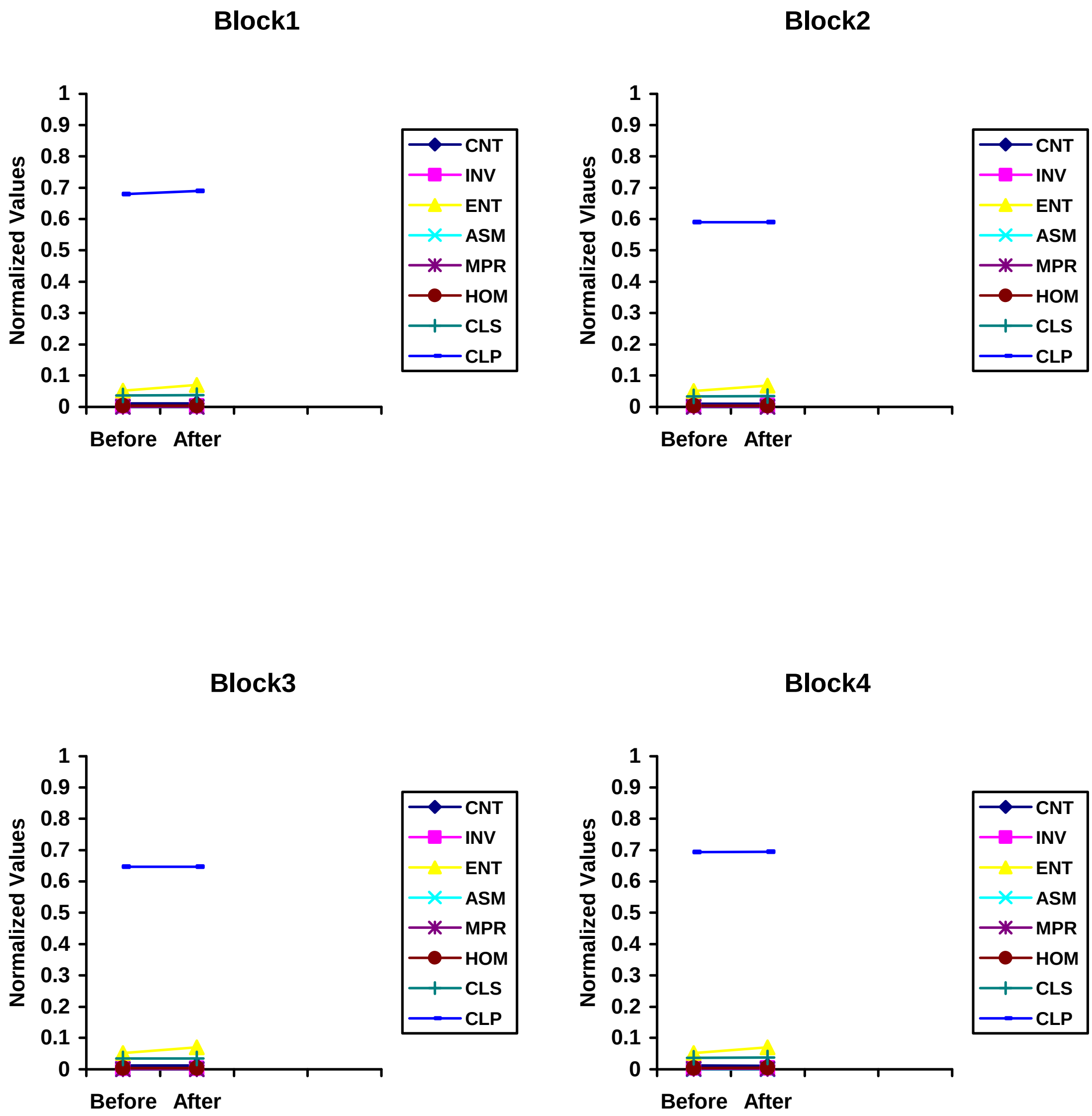


Figure (3-14): The behavior of blocks with selected features of the D18 image, with block size 64×64 and quantization level 16 in the two cases of before and after.

Tables(3-10) shows the extracted features from D18 image with quantization level 8.

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 8 in the two cases before and after

		Level -8				Level -8	
		Before	After			Before	After
CNT	Block1	2.9030	2.9475	INV	Block1	0.5071	0.5154
	Block2	2.7702	2.8138		Block2	0.5279	0.5376
	Block3	2.7235	2.7665		Block3	0.5304	0.5390
	Block4	2.9455	2.9901		Block4	0.5644	0.5732
	Block5	3.1217	3.1706		Block5	0.5082	0.5166
	Block6	2.7870	2.8309		Block6	0.5345	0.5432
	Block7	2.4627	2.5023		Block7	0.5354	0.5442
	Block8	2.4416	2.4793		Block8	0.5615	0.5708
	Block9	3.1460	3.1945		Block9	0.5073	0.5156
	Block10	2.8919	2.9373		Block10	0.5086	0.5170
	Block11	2.9092	2.9556		Block11	0.5061	0.5144
	Block12	2.3283	2.3651		Block12	0.5433	0.5522
	Block13	3.4984	3.5529		Block13	0.4935	0.5016
	Block14	2.9946	3.0398		Block14	0.5035	0.5119
	Block15	3.4098	3.4630		Block15	0.4917	0.4998
	Block16	2.9031	2.9475		Block16	0.5071	0.5154

To be continue

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
ENT	Block1	3.6875	5.0307
	Block2	3.7022	5.0540
	Block3	3.5649	4.8682
	Block4	3.7026	5.0563
	Block5	3.6778	5.0185
	Block6	3.5518	4.8474
	Block7	3.5244	4.7997
	Block8	3.5372	4.8573
	Block9	3.7268	5.0882
	Block10	3.6454	4.9605
	Block11	3.7381	5.0873
	Block12	3.4960	4.7657
	Block13	3.7785	5.1306
	Block14	3.7018	5.0530
	Block15	3.7753	5.1410
	Block16	3.3687	5.0307

		Level -8	
		Before	After
ASM	Block1	0.0373	0.0381
	Block2	0.0357	0.0363
	Block3	0.0437	0.0452
	Block4	0.0796	0.0801
	Block5	0.0401	0.0409
	Block6	0.0466	0.0474
	Block7	0.0427	0.0437
	Block8	0.0434	0.0439
	Block9	0.0376	0.0380
	Block10	0.0392	0.0401
	Block11	0.0348	0.0353
	Block12	0.0461	0.0469
	Block13	0.0360	0.0369
	Block14	0.0383	0.0391
	Block15	0.0350	0.0356
	Block16	0.0373	0.0381

To be continue

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
MPR	Block1	0.0716	0.0720
	Block2	0.0615	0.0612
	Block3	0.1036	0.1053
	Block4	0.1373	0.1389
	Block5	0.0989	0.1006
	Block6	0.1158	0.1177
	Block7	0.0887	0.0901
	Block8	0.0924	0.0931
	Block9	0.0868	0.0818
	Block10	0.0843	0.0857
	Block11	0.0730	0.0715
	Block12	0.0989	0.1005
	Block13	0.0787	0.0776
	Block14	0.0761	0.0771
	Block15	0.0815	0.0828
	Block16	0.0716	0.0728

		Level -8	
		Before	After
HOM	Block1	0.5547	0.5638
	Block2	0.5714	0.5808
	Block3	0.5742	0.5836
	Block4	0.6095	0.6190
	Block5	0.5567	0.5659
	Block6	0.5789	0.5883
	Block7	0.5768	0.5862
	Block8	0.5998	0.6097
	Block9	0.5540	0.5631
	Block10	0.5564	0.5656
	Block11	0.5539	0.5630
	Block12	0.5843	0.5938
	Block13	0.5463	0.5552
	Block14	0.5522	0.5614
	Block15	0.5431	0.5522
	Block16	0.5547	0.5638

To be continue

Table (3-10): Extracted features for each block (block size 32×32) of the D18 image with quantization level 8 in the two cases before and after

		Level -8	
		Before	After
CLS	Block1	370.32	376.38
	Block2	485.07	492.92
	Block3	306.07	311.05
	Block4	362.45	368.33
	Block5	349.31	354.98
	Block6	303.85	308.79
	Block7	330.08	335.43
	Block8	374.44	380.55
	Block9	389.66	396.03
	Block10	337.54	343.05
	Block11	439.90	447.53
	Block12	317.70	322.88
	Block13	361.17	367.04
	Block14	358.59	364.45
	Block15	413.39	420.14
	Block16	370.32	376.38

		Level -8	
		Before	After
CLP	Block1	3321.4	3376.3
	Block2	4550.3	4606.4
	Block3	2510.4	2626.2
	Block4	3210.7	3264.2
	Block5	3125.3	3171.6
	Block6	2579.4	2625.3
	Block7	2760.4	2816.4
	Block8	3354.4	3389.5
	Block9	3590.4	3637.9
	Block10	2935.4	2988.4
	Block11	4085.6	4130.6
	Block12	2634.2	2686.3
	Block13	3282.4	3333.5
	Block14	3242.0	3294.0
	Block15	3710.9	3844.0
	Block16	3334.5	3376.3

Figure (3-15) shows the results of selected features for each block normalization to the value one, with 16 block, it is clearly from the graph the similarity and satiability of feature values, between all blocks that see it in figure (3-13) and (3-14).

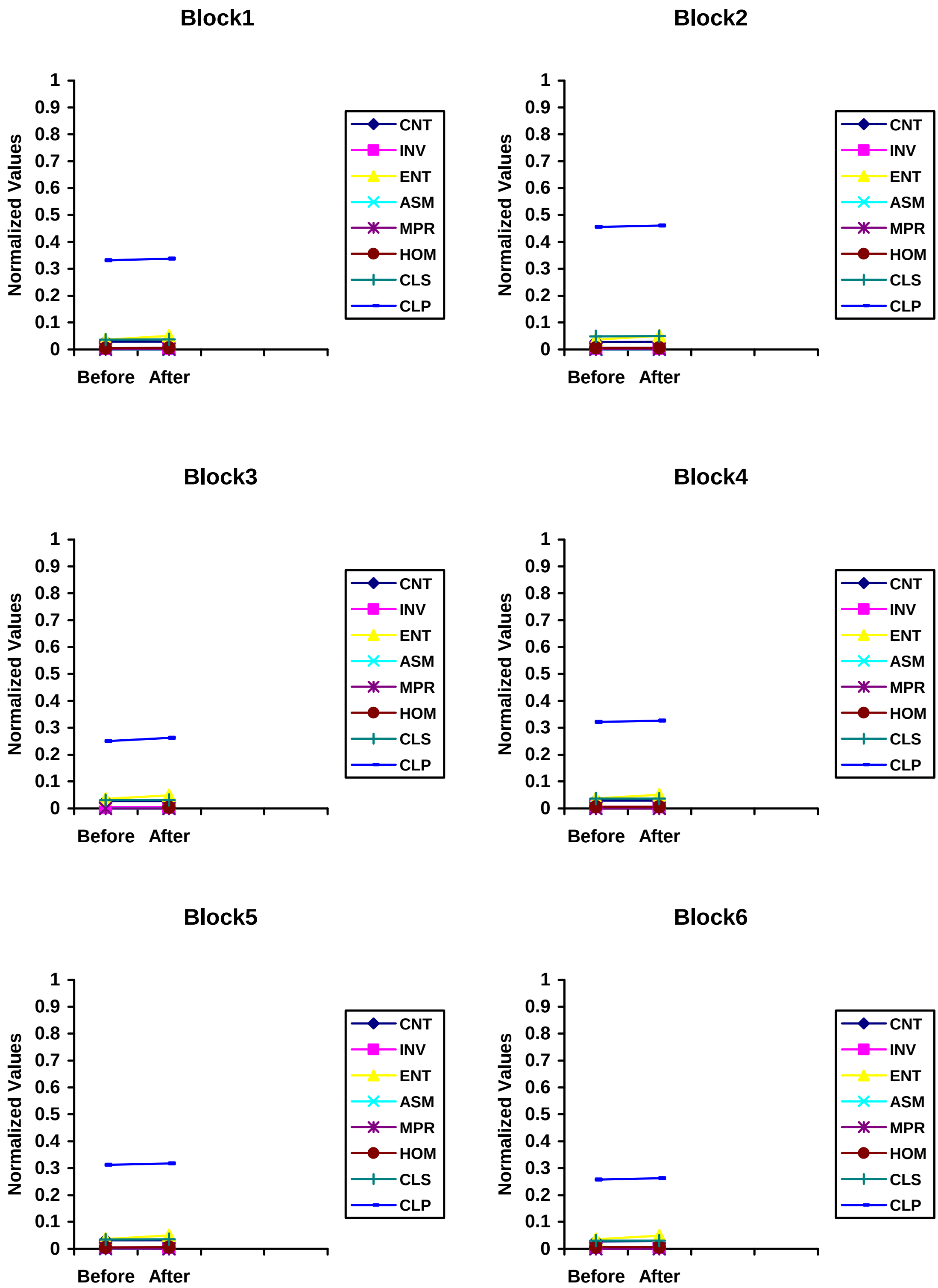


Figure (3-15): The behavior of blocks with selected features of the D18 image, with block size 32×32 and quantization level 8 in the two cases of before and after.

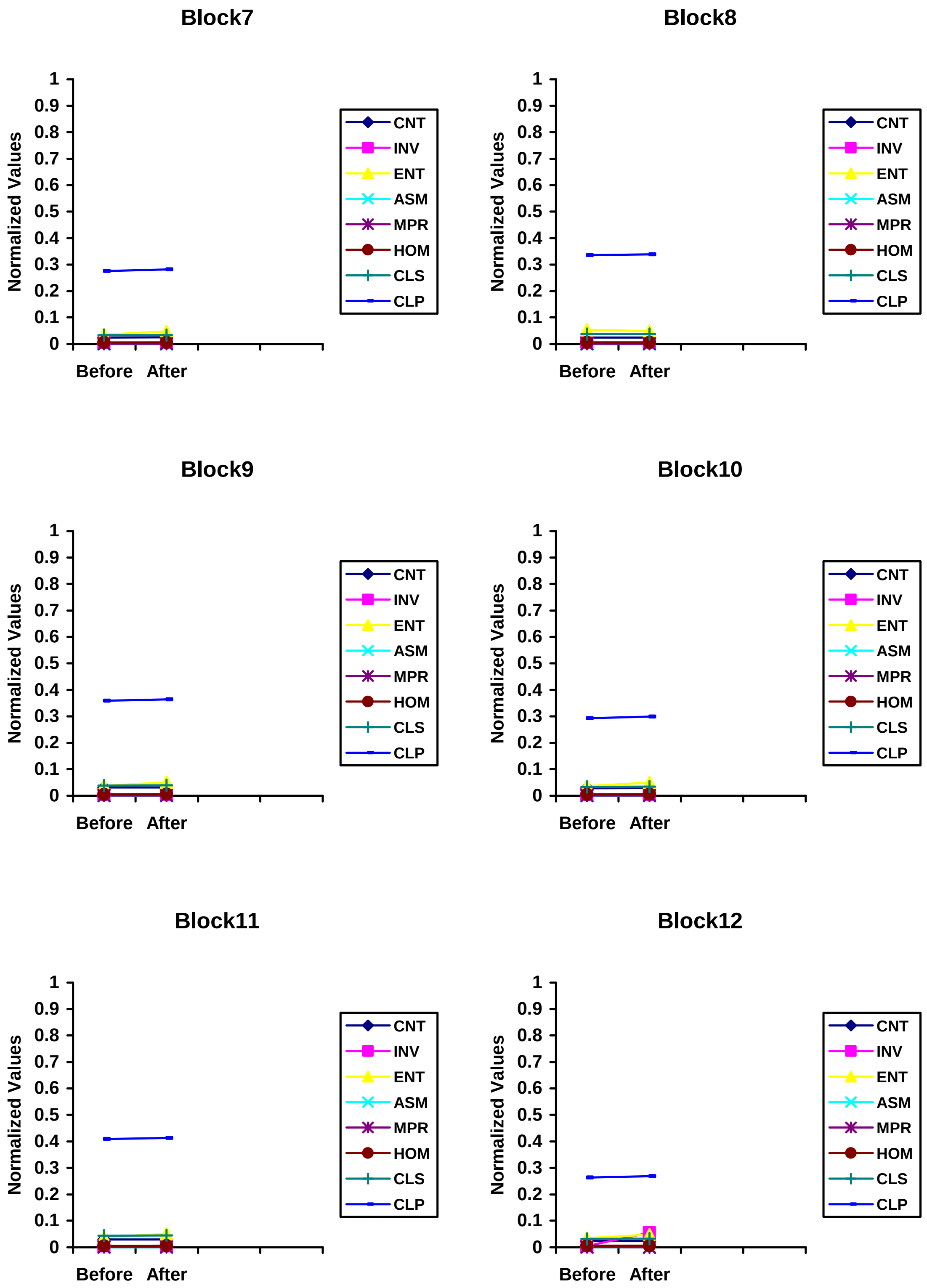


Figure (3-15): The behavior of blocks with selected features of the D18 image, with block size 32×32 and quantization level 8 in the two cases of before and after.

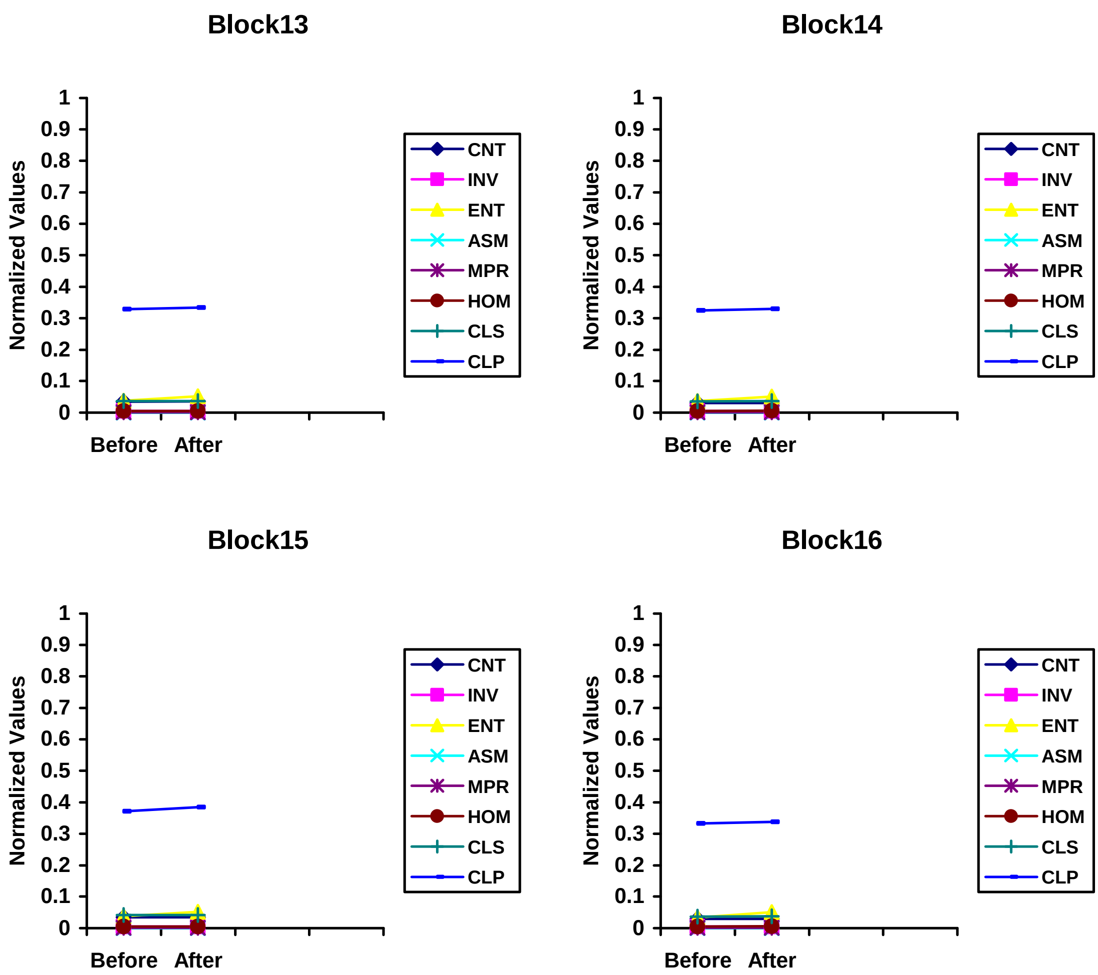
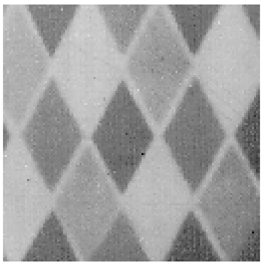


Figure (3-15): The behavior of blocks with selected features of the D18 image, with block size 32×32 and quantization level 8 in the two cases of before and after.

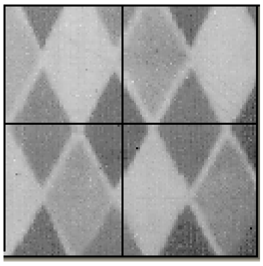
3.5.3 Experiment 3 (D84):

The third selected textured image used as a test material is D84 image. The D84 is of a size of (128 × 128) with 256 gray levels. The eight selected features are calculated for the original image and for the sub image for different block size 32 x 32 and 64 x 64 as be shown in figure (3-16) with different quantization level 8, 16, and 32.

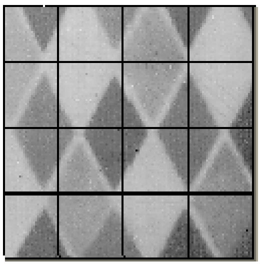
The features are calculated in two ways, the first one for the average Co-occurrence matrix and the second one for the Co-occurrence matrix of angle 0°, 45°, 90°, and 135° as be mentioned before that the two ways named before and after respectively. Four values for the same feature is extracted (one for each angle) for the second case, and then the average value for the four features is calculated.



(A)



(B)



(C)

Figure 3-16: Experiment 3
- **(A) Original Image D84,**
- **(B) Extracted Features with window size 64×64.**
- **(C) Extracted Features with window size 32×32.**

Table 3-11: The value of statistical features for textured image D84 with quantization level =8

	8 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	0.2741	0.8688	2.2929	0.1651	0.3044	0.8697	789.42	7879.9
After	0.2741	0.8732	3.0804	0.1663	0.3056	0.8731	792.53	7911.0

Table 3-12: The value of statistical features for textured image D84 with quantization level =16

	16 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	0.6691	0.7723	3.2014	0.0707	0.1720	0.7802	7376.1	153101
After	0.6691	0.7754	4.4260	0.0711	0.1727	0. 7833	7405.2	153704

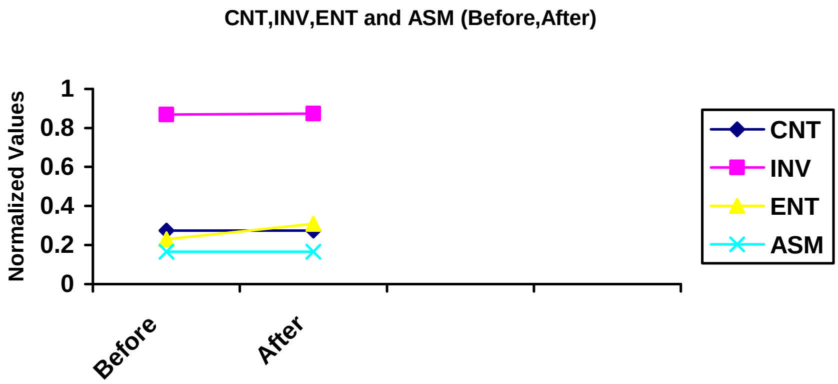
Table 3-13: The value of statistical features for textured image D84 with quantization level =32

	32 Levels							
	CNT	INV	ENT	ASM	MPR	HOM	CLS	CLP
Before	2.1527	0.6280	4.5306	0.0243	0.0708	0.6556	63189	2674571
After	2.1527	0.6306	6.1161	0.0244	0.0711	0.6583	63438	2685117

It is clear from these tables and from figure (3-17) that most of the selected features except the entropy feature are stable in the two cases before

and after since the values of entropy feature have perceptible slope in the two cases before and after.

Figure (3-18) shows the behavior of the selected features with different quantization level. It is clear from the figure that some of features (CNT, ENT, CLS, CLP) increased with increasing the quantization level and the others (INV, ASM, MPR, HOM) decreased with increasing the quantization level.



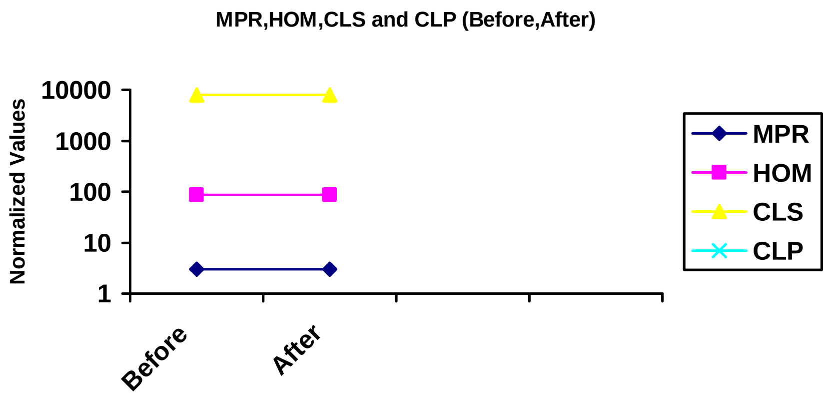


Figure (3-17): The behavior of the selected features in the two cases of before and after.

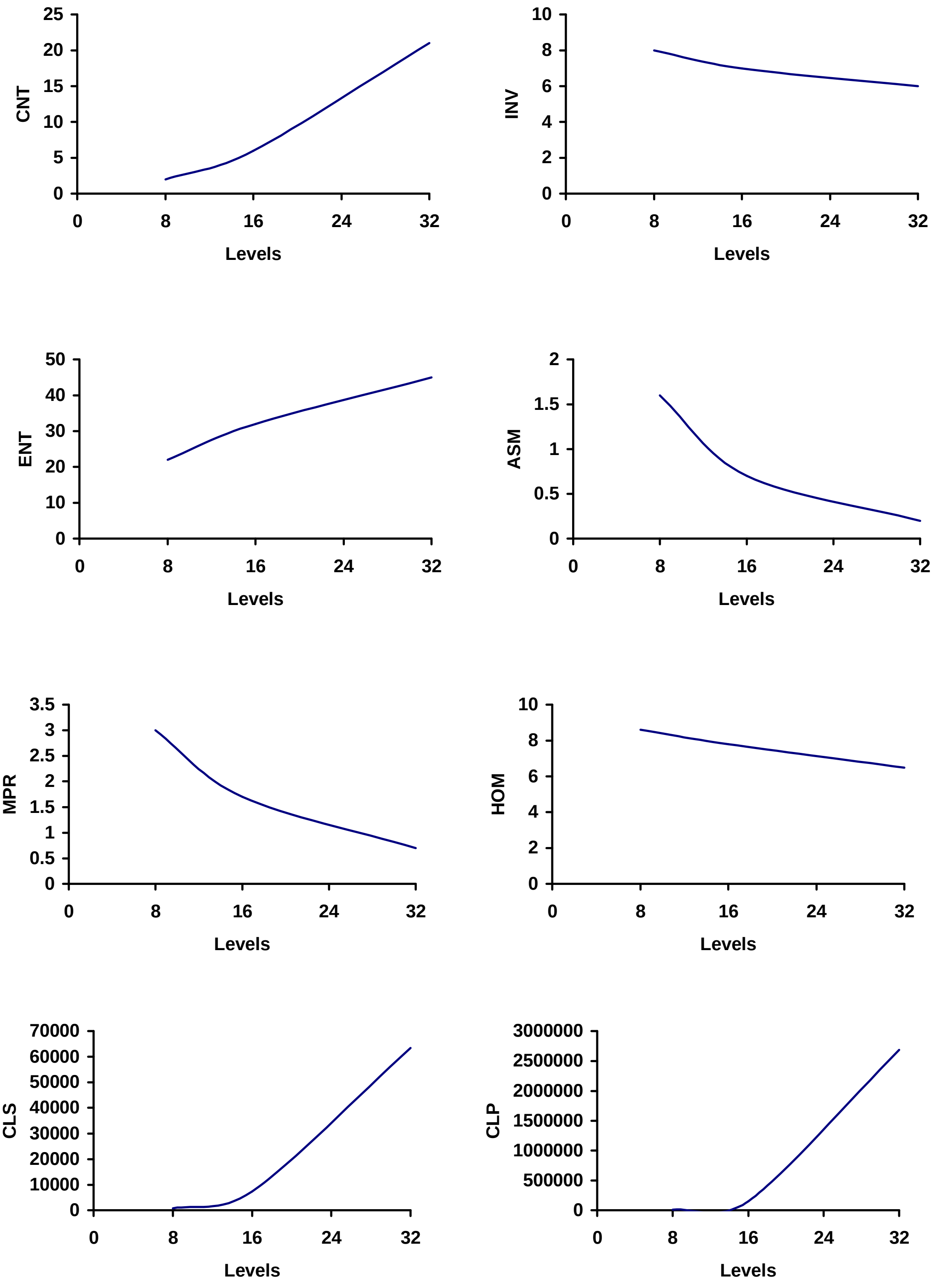


Figure (3-18): The behavior of the selected features with different quantization level (8, 16, and 32)

Table (3-14) shows the extracted features from D84 image with different block size 64×64 and with different quantization level (16, and 32).

Table (3-14): Extracted features for each block (block size 64×64) of the D84 image with quantization level 16 and 32 in the two cases before and after

		Level - 16		Level -32	
		Before	After	Before	After
CNT	Block1	0.1322	0.1327	0.4087	0.4101
	Block2	0.1629	0.1634	0.5159	0.5177
	Block3	0.1588	0.1593	0.4769	0.4785
	Block4	0.1722	0.1727	0.4487	0.4501
INV	Block1	0.1968	0.1975	0.1613	0.1619
	Block2	0.1907	0.1951	0.1572	0.1579
	Block3	0.1881	0.1889	0.1561	0.1568
	Block4	0.2368	0.2375	0.2013	0.2019
ENT	Block1	1.0774	1.4477	1.3768	1.8504
	Block2	1.1477	1.5421	1.4375	1.9374
	Block3	1.1686	1.5683	1.4436	1.9374
	Block4	1.1174	1.4877	1.4168	1.8904
ASM	Block1	0.0067	0.0068	0.0025	0.0025
	Block2	0.0050	0.0050	0.0019	0.0019
	Block3	0.0039	0.0040	0.0016	0.0016
	Block4	0.0467	0.0468	0.0042	0.0042

To be continue

Table (3-14): Extracted features for each block (block size 64×64) of the D84 image with quantization level 16 and 32 in the two cases before and after

		Level - 16		Level -32	
		Before	After	Before	After
MPR	Block1	0.0618	0.0621	0.0340	0.0341
	Block2	0.0485	0.0487	0.0296	0.0230
	Block3	0.0309	0.0310	0.0172	0.0171
	Block4	0.1018	0.1021	0.0743	0.0741
HOM	Block1	0.1981	0.1989	0.1666	0.1673
	Block2	0.1927	0.1935	0.1638	0.1645
	Block3	0.1898	0.1905	0.1626	0.1633
	Block4	0.2381	0.2389	0.2066	0.2073
CLS	Block1	2289.6	2298.6	19428.0	19504.8
	Block2	1913.2	1920.8	16363.3	16428.0
	Block3	1688.2	1694.9	14540.1	14597.2
	Block4	2289.6	2298.7	19428.0	19504.9
CLP	Block1	50150	50349	865893	869318
	Block2	40066	40135	645876	699728
	Block3	34120	34265	560135	602701
	Block4	50150	50349	865893	869318

The results of the previous tables of Experiment 3 would be presented in the same way that experiment 2 . Figure (3-19) and figure (3-20) presents the behavior of the selected features for each block in the D84 image. Since the block size in this case is 64×64 with quantization level 16 and 32 respectively. It should be mentioned that the values of the features are normalized to the value one. The results shows that there is no clearly difference in the extracted feature value in the two cases before and after except the entropy feature, where the changes is perceptible in the two cases before and after.

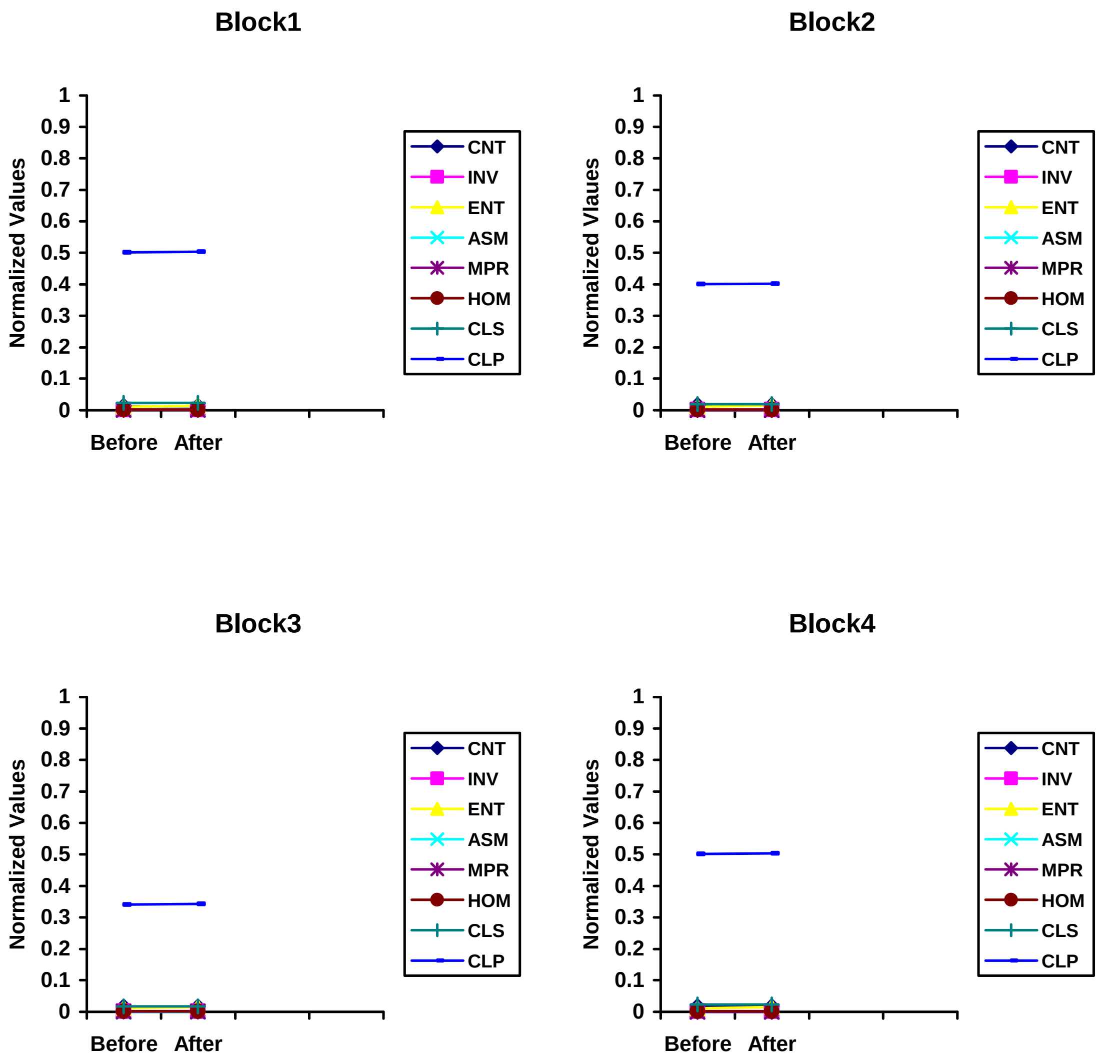


Figure (3-19): The behavior of blocks with selected features of the D84 image, with block size 64×64 and quantization level 16 in the two cases of before and after.

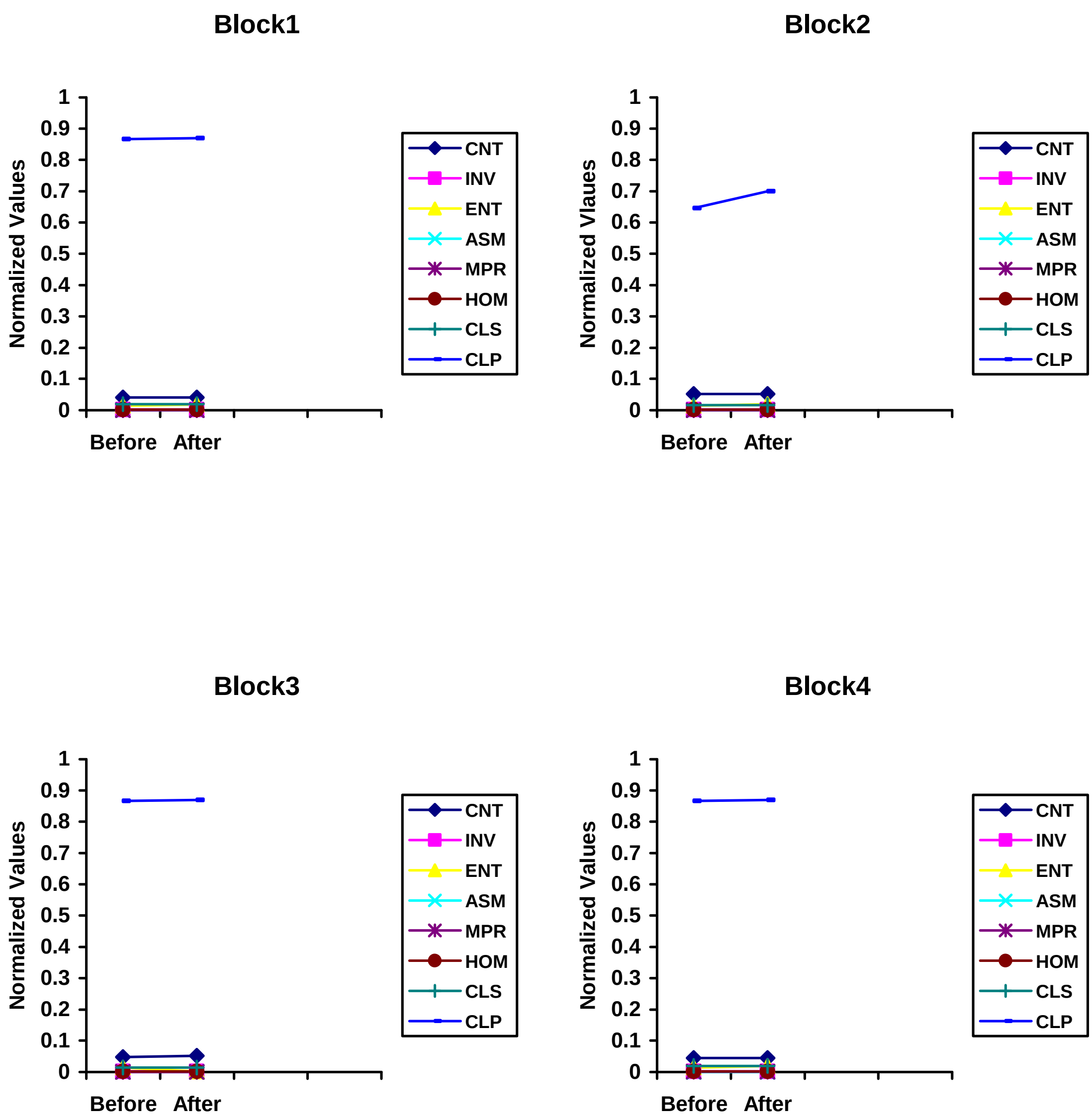


Figure (3-20): The behavior of blocks with selected features of the D84 image, with block size 64×64 and quantization level 32 in the two cases of before and after.

Chapter Four

Conclusions and Suggestions for Future Work

4.1 Introduction

In this chapter, the conclusions of this work will be given with some recommendations for future work.

4.2Conclusions

The conclusions, which are derived from the results of this work, can be summarized as follows:

1. There is no effect for the block size on the values of the extracted features. This property leads us, for any textured sample, the block size must be chosen with minimum block size to reduce the dimensionality of the textured sample to reduce the execution time by reducing the number of arithmetic operation.
2. The effect of the quantization level on the values of the extracted features is clear. Since the value of some of the selected features (CNT, ENT, CLS, and CLP) increased with increasing the quantization level and the other features (INV, ASM, HOM, and MPR) decreased with increasing the quantization level. In spite of the effects of the quantization level, on the value of the extracted features, but the behavior the selected feature is not change. This property leads us, for any textured sample, the quantization value must be chosen with minimum quantization level to reduce the dimensionality of the Co-occurrence matrix of the textured sample

to reduce the execution time and the number of arithmetic operation.

3. As be mentioned before, the features are extracted in two way named before and after, the main point can be concluded from this work that, the extracted value for most the selected features are stable except the entropy feature where, the difference between the extracted entropy feature value is noticeable. This property is important and can be utilized to increase the discrimination power in the classification process.

4.3 Suggestions for the Future Work

The following are some of recommendations suggested for future works:

1- This work can be extended by studying and analyzing the effect of the distance parameter (d) in the Co-occurrence matrix on the feature extraction.

2- Studying and analyzing an additional characteristic features rather than be chosen in this study.

3- This study can be applied on real images like satellite images, biomedical images. For this purpose, non-uniform segmentation (like split and merge method) can be adopted.

4. Studying and analyzing the behavior of extracted feature after applying some of the transforms (Fourier, cosine, wavelet, etc.).

Chapter Four: Conclusions and Suggestions for Future Work

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تاريخ المناقشه:٢٨-٦-٢٠٠٦

DEDICATION

To my Family

Sarah

2006

List of Abbreviations

ASM	Angular Second Moment
COR	Correlation
CLP	Cluster Prominence
CLS	Cluster Shade
CNT	Contrast
EDM	Element Difference Moment
ENE	Energy
ENT	Entropy
HOM	Homogeneity
INV	Inverse Difference Moment
MPR	Maximum Probability
TICS	Texture Image Classification System

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Appendix

Chapter One

Overview

Chapter Two

Texture Analysis

Chapter Three

System Development And Implementation

Chapter Four

Conclusions And Suggestions For Future Work

References

Republic of Iraq
Ministry of Higher Education & Scientific Research
Al-Nahrain University

Statistical Textural Features Analysis for Gray Images

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SUBMITTED TO THE
COLLEGE OF SCIENCE, Al-NAHRAIN UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF MASTER OF SCIENCE IN
COMPUTER SCIENCE

By

Sarah Abbas Asem Al-Naqshbandi
(B.Sc. 2003)

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June	**Jamadi Al-Akher**

وزارة التعليم العالي و البحث العلمي
جامعة النهرين
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رسالة مقدمة إلى كلية العلوم، جامعة النهرين كجزء من متطلبات
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Certification of the Examination Committee

We the examination committee certify that we have read this thesis titled "**Statistical Textural Features Analysis for Gray Images**" and we have examined the student **Sarah Abbas Al-Naqshbandi** in its contents and what is related to it, and in our opinion it meets the standard of a thesis for the degree of Master of Science in Computer Science.

Signature:
Name: Assistant Prof. Dr. Emad H. Al-Hussainy **(Chairman)**
Date: / / 2006

Signature:
Name: Assistant Prof. Dr. Kais J. Al-Jumaily (**Member**)
Date: / / 2006

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Name: Assistant Prof. Dr. Ban N. Al-Kalak (**Member**)
Date: / / 2006

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Name: Assistant Prof. Dr. Laith A.-A. Al-Ani **(Supervisor)**
Date: / / 2006

Approved by the Dean of the College of Science, Al-Nahrain University

Signature:
Name: Dr. Laith Abdul Aziz Al-Ani (**The Dean)**
Date: / / 2006

Certification of the Examination Committee

We the examination committee certify that we have read this thesis titled "*s*" and we have examined the student Sarah Abbas Al-Naqshbandy in its contents and what is related to it, and in our opinion it meets the standard of a thesis for the degree of Master of Science in Computer Science.

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Name: Assistant Prof. Dr. Emad H. Al-Hussainy
Title: Chairman
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الملخص

تعتبر عملية استخراج المعالم المميزة (characteristic features) إحدى الطرق المعتمدة لغرض تميز الأنماط في الصور، كما تعتبر عملية استخراج المعالم المميزة بشكل عددي إحدى الطرق المعتمدة لغرض تميز الأنماط في الصور الرقمية، كما تعتبر عملية استخراج المعالم المميزة باعتماد مصفوفة التواجد (Co-occurrence matrix) إحدى أهم الطرق المستخدمة لغرض تميز الأنماط في الصور النسيجية.

يهدف البحث إلى دراسة المعالم المميزة للصور النسيجية ولهذا الغرض تم اختيار ثمان من المعالم أو المتغيرات وهي:

(Maximum probability, entropy, homogeneity, cluster shade, cluster prominence, contrast, angular second moment and inverse difference moment)

في هذا البحث تم استخدام طريقتين لحساب هذه المتغيرات باعتماد مصفوفة التواجد، ففي الطريقة الأولى تم حساب المتغيرات اعتمادا على معدل مصفوفة التواجد والمحسوبة للزوايا (٠°، ٤٥°، ٩٠° ، و١٣٥°) أما الطريقة الثانية فقد تم حساب المتغيرات اعتمادا على مصفوفة التواجد ولكل زاوية من الزوايا (٠°، ٤٥°، ٩٠° ، و١٣٥°) حيث يتم استخراج أربع قيم لكل من المتغيرات المختارة و من ثم يتم حساب المعدل لكل من هذه المتغيرات

ولتنفيذ الطرق المقترحة في هذا البحث تم اختيار ثلاثة أشكال من الصور النسيجية والتي تم توظيفها كصور اختباريه لحساب المتغيرات المختارة.

تم تكميم الصور لمستويات مختلفة (٨ ،١٦، ٣٢)ومن ثم تم تجزئة الصور إلى مربعات بأبعاد مختلفة(٦٤×٦٤ و ٣٢×٣٢) ثم تم تطبيق الطرق المقترحة على كل صورة من الصور المختارة ولكل حالة من الحالات المشار إليها.

أظهرت النتائج إن معظم قيم المتغيرات المحسوب متطابقة في كلا الطريقتين ولكل حالة من حالات التكميم و التجزئة عدا قيم أل entropy حيث أظهرت القيم تغيرا محسوسا في كلا الطريقتين ولكل حالة من حالات التكميم و التجزئة. يمكن توظيف هذه النتيجة لغرض زيادة الدقة في تصنيف الصور النسيجية عندما تكون المناطق المختلفة ذات الطبيعة النسيجية متقاربة من بعضها من حيث الشكل.