

# MEDICAL IMAGE SEGMENTATION: GRANULAR COMPUTING APPROACH

*Dissertation Submitted to JAWAHARLAL NEHRU UNIVERSITY  
In partial fulfillment of the requirements for the award of the degree of*

**Master of Technology  
In  
Computer Science & Technology**

**By**

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**Under the supervision of**

*Prof. Sonajharia Minz*

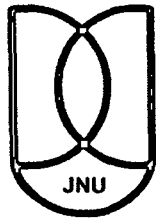


**SCHOOL OF COMPUTER & SYSTEMS SCIENCES**

**Jawaharlal Nehru University**

**New Delhi – 110 067, INDIA**

**JULY 2010**



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## CERTIFICATE

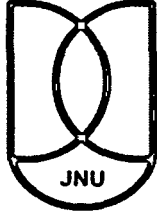
This is to certify that this dissertation entitled “**Medical Image Segmentation: Granular Computing Approach**” submitted by **Mary Stela Lakra**, to the School of Computer and Systems Sciences, Jawaharlal Nehru University, New Delhi, for the award of degree of **MASTER OF TECHNOLOGY**, is a bonafide work carried out under my supervision.

The study pertains to this dissertation has not been submitted in part or in full, to any other University or Institution for the award of any other degree.

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## DECLARATION

This is to certify that the dissertation titled “**Medical Image Segmentation: Granular Computing Approach**”, which is being submitted to the **School of Computer & System Sciences, Jawaharlal Nehru University, New Delhi**, in partial fulfillment of the requirements for the award of **Master of Technology in Computer Science & Technology** is a bonafide work carried out by me. This research work has been carried out the under the supervision of **Prof. Sonajharia Minz**.

The study pertaining to this dissertation has not been submitted in part or in full, to any other University or Institution for the award of any other degree.

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*Dedicated to*  
*My loving Parents*

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(MARY STELA LAKRA)

# ABSTRACT

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Image Segmentation is an important part of the image processing for analytical study. Image segmentation is defined as the partitioning of an image into non-overlapping constitutes regions which are homogenous with respect to the similarity of textures and intensities. Image segmentation is widely studied in this dissertation. The Roughness Measure for segmentation of color images is proposed by M.M. Mushrif and A. K. Ray, however this method has not been reported to applied on medical images. Analysis of the medical images can contribute to the domain of healthcare; therefore these studies can be helpful. In this dissertation, granular computing approach has been used by granulating the medical images, and studying the outcome after granulating the image using various window sizes of granules. The granulation of image data can contribute towards data reduction.

The study focuses on observing the performance of the base algorithm for the medical images and the granulated medical images. The dissertation includes implementation of the algorithm resulting in the application developed in C language. The experiments have been carried out and the results have been analyzed with respect to the objectives of the study. The outcomes in terms of evolution parameters are number of Clusters and number of Regions that are showing no significant changes in the performance. The visual analysis of the medical images are showing better performance for detecting the area of interest like infected tissues, high density mass, irregular lesion etc. It is proposed that granular computing application for medical image processing especially for medical image segmentation may be further explored as it promises a significant computation reduction. Granular Image provides the extension to the base algorithm. It may prove helpful in other applications of the medical image processing.

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# CHAPTER 1

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## INTRODUCTION

### 1.1 Overview

To human, an image is not just a random collection of pixels; it is a meaningful arrangement of regions and objects. Image Segmentation is an important area in the field of image processing and computer vision. It is a fundamental part of the “low level” aspect of computer vision and has many practical applications such as in medical imaging, industrial automation and satellite imagery. Segmentation is an important tool in medical image processing and it has been useful in many applications [9]. The result of segmentation is a partition of a gray-level image (medical imaging) into a number of regions, which are homogeneous according to some criteria and belong to either the foreground or the background. Each region can be considered as granules, whereas granular computing is useful in finding meaningful patterns in data by expressing and processing chunks of information (granules). Rough set, a concept also used for granular computing introduced by Zdzislaw Pawlak, is concerned about the notion of roughness [3]. Rough sets are information granules capable of capturing the effect of roughness arising when dealing with the concept in the setting of some generic information granules.

Medical imaging has become an individual means in modern healthcare, often providing the way of studying disease and the human physical condition. Medical images are gray scale images. Gray scale images are different from one-bit black and white binary images. In the perspective of computer imaging, binary images are images with only two colors, black & white. In medical imaging, segmentation is important for feature extraction, image measurement and image display. Gray scale images have many shades of gray in between. Gray scale images are also called monochromatic, denoting the absence of any chromatic variation [11]. Some examples of medical imaging are CT scan,

MR Imaging, X-rays, tomography images, angiography images, ultrasonic images, and mammography.

Image segmentation is very essential and critical to image processing and pattern recognition. Segmentation can be defined as the identification of “meaningful” image components. It is a fundamental task in image processing providing the basis for any kind of further high level image analysis. In medical image processing, a wide range of applications is based on segmentation [9]. Level of subdivision is application dependent. Image analysis application is highly dependent on the success of the autonomous segmentation of object or segmented image. This may, for instance, involve the detection of a brain tumor from MR or CT images. Segmentation is one of the first steps leading to image analysis and interpretation.

## 1.2 Problem Description

The main purpose of this dissertation is to consider segmentation of grayscale images such as medical imaging. A gray scale or gray level image is the one in which the colors are the shades of gray between black and white. The Gray scale image boundaries between object regions are often ill defined because of grayness or spatial ambiguities. Medical images contain fuzzy contours, poor image contrast and artifacts that results in missing or diffuse organs and tissue boundaries. Mohabey and A.K. Ray introduced the concept of Histon which is a contour plotted on the top of the histogram by considering a similar color sphere of a predefined radius around a pixel [8]. Segmentation using rough-set theoretic approach [6], M.M. Mushrif & A.K. Ray has used the concept of Histon. The roughness index has been calculated that uses the roughness measure for each pixel for the color image.

A number of techniques have been used for segmentation of mostly <sup>color</sup> images like Markov random field (MRF), Models based approach, Atlas-guided approach, c-mean clustering technique etc. This study also includes application of granular computing approach by

granulating the image and using the chunk of information rather than the objects for measuring similarity, distinguishability and functionalities for segmentation. In the literature use of Granules have been proposed towards data reduction in general data size remains the same but the set of information for processing reduces. Therefore, this study includes experiments by considering  $n \times n$  window granulation of the image data say  $G_{n \times n}$ . After granulation the average intensity of all the pixels in the granule is proposed to be the intensity of the granule. The similarity measure has been used for region merging while the proximity measure has been used for clustering by applying 8-connected component label based approach.

The study aims to investigate the performance of roughness measure based algorithm [8] for segmentation of medical imaging and to extend the application of this algorithm on granulated images. The sets of two experiments have been designed to achieve the following objectives:

1. To compare the performance of segmentation of medical images using Histogram approach and the one using Roughness Measure.
2. To evaluate and compare performance of Roughness Measure based algorithm on granulated images of two different size of granule.

### **1.3 Organization of Dissertation**

Chapter2 is study of granulation approach and rough sets theory for medical imaging. Histon concept and roughness measure has been described. In detail Image segmentation have been looked on its various techniques and methods based on properties of discontinuity and similarity for finding homogenous region and object. Chapter3 describes the view of roughness measure using Histon as base paper for dissertation work; there have been given some criteria to choose the peak and selecting valleys. Granular computing approaches have been discussed for granule using window of size  $n \times n$  ( $G_{n \times n}$ ). The proposed algorithm has been applied on image data to make

granulated image which provides an extension to the concept for medical image. The salient features of the functionality are also described.

Chapter4 presents the detail of experiments; four types of medical images had been observed for the application of the roughness measure based algorithm and proposed Granular computing based image segmentation. Experiments had been performed for algorithms in terms of number of Clusters and number of Regions, also the visible prospective. Conclusion drawn out of the experiments has been summarized in chapter 5. The dissertation sum up with the major finding of the work and future work extension in area of granular computing based techniques for medical image segmentation and also in other image processing tasks.

## CHAPTER 2

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### RELATED WORK

#### 2.1 Granular Computing

Granular computing (GrC) is a new field of study that has emerged from many different disciplines and fields, including general systems theory, social networks, artificial intelligence, human problem solving, theory of computation and information processing. Granular computing focuses on clustering information entities into granules, in terms of similarity, indistinguishability and functionalities. It follows the human ability to perceive things in different levels of abstraction (granularity) to concentrate on a particular level of interest while preserving the ability to instantly switch to another level in case of need. Granular computing is useful in finding meaningful patterns in data by expressing and processing chunks of information (granules) [3].

A Granule may be interpreted as one of the numerous, small particles forming a larger unit. Granules are regarded as the primitive notion of granular computing. Granules are regarded as the primitive notion of granular computing. One can define operation on granules so that one can operate on granules, such as combining many granules to form a new granule (Construction) or decomposing a granule into many granules [4].

“Granulation of an image or object  $I$ , leads to a collection of granules of  $I$ , with a granule being a clump of points or objects drawn together by indistinguishability, similarity, proximity or functionality”[14]. The concept of granularity is closely related to the concept of properties, on the basis of which we may obtain a clump of objects forming a granule in some possible world, where we do not focus our attention on individual pixels and process them as such but we group them together into semantically meaningful constructed familiar objects (features) we deal with in

everyday life. Such features involve regions that consist of pixels drawn together because of their proximity in the image, similar texture, color etc. [5] [12].

Granulation involves the process of two directions in problem solving, construction and decomposition. The construction concerns grouping smaller granules that share similarity, indistinguishability, and functionality to a larger granule. The decomposition involves the process of dividing a larger granule into smaller, lower level granules [13]. Granules can be treated as a primitive notion of granular computing. The physical meaning of granules can be made clear only when a particular application is considered. Some of the applications are [5]:

1. In modeling complex systems, granules may be the components of systems at different levels.
2. In programming, granules may be various modules of a software system.
3. In the theory of small groups, granules are small groups.
4. In any organization, granules may be various divisions and departments at different levels.
5. Abstracting from all these concrete examples, a granule can be considered as a focal point of our interest at a certain stage in problem solving.

## 2.2 Rough Sets Theory

**Definition 1.1 (Information System)** According to the definition given by Pawlak (1991), an Information System is a pair  $S = (U, A, V, f)$  or a function  $f: U \times A \rightarrow V$ , where  $U$  is a non-empty finite set of  $N$  objects  $\{x_1, x_2, \dots, x_N\}$  called the universe,  $A$  is a non-empty finite set of attribute  $a$ , and  $V$  value set such that  $a: U \rightarrow V_a$  for every  $a \in A$ ,  $V_a$  is the set of values of attribute  $a$ , called the domain of  $a$ .

**Definition 1.2 (Indiscernibility Relation)** Every  $A$  Subset of attributes  $B \subseteq A$  defines an equivalence relation (called an indiscernibility relation) on  $U$ . This relation is defined as



$$IND(B) = \{(x, y) \in U \times U : \text{for every } a \in B, a(x) = a(y)\}$$

**Definition 1.3 (Lower and Upper Approximation)** Lower approximation  $\underline{BX}$ , Upper approximation  $\overline{BX}$ , and Boundary  $BND_B(X)$ , a lower approximation  $\underline{BX}$  of a set  $X$ , contains all equivalence classes  $IND(B)$  that are proper subsets of  $X$  upper approximation  $\overline{BX}$  contains all equivalence classes  $IND(B)$  that have objects in common with  $X$

The lower and upper approximations can be defined as follows:

$$\overline{BX} = \cup \{Y \in U \mid IND(B): Y \cap X \neq \phi\}$$

$$\underline{BX} = \cup \{Y \in U \mid IND(B): Y \subseteq X\}$$

In the Rough Sets Theory, the approximations of sets are introduced to deal with inconsistency. Rough Sets approximation traditional used the pair of sets named the lower and the upper approximation of the set.

**Definition 1.4 (Boundary Region)** The Boundary Region is the difference between upper and lower approximation of a set  $X$  consists of equivalence classes have one or more elements in common with  $X$ . It is given by the following Boundary  $BND_B(X)$  is the set  $\overline{BX} \setminus \underline{BX}$  i.e. the set of all objects in  $\overline{BX}$  that may not contained in  $\underline{BX}$ . This is the set of elements, which cannot be classified to  $X$  or to  $\neg X$  using the knowledge  $B$ .

## 2.3 Roughness Measure

The borderline region actually represents the inexactness of the set  $X$  with respect to the knowledge  $B$ . The greater the borderline region of the set more is the inexactness. This idea can be expressed more precisely by the accuracy defined as

$$\alpha_B(X) = \frac{|BX|}{|B|} \text{ for } X \neq \phi$$

Where  $|\cdot|$  is the cardinality operator, the accuracy measure capture the degree of completeness of the knowledge about the set  $X$ , Roughness measure or roughness index of  $X$  or B-roughness of  $X$ , given by

$$\rho_B(X) = 1 - \alpha_B(X)$$

Where  $0 \leq \rho_B(X) \leq 1$ , for every  $B$  and  $X \subseteq U$ . If  $\rho_B(X) = 0$ , the borderline region of  $X$  is empty and the set  $X$  is B-definable i.e.  $X$  is crisp and precise with respect to the knowledge  $B$ , and otherwise, the set  $X$  has some non-empty B-borderline region and therefore is B-indefinable i.e.  $X$  is rough set has a non-empty boundary region [6].

### 2.3.1 Rough Image

We can define rough image processing as the collection of all approaches and techniques that understand, represent and process the images, their segmentation and features as rough sets. The ability of rough sets to handle and represent image, followed by the various rough based approaches developed for handling the different functional aspects to solve medical problems. Rough sets provide reasonable structures for the overlap boundary given by domain knowledge. The object space can be modelled as a finite subset of the Euclidean space when the object images captured via an imaging system. Rough sets can bound such sets and provide a mechanism for modeling the uncertainty in the image of the object.

**Definition 1.6 (Rough image)** Let the universe  $U$  is an image consisting of a collection of pixels. Then, if partition  $U$  into a collection of non-overlapping window of size  $M \times N$ , each window can be considered as a granule  $G$ . Given this granulation, object regions in image can be approximated by rough sets.

A rough image is a collection of pixels along with the equivalence relation induced partition of an image into sets of pixel lying within each non-overlapping window over the image. With this definition, the roughness of various transforms (or partitions) of image can be computed using image granules for windows of different sizes. In grayscale images boundaries between object regions are often ill-defined because of grayness or spatial ambiguities. This uncertainty can be effectively handled by describing the different object as rough sets with upper and lower approximation, respectively as outer and inner approximations of an image region in terms of granules.

**Rough sets in Medical image segmentation [7]:** The basic idea of segmentation-based rough sets is that while some cases may be clearly labeled as being in set  $X$  called the positive region in Rough Sets theory, and some cases may be clearly labeled as not being in set  $X$  called the negative region, limited information prevents from labeling all possible cases clearly. The remaining cases cannot be distinguished and lie in what is known as the boundary region.

Segmentation of Medical Image involves three main image related problems, Image contains noise that can alter the intensity of a pixel such that its classification becomes uncertain, image exhibit intensity non-uniformity, where the intensity level of a single tissue class varies gradually over the extent of the image, and the images have finite pixel size and are subject to partial volume averaging, where individual pixel volumes contain a mixture of tissue classes so that intensity of a pixel in the image may not be consistent with any one class.

### **2.3.2 Histon: Encrustation of the Histogram**

The new concept of encrustation of the histogram is called The Histon. This interesting approach for color image segmentation using rough sets theory was presented by Mohabey and Ray. The concept encapsulates the fundamentals of color image segmentation in Rough sets theoretic sense. Here the concept of an approximation set,

consisting of the upper approximation and the lower approximation has been utilized to ease the process of segmentation of color images.

The concept of the Histon has following dual functionality [8].

1. The first is to present a new means for visualization of color information for the similar color regions in an image to evaluate it.
2. The second aspect is to present a technique for performing boundary region analysis and in the process of segregation of the elements at the boundary and thus in the process of segmentation.

The concept is hereby called as a Histon because, it is basically a contour plotted on top of an existing Histogram. The main inspiration is to build a Histon on top of the Histograms of the primary color components red, green, and blue; such that the collection of all pixels data falling under the same color sphere are visualized as belonging to one singular value. The Histogram of the image for each of the R, G, and B components can be computed as follows [6]:

$$h_i(g) = \sum_{m=1}^M \sum_{n=1}^N \delta(I_i(m,n) - g)$$

for  $0 \leq g \leq L - 1$ , and  $i = \{R, G, B\}$

Where  $\delta(\cdot)$  the Dirac impulse function and L is the total number of intensity levels in each of the color components. The value of each bin is the number of image pixels having intensity g. The Euclidean distance between two pixels  $I(m,n)$  and  $I(p,q)$  is given by

$$d(I(m,n), I(p,q)) = \sqrt{(I_R(m,n) - I_R(p,q))^2 + (I_G(m,n) - I_G(p,q))^2 + (I_B(m,n) - I_B(p,q))^2}$$

For a P x Q neighborhood around a pixel  $I(m,n)$ , the total distance of all of the pixel in the neighborhood and the pixel  $I(m,n)$  is then given by :

$$d_T(m, n) = \sum_{p \in P} \sum_{q \in Q} d(I(m, n), I(p, q))$$

The pixels in the neighborhood fall in the sphere of the similar color if the distance  $d_T(m, n)$  is less than *expanse*. A matrix  $X$  of the size  $M \times N$  has been defined such that an element  $X(m, n)$  is given by

$$X(m, n) = \begin{cases} 1 & d_T(m, n) < \textit{expanse} \\ 0 & \textit{otherwise} \end{cases}$$

Consider  $H$  to be the Histon [8].

$$H_i(g) = \sum_{m=1}^M \sum_{n=1}^N (1 + X(m, n)) \delta(I_i(m, n) - g)$$

for  $0 \leq g \leq L - 1$  and  $i = \{R, G, B\}$

For the purpose of finding similar colors, sphere of similar color has been applied. In essence a similar color sphere is the Granule in the color space, such that all colors falling in that Granule that can be classified as one color.

For each intensity value on the base Histogram, calculate the value of the number of pixels which fall in its sphere. This count will be a count of frequency of the pixel intensity in which some other pixels are summed. This count is the value of the Histon at that particular intensity value with reference to the base Histogram. This computation is evaluated for all pixel intensity values as in the base Histogram, leading to the formation of the Histon for image shown in figure 2.1.

The Histon provides expansion to the gradually increasing peak with twice of the Histogram value for pixels per intensity.

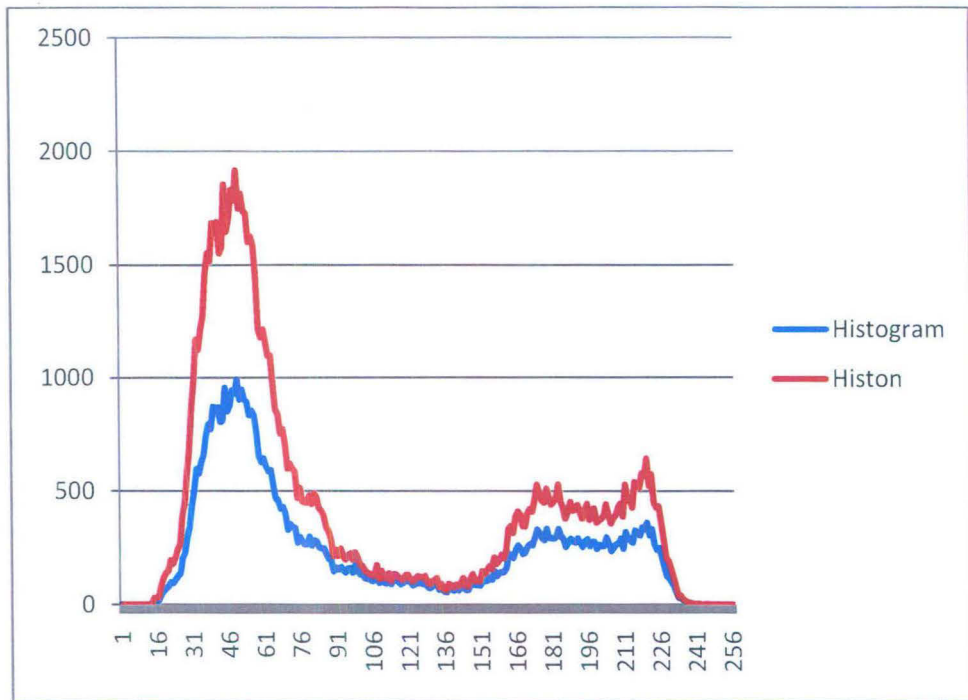


Figure 2.1: Encrustation of Histon over Histogram

## 2.4 Medical Image Segmentation

Technically, an image is a two dimensional array perceived by the human visual system. Moving pictures like videos and movies are sequence of images displaying at the rate of few images/second (PAL Standard 25fps, NTSC 30fps). When an image is digitized, it becomes a digital image. An image is a collection of measurements in 2-Dimensional or 3-Dimensional space, in 2-D image, the location of each measurement is called a pixel and in 3-D images it is called a voxel. In medical images, these measurements or image intensities can be radiation absorption in X-ray imaging, acoustic pressure in ultrasound, or radio frequency signal amplitude in MRI [15]. The reason for differentiating such images from any other sort of color image is that lesser data required being stored for each pixel. In fact a 'gray' color is one in which the red, green and blue components all have equal intensity in RGB space have shown in figure 2.2, and hence, for each pixel it requires only one intensity value against three intensity values for full color image.

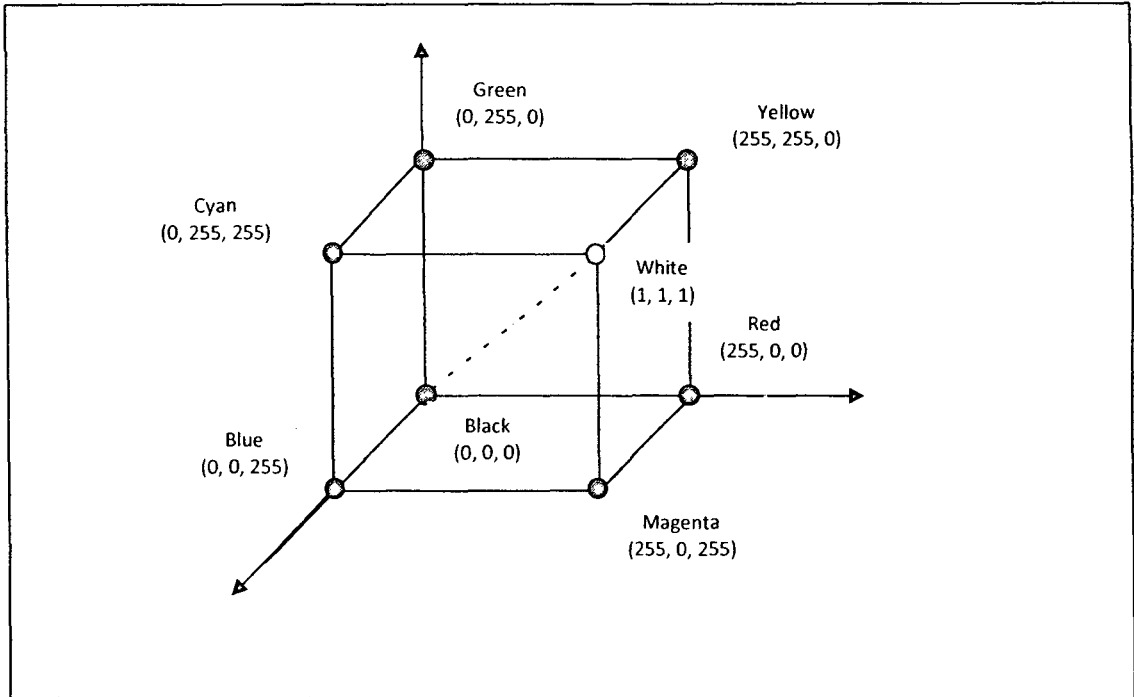


Figure 2.2: The eight corners of RGB cube

A digital image is an array of a number of picture elements called pixels. Each pixel is represented by a real number or a set of real numbers in limited number of bits. Based on the accuracy of the representation, we can classify images into three categories, black and white images, gray scale images and color images [1].

The characteristics of each type of images are as follows [1]:

1. For black and white images, each pixel is represented by one bit. These images are sometimes referred to as bi-level, binary, or bi-tonal images.
2. For gray scale images, each pixel is represented by a luminance (or intensity) level. For pictorial images, typical gray scale images are represented by 256 gray levels, or 8 bits. For document images, 4-7 bits are usually sufficient.
3. Color images have multiple components. Each pixel of a color image can be represented by luminance and chrominance components.

Digital images have a broad spectrum of applications. These include imaging applications in office automation, insurance claim processing, bank check processing,

government tax processing and many others. Medical imaging, photographic processing and imaging applications in security industry are examples of gray scale image applications.

Medical image processing has modernized the way of analyzing medical images and extracting and visualizing anatomical regions of interest. Image processing is a method of signal processing that takes an image as input, like photographs or frame of video; and outputs either an image or a set of characteristics or parameters related to the image. Most of the image processing techniques normally involve processing the image as a 2-D signal and applying standard signal-processing techniques to it. Some image processing operations are given below:

- Color corrections such as brightness and contrast adjustments, quantization, or color translation to different color space.
- Digital compositing or optical compositing
- Image registration, the alignment of two or more images
- Image recognition
- Image segmentation etc.

Segmentation is a method of dividing an image space into some non-overlapping meaningful homogeneous regions that are holding some homogeneous properties. Segmentation of 2-D and 3-D images allows medical data analysis that can help in automatic feature detection, visualization, image-guided surgery and also for registration of different images.

**Medical Image Segmentation:** Segmentation partitions an image into its component regions or objects. The level to which the subdivision is carried depends on the problem being solved. That is, segmentation should stop when the objects of interest in an application have been isolated. We can further analyze each of the objects present in the image or subdivide or extract the information which can be useful for vision applications. Image segmentation is defined as the partitioning of an image into



non-overlapping, constitutes region which are homogenous with respect to some characteristics such as intensity or texture [15]. In this study, it is assumed that the image is collection of granules. On image, granulation is applied to make granule using window of size  $n \times n$ . Granule is a clump of objects put together based on some properties.

Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. . This is the process of subdividing an image into the constituent part or object in the image, so we can further analyze each of the objects present in the image or subdivide or extract the information which can be useful for vision application.

Granulation process provides a meaningful designation to each region or class. Image analysis applications highly dependent on the success of the autonomous segmentation of object or segmented images. Image segmentation is used to identify objects and boundaries, and it assign a label to each pixel according to the visual characteristics [16]. Segmentation algorithms for monochrome images generally are based on one of two basic properties of image intensity values:-

1. **Discontinuity:** - In this category, the approach is to partition an image based on abrupt changes in intensity, such as edges in an image.
2. **Similarity:** - This second category is based on partitioning an image into regions that are similar according to a set of predefined criteria.

### 2.4.1 Discontinuity Based Segmentation

Methods suitable for detecting intensity discontinuities such as points, lines, and edges in image is looking for discontinuities is to run a mask through the image. The mask involves procedure to compute the sum of products of the coefficients with the intensity levels contained in the region encompassed by the mask.

$$R = w_1 z_1 + w_2 z_2 + \dots + w_9 z_9, \quad R = \sum_{i=1}^9 w_i z_i$$

That is, the response,  $R$ , of the mask at any point in the image is given by [2]. (For 3x3 mask), where  $z_i$  is the intensity of the pixel associated with the mask coefficient  $w_i$ .

**Point Detection:** The detection of isolated points embedded in areas of constant or nearly constant intensity in an image is straightforward in principle. Using the mask shown in figure 2.3, it will define that an isolate point has been detected at the location on which the mask is centered if  $|R| \geq T$  where,  $T$  is a non-negative threshold.

-1	-1	-1
-1	8	-1
-1	-1	-1

Figure 2.3: The 3x3 mask for point detection

**Line Detection:** The next level of complexity is line detection. Consider the mask in fig. 3, if the first mask were moved around an image, it would respond more strongly to lines (one pixel thick) oriented horizontally. With a constant background, the maximum response would result when the line passed through the middle row of the mask. Similarly, the second mask in fig. 4 responds best to lines oriented at  $+45^\circ$ ; the third mask to vertical lines; and the fourth mask to lines in the  $-45^\circ$  direction. The coefficients of each mask sum to zero, indicating a zero response from the mask in areas of constant intensity.

-1	-1	-1
2	2	2
-1	-1	-1

(a)

-1	-1	2
-1	2	-1
2	-1	-1

(b)

-1	2	-1
-1	2	-1
-1	2	-1

(c)

2	-1	-1
-1	2	-1
-1	-1	2

(d)

Figure 2.4: (a) Horizontal mask, (b)  $+45^\circ$  mask, (c) Vertical mask, (d)  $-45^\circ$  mask

**Edge Detection:** Edge detection is the most common approach for detecting meaningful discontinuities in intensity values. These discontinuities are detected by using first- and second-order derivatives. The first-order derivative of choice in image processing is the gradient. The gradient of a 2-D function,  $f(x, y)$ , is defined as the vector:

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

The magnitude of this vector is

$$\nabla f = \text{mag}(\nabla f) = [G_x^2 + G_y^2]^{1/2} = [(\partial f / \partial x)^2 + (\partial f / \partial y)^2]^{1/2}$$

To simplify computation, this quantity is approximated sometimes by omitting the square-root operation,

$$\nabla f \approx G_x^2 + G_y^2$$

Or by using absolute values,

$$\nabla f \approx |G_x| + |G_y|$$

These approximations behave as derivatives; that is, they are zero in areas of constant intensity and their values are proportional to the degree of intensity changes in area whose pixel values are variable. The magnitude of the gradient or its approximations simply called as "the gradient." A fundamental property of the gradient vector is that it points in the direction of the maximum rate of change of  $f$  at coordinates  $(x, y)$ . The angle at which this maximum rate of change occurs is:

$$\alpha(x, y) = \tan^{-1} \left( \frac{G_y}{G_x} \right)$$

Second-order derivatives in image processing are generally computed using the Laplacian filter of a 2-D function  $f(x, y)$  is formed from second-order derivatives, as follows:

$$\nabla^2 f(x, y) = \frac{\partial^2 f(x, y)}{\partial x^2} + \frac{\partial^2 f(x, y)}{\partial y^2}$$

The Laplacian is seldom used by itself for edge detection because, as a second-order derivative, it is unacceptably sensitive to noise, its magnitude produces double edges, and it is unable to detect edge direction. But its property can be used for edge location. The basic idea behind edge detection is to find places in an image where the intensity changes rapidly, using one of two general criteria:

1. Find places where the first derivative of the intensity is greater in magnitude than a specified threshold.
2. Find places where the second derivative of the intensity has a zero crossing.

There are some other Edge Detector named as Sobel, Prewitt, Roberts, Laplacian of a Gaussian (LoG), Zero Crossing, and Canny.

## 2.4.2 Similarity Based Segmentation

In image each pixels content intensity value. There are some techniques based upon a similarity property to Differentiate between pixels. These techniques are Histogram based Thresholding technique, Region Growing technique, Region Splitting and Merging technique. Histogram based approach are efficient in comparison to other image segmentation methods. In this technique histogram is being calculated from all the pixels of the image, and then peaks and valleys are drawn out of histogram. These peaks and valleys provide threshold value, which are used to locate the region in the image. This similarity property based technique divides lighter and darker region according to threshold value. Thresholding can be used to create binary images. If more than one threshold value has been selected to separate regions it is called multi-Thresholding

technique. There are various types of threshold like Global Threshold, Dynamic Threshold, Optimal Threshold, Local Threshold etc.

Thresholding technique is based upon a simple concept. A parameter called the brightness threshold is chosen and applied to the image  $(x, y)$  as follows [2], [9]:

If the algorithm assumes that we are interested in light objects on a dark background.

$$(x, y) = 1 \quad (x, y) \geq \text{Else} = 0$$

For dark objects on a light background we would use

$$(x, y) = 1 \quad (x, y) < \text{Else} = 0$$

The output is the label "object" or "background" which, due to its dichotomous nature, can be represented as a Boolean variable "1" or "0". If there are different three intensity regions then,

$$f(x, y) > T2 \Rightarrow f(x, y) \in O2$$

$$\text{if } T1 < f(x, y) \leq T2 \Rightarrow f(x, y) \in O1$$

$$\text{if } f(x, y) < T1 \Rightarrow f(x, y) \in \text{background}$$

Depending upon the threshold value it can be categorized in different Thresholding techniques whereas,

$$T = T[x, y, p(x, y), f(x, y)]$$

Where,  $(x, y) \Rightarrow$  Pixel location in an image,

$$f(x, y) \Rightarrow \text{Pixel intensity at } (x, y),$$

$$p(x, y) \Rightarrow \text{Local property in a neighborhood centered at } (x, y)$$

If  $T[f(x, y)] \Rightarrow$  Then it will be global Thresholding

$T[f(x, y), p(x, y)] \Rightarrow$  It will be local Thresholding

$T[(x, y), f(x, y), p(x, y)] \Rightarrow$  Dynamic Thresholding

Global Thresholding is one way to choose a threshold by visual inspection of the image histogram. The histogram in figure 2.5 clearly has two distinct modes; as result, it is easy to choose a threshold  $T$  that separates them. Another method of choosing  $T$  is by trial and error method, picking different thresholds until one is found that produces a good result as judged by the observer. For choosing a threshold automatically, Gonzalez and Woods [2002] describe the following iterative procedure:

1. Select an initial estimate for  $T$ . (A suggested initial estimate is the mid-point between the minimum and maximum intensity values in the image.)
2. Segment the image using  $T$ . This will produce two groups of pixels:  $G_1$  consisting of all pixels with intensity values  $\geq T$ , and  $G_2$ , consisting of pixels with values  $< T$ .
3. Compute the average intensity values  $\mu_1$  and  $\mu_2$  for the pixels in regions  $G_1$  and  $G_2$ .
4. Compute a new threshold value:

$$T = \frac{1}{2}(\mu_1 + \mu_2)$$

5. Repeat step 2 through 4 until the difference in  $T$  in successive iteration is smaller than a predefined parameter  $T_0$ .

Global Thresholding methods can fail when the background illumination is uneven. A common practice in such situation is to preprocess the image to compensate for the illumination problem and then apply a global threshold to the preprocessed image.

$$\begin{aligned} g(x, y) &= 1 \quad \text{if } f(x, y) \geq T(x, y) \\ &= 0 \quad \text{if } f(x, y) < T(x, y) \end{aligned}$$

$$\text{Where } T(x, y) = f_0(x, y) + T_0$$

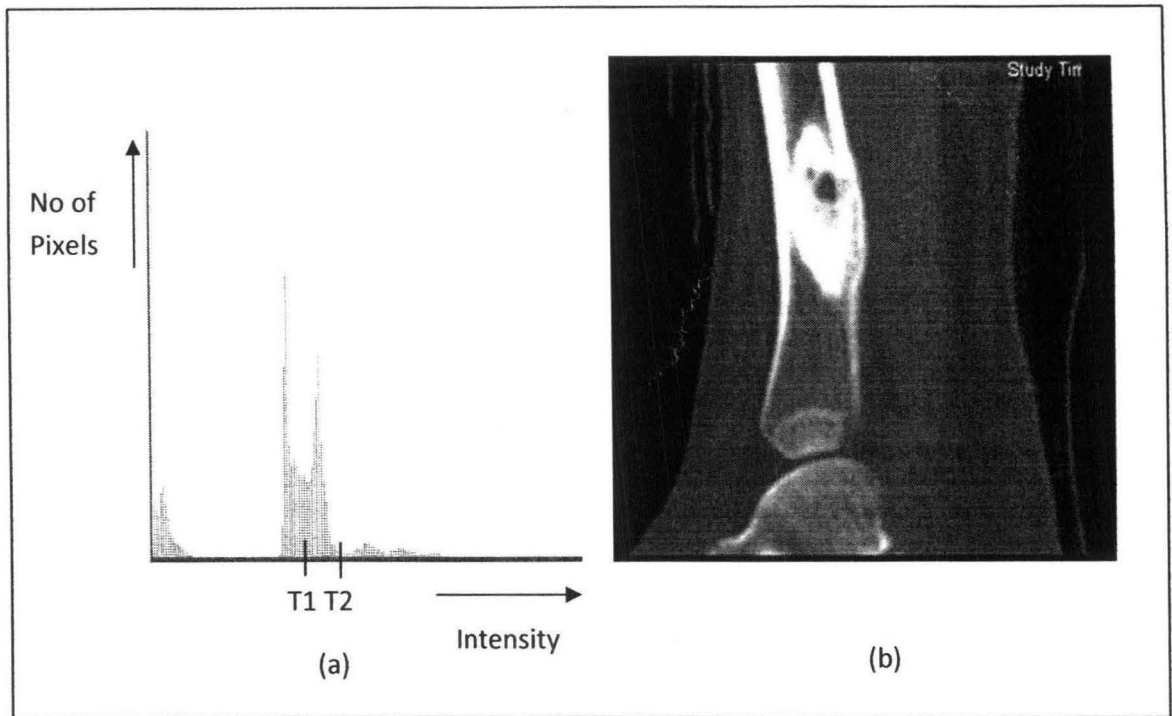


Figure 2.5: (a) Image of Histogram, (b) CT Scan image

This process is equivalent to Thresholding  $f(x,y)$  with a locally varying threshold function  $T(x,y)$ .

Region growing is procedure that groups the pixels or sub regions into larger region based on predefined criteria for growth. The basic approach is to start with a set of "seed" points and from these grow regions by appending to each seed those neighboring pixels that have predefined properties similar to the seed.

Let  $R$  represent the entire image region. We may view segmentation as a process that partitions  $R$  into  $n$  sub regions,  $R_1, R_2, \dots, R_n$ , such that [2]

- (a)  $\coprod_{i=1}^n R_i = R$ . (The segmentation must be completed; that is, every pixel must be in a region.)
- (b)  $R_i$  is a connected region,  $i = 1, 2, \dots, n$ . ( Point in a region be connected in some predefined sense (e.g., 4- or 8-connected).)
- (c)  $R_i \cap R_j = \emptyset$  for all  $i$  and  $j$ , and  $j, i \neq j$ . (the regions must be disjoint)

(d)  $P(R_i) = \text{TRUE}$  for  $i = 1, 2, \dots, n$ , (It deals with the properties that must be satisfied by pixels in a segmented region.)

(e)  $P(R_i \sqcup R_j) = \text{FALSE}$  for any adjacent regions  $R_i$  and  $R_j$ . (It indicates that adjacent region  $R_i$  and  $R_j$  is different in the sense of predicate  $P$ .)

Here  $P(R_i)$  is logical predicates defined over the points in set  $R_i$  and  $\emptyset$  is the null set.



## CHAPTER 3

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# GRANULATION BASED MEDICAL IMAGE SEGMENTATION

The base algorithm proposed by M. M. Mushrif and A. K. Ray uses the concept of Histon [8] and Roughness Measures [6] for segmentation of full color image. This algorithm has not been reported to be applied on gray scale images and medical images. Hence, Granulation approach has been applied on the images. These images are partitioned in small windows  $G_{m \times n}$  of regular size, where  $m$  and  $n$  are dimensions of the window. These windows are Granules, which leads to the construction of a modified image with reduced data but size remains the same. This modified image is then used to find peak and valley in histogram and graph of roughness based on similarity on the image for segmentation.

### 3.1 Base Algorithm

In base algorithm, Roughness measure at each intensity level is calculated and threshold method is applied on it for image segmentation process. This algorithm is used to see the results in RGB based full color image. The Histon is calculated through Euclidean distance between two pixels (on the basis of color space), for 3x3 neighbors for each pixel.

#### 3.1.1 Histon Computation

Consider  $I$  to be the medical image with intensity of gray scale values of size of  $M \times N$ . Therefore the Histogram of the image can be computed as follows [6]:

$$h(g) = \sum_{m=1}^M \sum_{n=1}^N \delta(I(m,n) - g)$$

for  $0 \leq g \leq L - 1$

Where  $\delta(\cdot)$  the Dirac impulse function and  $L$  is the total number of intensity levels in gray scale image. The value of each bin of  $g$  is having the number of image pixels of same intensity. The Euclidean distance between two pixels  $I(m, n)$  and  $I(p, q)$  is given by equation below, but Euclidean distance will be same as Manhattan distance if it is calculated for two points.

$$d(I(m, n), I(p, q)) = \sqrt{(I(m, n) - I(p, q))^2} = |I(m, n) - I(p, q)|$$

The  $P \times Q$  neighborhood is around a pixel  $I(m, n)$ , to calculate the total distance of the all pixels in the neighborhood with the pixel  $I(m, n)$  is then given by:

$$d_T(m, n) = \sum_{p \in P} \sum_{q \in Q} d(I(m, n), I(p, q))$$

The pixels in the neighborhood fall in the sphere of the similar color if the distance  $d_T(m, n)$  is less than expanse. Color expanse for the gray scale image is taken 60 after experiment the outcomes. A matrix  $X$  of the size  $M \times N$  has been defined such that an element  $X(m, n)$  is given by:

$$X(m, n) = \begin{cases} 1 & d_T(m, n) < \text{expanse} \\ 0 & \text{otherwise} \end{cases}$$

Histon has been calculated as,

$$H(g) = \sum_{m=1}^M \sum_{n=1}^N (1 + X(m, n)) \delta(I(m, n) - g)$$

for  $0 \leq g \leq L - 1$

### 3.1.2 Roughness Measure Computation

The Histogram value of the  $g^{\text{th}}$  intensity is the set of pixels, which definitely belongs to the class of intensity  $g$  and therefore, can be considered as the lower approximation and the Histon value of the  $g^{\text{th}}$  intensity represents all the pixels, which belongs to the class of similar color and therefore, may be considered as the upper approximation. The vector of roughness measure can be defined as

$$\rho(g) = 1 - \frac{|h(g)|}{|H(g)|}$$

$$\text{for } 0 \leq g \leq L - 1$$

### 3.1.3 Criteria to Select Peak and Valley

Roughness index gives global distribution of uniform regions in the image. Peaks and valleys in the graph of roughness index and its threshold applied to the image. Selection of right peaks and threshold are important criteria to produce good segmentation results, hence the selection of significant peaks is based on distance between two peaks and height of the peaks. After the significant peaks are selected, valleys are obtained by finding the minimum values between every two peaks. According to [6], criteria for obtaining the significant peak

- (i) The peak is significant if the height of the peak is greater than 20% of the average value of roughness index for all the pixel intensities.
- (ii) The peak is significant if the distance between two peaks greater than 10.

## 3.2 Granulation Based Segmentation Method

Granulation approach is applied on medical image, to study whether it is forming object or region of interest. Granulation has been done by making granules of window size  $m \times n$ . It is of regular shape which reduces the data information by assigning mean value of

window to all pixels in the window, whereas image's original size remains the same. After that roughness measure is calculated and subsequently peaks and valleys are identified, which is applied on an original image for segmentation process. There are two types of granule windows taken for experimentation:

**Granule window size 2x2 ( $G_{2 \times 2}$ ):** Granule of size 2x2 window has been applied to the image by calculating the mean of the pixel in the window and putting the resultant value on each pixel of the same window as shown in figure, where p1, p2, p3, p4 are pixels lying under window and this window will make one granule, where each pixel will be assigned mean value of window. Likewise other window would be selected in same manner. Here, window of size m x n ( $n=m=2$ ) is taken every time, in sequential manner.

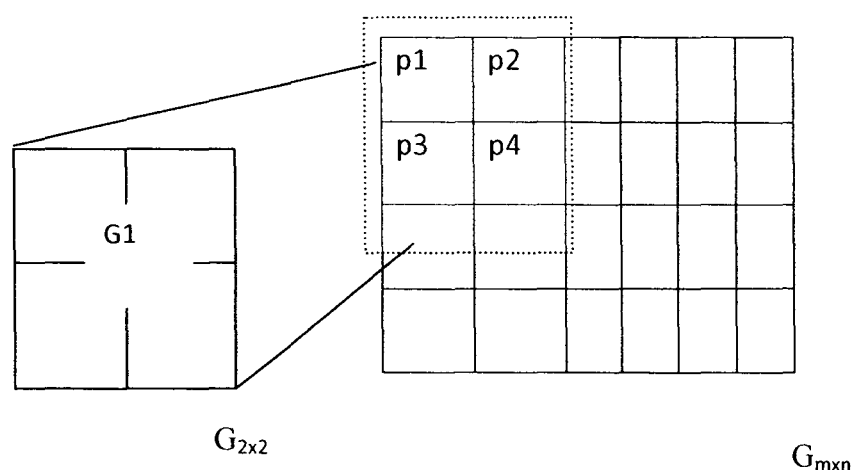


Figure 3.1: Granule using window size 2

**Granule window size 3x3 ( $G_{3 \times 3}$ ):** Granule of size 3x3 window has been also done in same manner as for granule size of 2, where window size of m x n ( $n=m=3$ ) is used and it will continue till end of the pixel in the image, sequentially. Applying bigger size of window will reduce more data information of the image but will not reduce the original dimension of the image.

## 3.3 Proposed Granulation Based Algorithm

The procedure for the Medical Image segmentation using Granulation approach is presented below and it consist of following steps:

*Step 1: Convert an image into modified image by applying granule window  $G_{m \times n}$ . It leads to same value in each pixel of window.*

*Step 2: Calculate the histogram using Dirac Impulse function for*

*$\delta(x) = +\infty$ , when  $x = 0$ ; else 0, when  $x \neq 0$ . It is calculated for all the pixels of image.*

*Step 3: Calculate the Histon value for each pixels in the image.*

*Step 4: Calculate the Roughness Measure.*

*Step 5: Find out significant peak.*

*Step 6: Obtain valleys by finding the minimum values between every pair of peaks.*

*Step 7: Select threshold values and apply it on image to get regions.*

*Step 8: Apply modified 8-connected component labeling approach to make clusters out of regions.*

## 3.4 Implementation

### 3.4.1 System Specification

#### Software Requirements

- i) Platform: Windows XP SP2
- ii) Framework: None
- iii) IDE: Dev C++

- iv) Packages: gcc, win32
- v) Applications:
  - Any image viewer, windows picture and fax viewer suffice
  - Any text editor, notepad in windows will suffice
- vi) Utility: Image conversion utility for converting images to BMP

### Hardware Requirements

- i) Processor: Intel Pentium 4/Dual Core (1.5/1.7 GHz)
- ii) RAM: 512 MB Minimum, 1 GB preferred
- iii) Hard disk Space: 800 MB Minimum Free Space
- iv) VDU: Color VGA with minimum resolution of 800x600 dpi
- v) Input: Keyboard, MM preferred
- vii) Pointing Device: Mouse, optical preferred

### 3.4.2 Implementation Details

The proposed algorithm is implemented and an interactive application has been developed in C language. Throughout the study Roughness Measure and Granulation based method for Image Segmentation are applied on four image data.

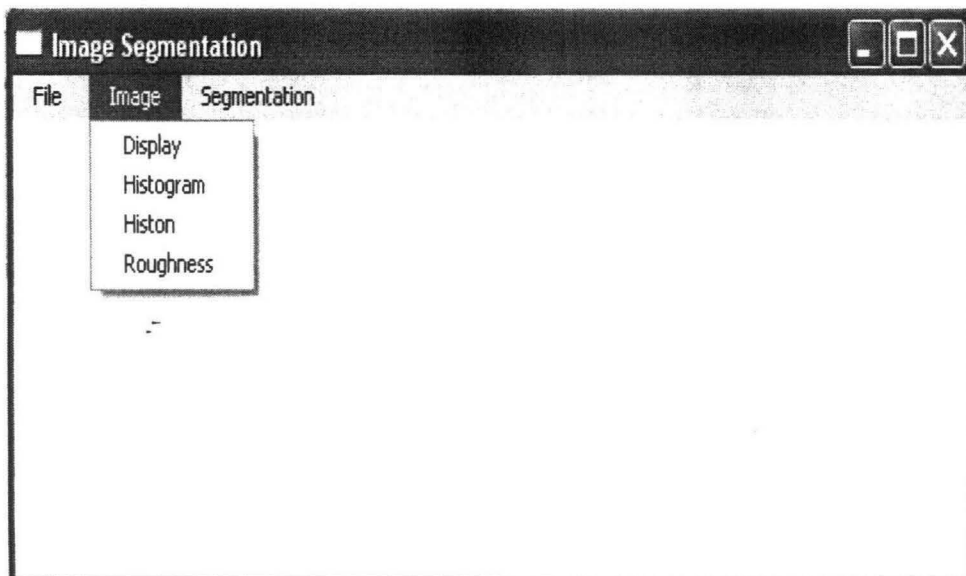


Figure 3.2: Snap Shot 1

### The salient features of the application are:

i) The application is a GUI based application that is capable of displaying all results. Any Bitmap (.BMP) Image can be loaded using menu option File->Load. Image is loaded and converted into two dimensional array of image pixel value (grayscale intensity value). If image is not a grayscale but colored one then it is converted into grayscale. The loaded image can be displayed through menu option Image->Display. Granulation is applied on the array.

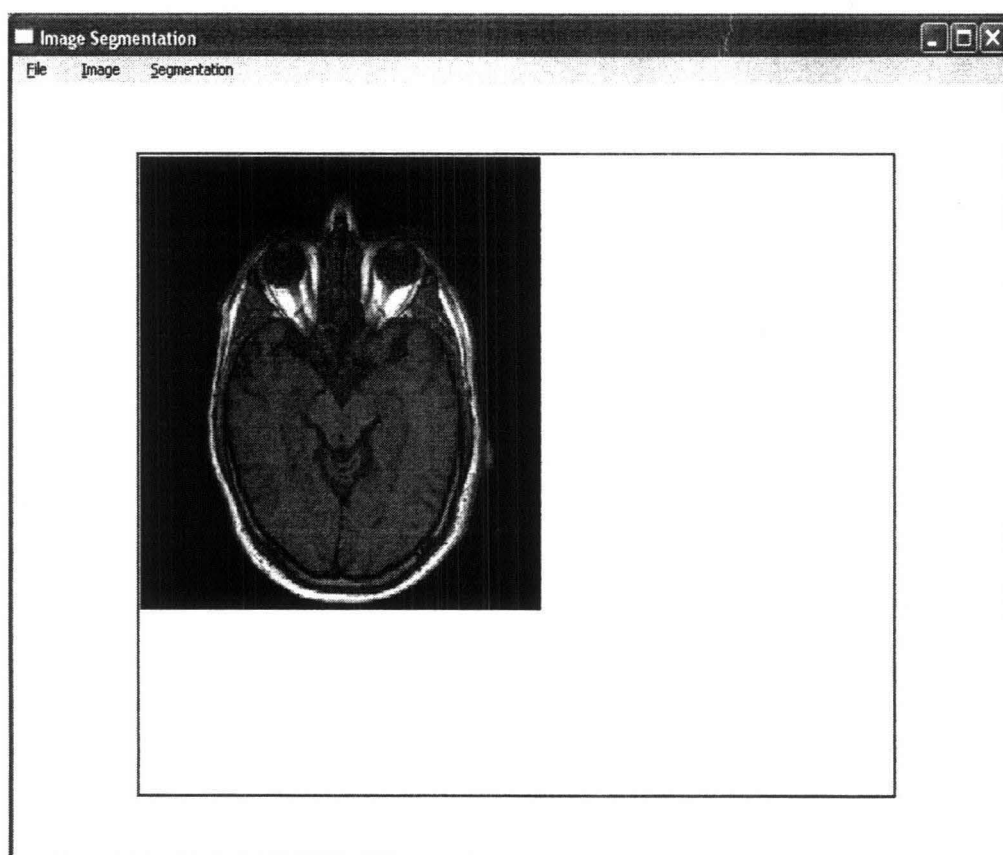


Figure 3.3: Snap Shot 2

ii) Histogram implemented to display the image by considering no. of pixel vs. intensity. The visual of the Histogram is accessible through menu option Image -> Histogram.

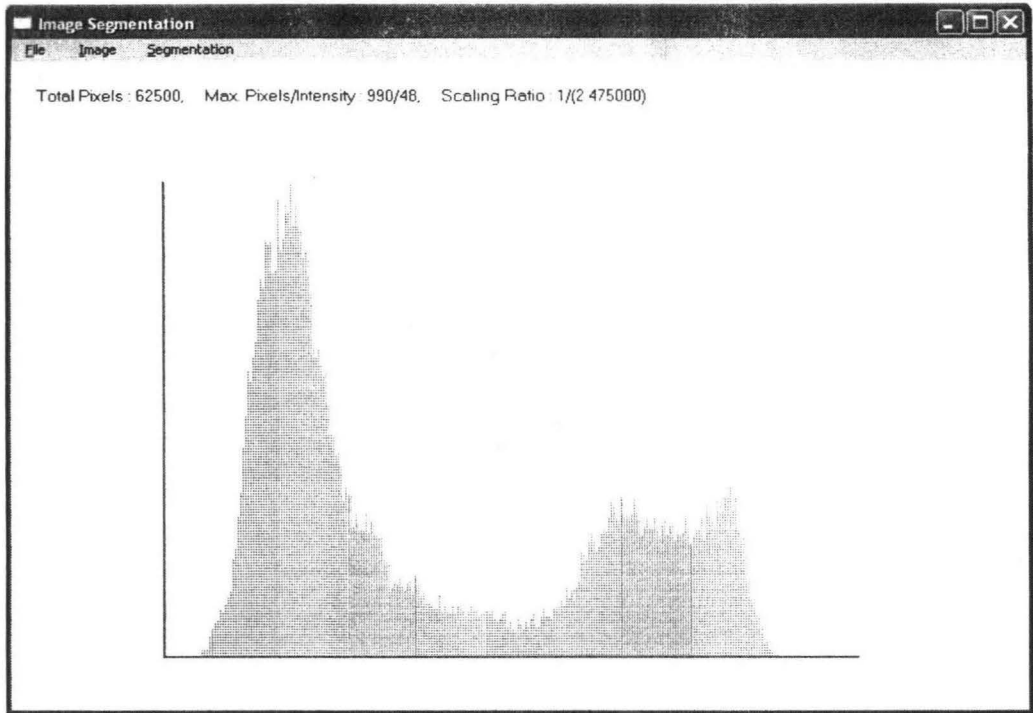


Figure 3.4: Snap Shot 3

iii) Histon is implemented as presented in section 3.1.1 after determining each pixel's relativity with its neighborhood. The pixels are assigned weightage of 2 or 1 depending upon whether they are relative to their neighborhood or not. The pixel's weightage are then added to their associated intensity bin. The visual of Histon is accessible through menu option Image->Histon.

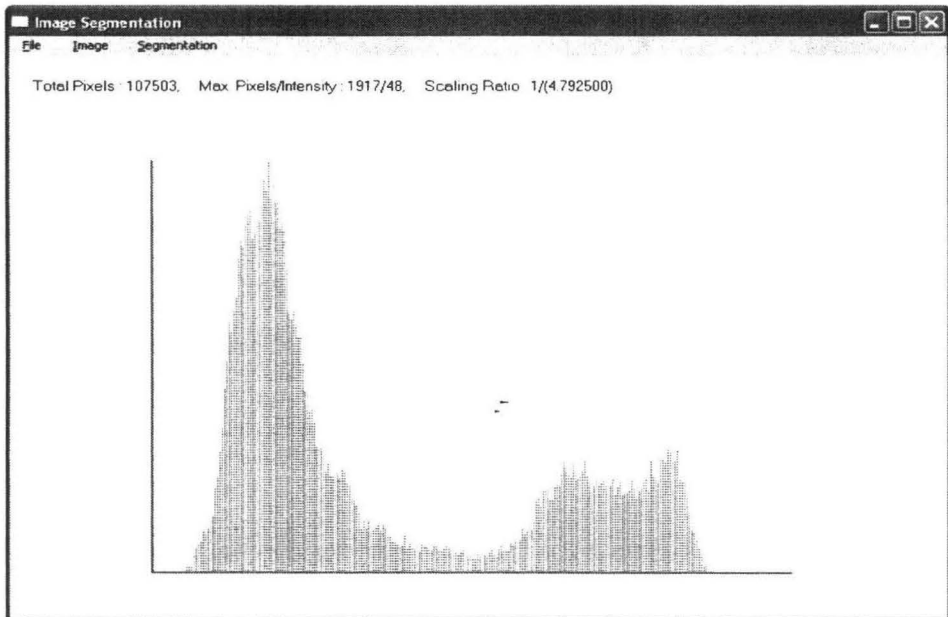


Figure 3.5: Snap Shot 4



Roughness is calculated by taking Histogram as lower approximation and Histon as upper approximation. It is accessed through menu option Image->Roughness.

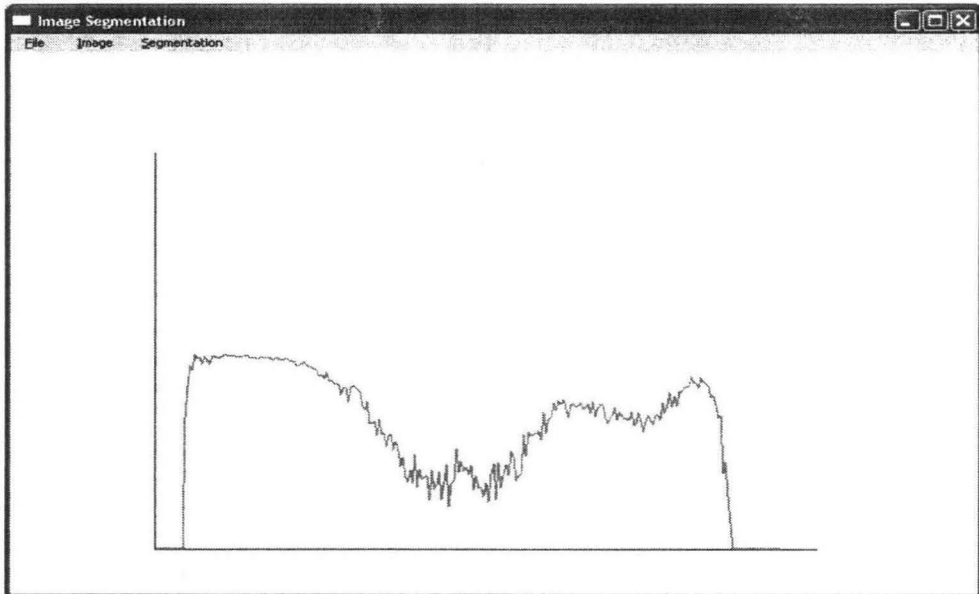


Figure 3.6: Snap Shot 5

iv) The Regions are identified by segmenting the image using peak values and each pair of consecutive valleys on the histogram. Results of region in form of pixel information are stored in .txt, which is presented here:

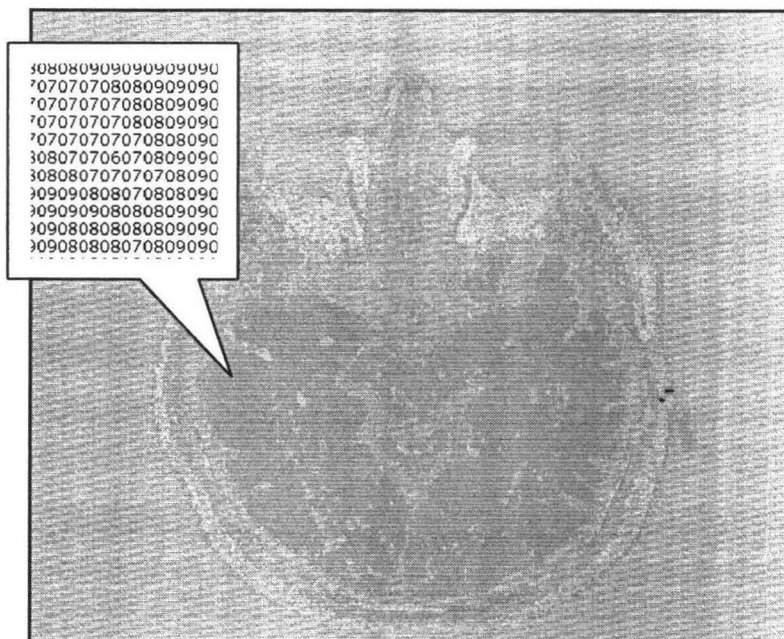


Figure 3.7: Regions of MRI

Each region is marked by a color values randomly assigned to similar pixels, i.e., a particular color in display image represents a region. Region is accessed through menu option Segments->Region.

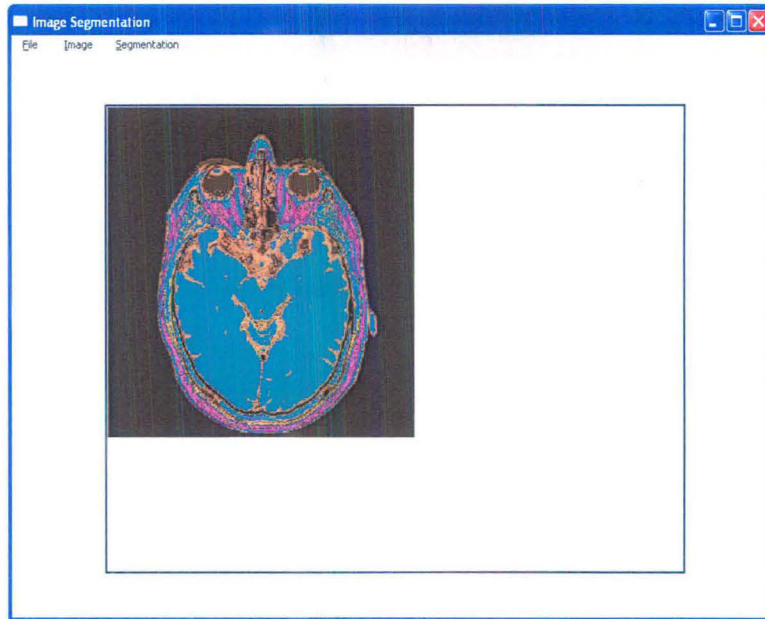


Figure 3.8: Snap Shot 6

Initially, all regions are visible. Left click on any region displays that colored region.

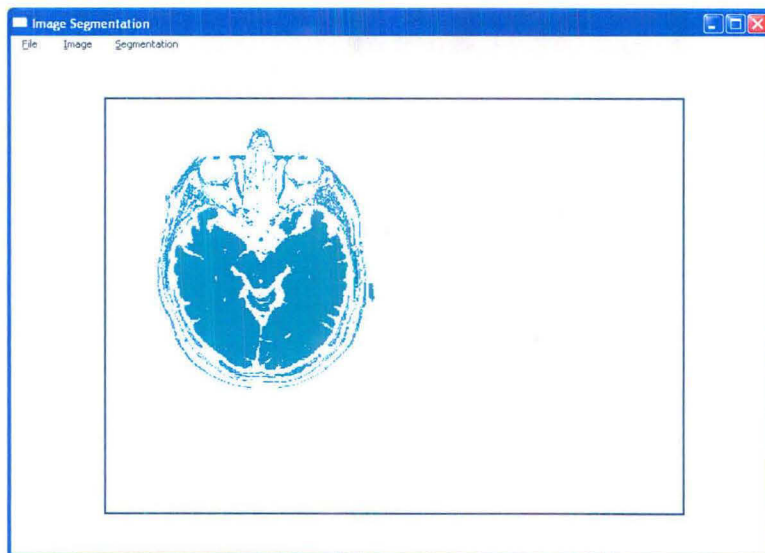


Figure 3.9: Snap Shot 7

Right click on any region will display the actual image under the clicked region.

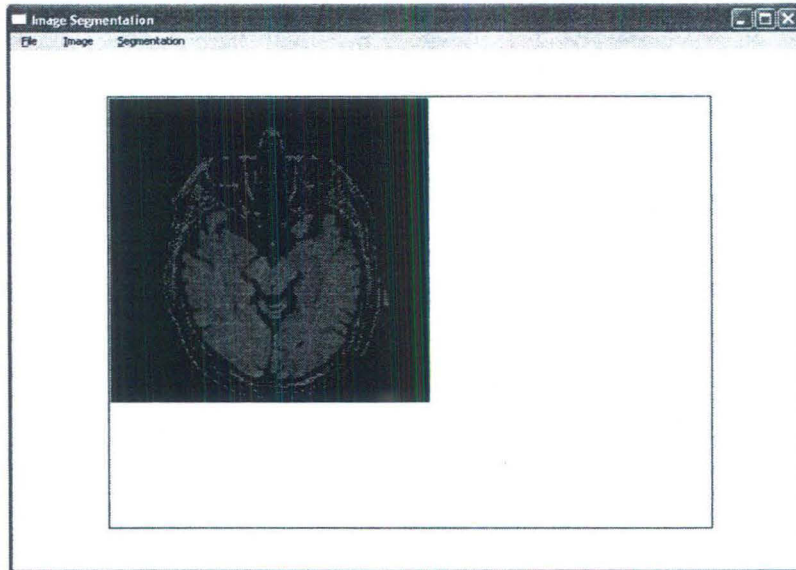


Figure 3.10: Snap Shot 8

v) The application finds clusters in identified regions using 8-connected component labeling. All results are stored in related text files which are clusters.txt, max\_clusters.txt, region\_range.txt, regions.txt, rough.txt, peaks.txt.

The results of the experiment are stored in .txt file in form of information of intensity of each pixel; it has been used for evaluating regions and the clusters. The glimpse of MRI image of brain using text file for storing region values presented in figure 3.7 which is useful for further calculation of clustering and region merging.

## CHAPTER 4

### EXPERIMENTS AND RESULTS

#### 4.1 Data Description

The Image formats supported by the application are 8 bit Bitmap and 24 bit Bitmap. The file extension of supported format is “.BMP”. Bitmap image stores the information of each pixel in 1 byte in 8 bit format or 3 byte in 24 bit format.

The 1 byte value pertains to pixel intensity in grayscale image or it may be an index to color palette of RGB (Red, Green, Blue) triplet. The value range is always 0-255 (unsigned char value range).

The 3 byte value directly stores the RGB triplet value in reverse order (BGR). Color palette is not present in 24 bit BMP. Each byte of triplet represents the intensity of its particular color channel. For experiment four medical images are used, these are **T<sub>1</sub> Weighted Axial MRI of Brain (320x320)**, **CT-Scan of Orthopedic image (320x311)**, **Ultra Sound image of uterus (320x266)**, **Mammogram of the breast (400x292)**. Structure of Bitmap file format supported is present in table 1.

**Table 4.1 Bitmap File Format**

<b>BMP File Header</b>	14 Byte
<b>Bitmap Information (DIB header)</b>	40 Byte
<b>Color Palette</b>	0 byte (24 bit BMP) or 1024 byte (8 bit BMP)
<b>Bitmap Data</b>	Variable Size.

The application developed for the work of dissertation basically deals with grayscale image. Grayscale image contains gray shades (shades between black and white without any color component) in each image pixel. Grayscale image is mainly stored as 8 bit

bitmap with each pixel byte holding grayscale intensity referring to color palette entry that again is a grayscale combination of RGB (same value in each one of RGB makes it grayscale value). The 24 bit image can also be used as grayscale image. A triplet of 3 byte can have same value to represent a grayscale pixel.

## 4.2 Experiments & Results

The experiments of four different medical images are used to evaluate the performance of the algorithm in terms of no. of cluster and region. The performance of the base algorithm was evaluated for Roughness Measure and Histogram to find out peaks and valleys for segmentation. The first experiment is to observe the outcome of the segmentation in terms of data and visual empirical aspects. The second experiment is proposed to extend the base algorithm techniques. It is by performing granulation on the image,  $G_{2 \times 2}$  and  $G_{3 \times 3}$  window size is used to make granule and draw out a modified image. In this modified image Roughness Measure has been calculated. The Gray scale based image in best with the expanse value 60. After finding peaks and values, its threshold value applied to the image which is taken to do experiment and then results are evaluated.

### 4.2.1 Experimental Details

Experiments have been perform on the four medical data image, which evaluate clusters and region and give visual empirical view on the segmented region and cluster of the image. In this section outcome of execution of the base algorithm and proposed Granular Computing based approach for MRI image has been also presented. Base algorithm has been executed for MRI image. The proposed algorithm was also executed for the two generated images each of granule window size  $G_{2 \times 2}$  and  $G_{3 \times 3}$ . Respectively the details of implemented results are presented below.

- (1) Convert an image into modified image by applying a Granule window  $n \times n$ .
- (2) Generate Histogram using Dirac Impulse function.

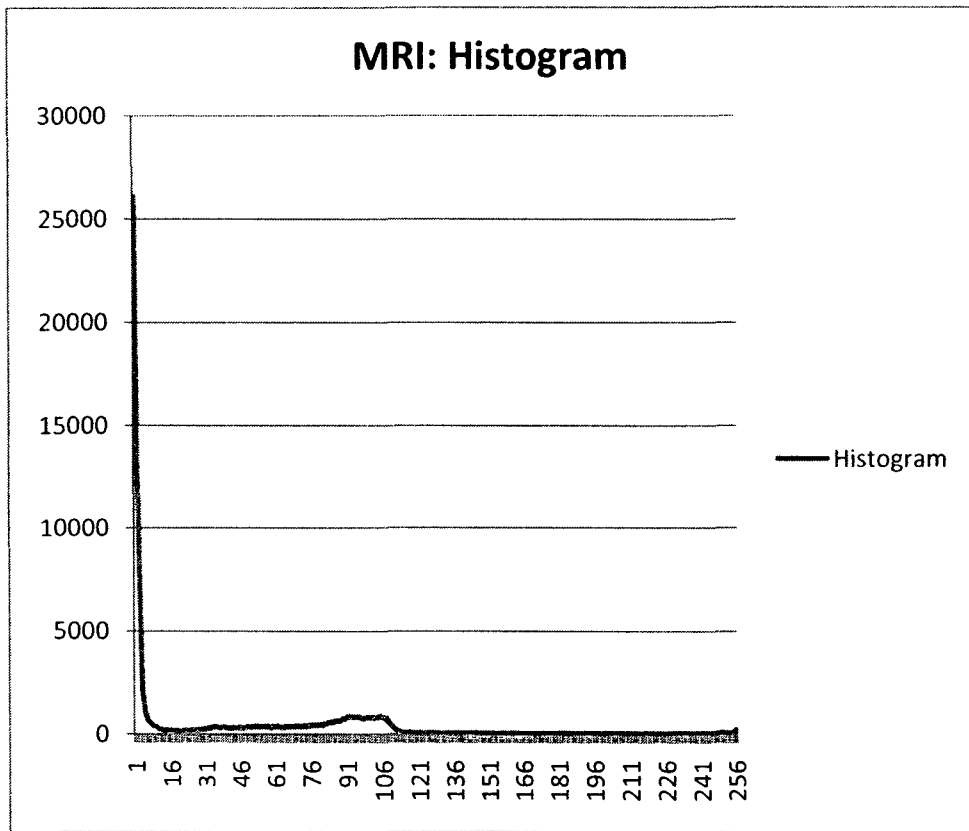


Figure 4.1: Histogram for MRI

(3) Generate Histon using Histogram and a matrix X calculated by expanse. The expanse is taken 60 for medical image which have been giving the best result for medical images. Calculate the Euclidean distance between two pixels  $I(m, n)$  and  $I(p, q)$ ; this is useful to calculate the expanse. For computing the Histon, the selection of two parameters are very important, the neighborhood and the expanse. Neighborhood is the window 3 x 3 that decides the pixels involved in the calculation of expanse which is selected to compute total distance of all the pixels. Neighborhood pixels and the pixel  $I(m, n)$  are calculated for the matrix X of size MxN.

(5) Calculate the roughness measure for each pixel as Roughness index of intensity.

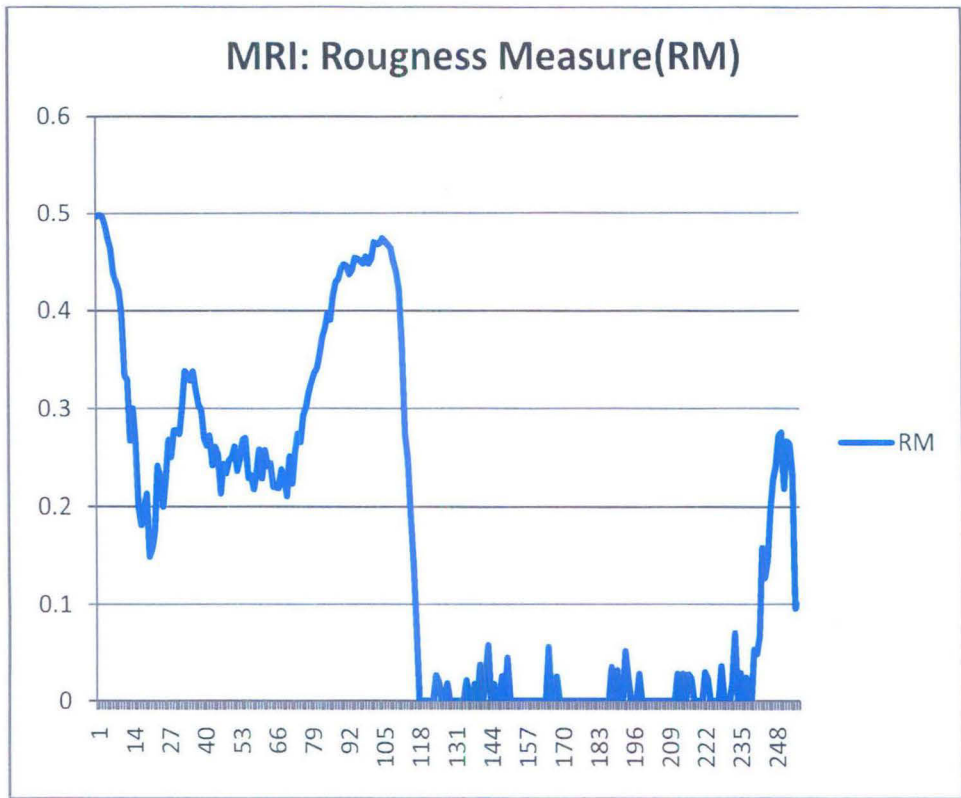


Figure 4.2: RM for MRI Image

Step 6: Find significant Peaks and valleys for Histogram and for Roughness Index.

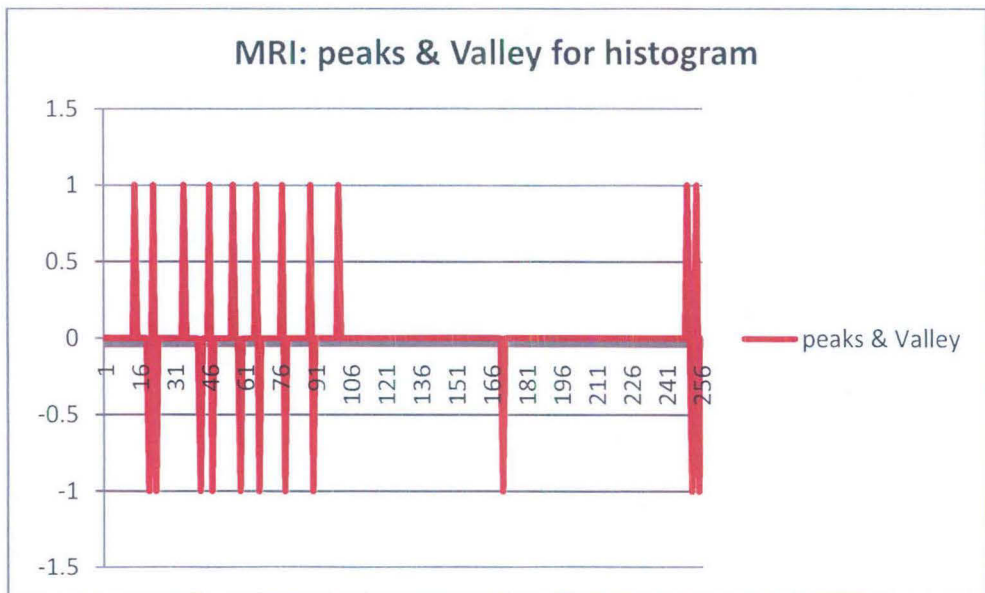


Figure 4.3: Peaks and Valleys of RM for MRI

(7) Select threshold values and apply on to segment the image and to get regions base on similarity.

(8) Find out cluster through region by using 8-connected component labeling method. It also helps to color cluster for visibility aspect of medical image.

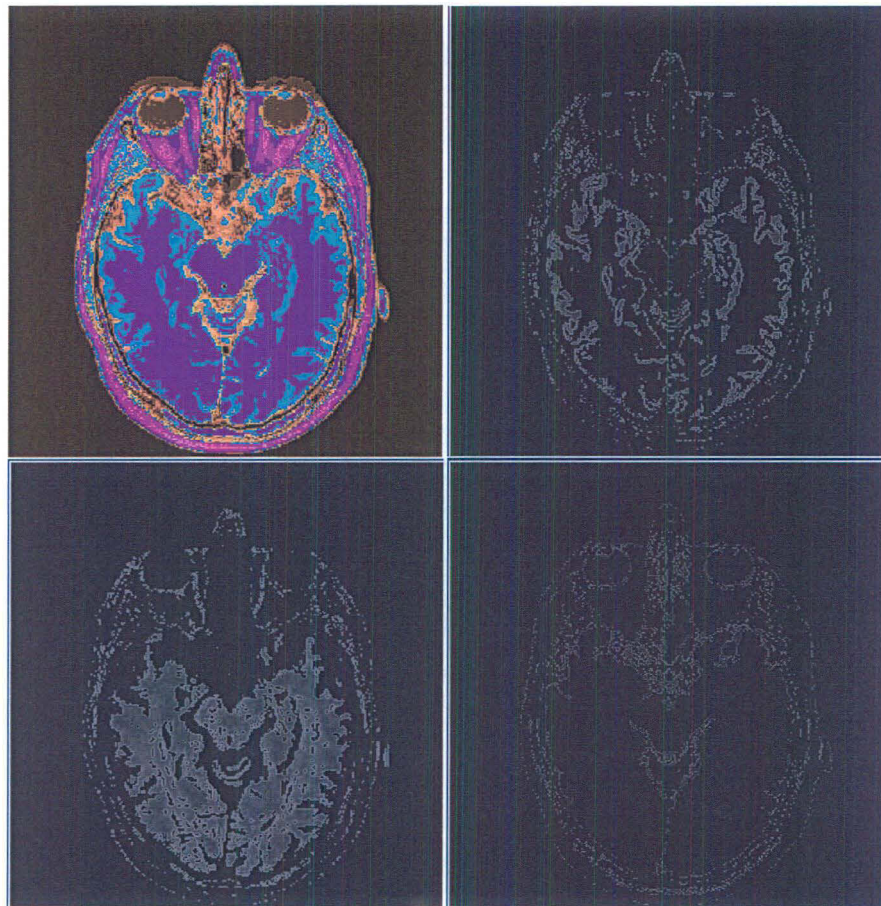


Figure 4.4: Regions of MRI Image

### 4.2.2 Results and Analysis

The result of segmentation of four medical MRI, CT Scan, Ultra Sound, Mammography images have been observed in terms of number of Cluster and number of Regions for the base algorithm and the proposed algorithm. The performances are measured for Histogram (Hist) and Roughness Measure (RM). The Proposed algorithm has been executed for the performance over Histogram and Roughness Measure. The outcomes



of segmentation of the four images using image histogram and the base algorithm using Roughness Measure (RM) is presented in table 4.2, 4.3, 4.4 and 4.5, further the results of the second experiment using the proposed granulation based algorithm for medical images have also been observed. The outcomes in terms of number of Clusters and number of Regions for segmentation of all the four medical images MRI, CT-Scan, Ultra Sound, Mammogram for granulated images names  $G_{2 \times 2}$  and  $G_{3 \times 3}$  have been presented in table. The observation have been presented again for histogram based segmentation and Roughness Measure (RM).

It may be observed that all the four medical images are from different types of sources. Therefore the outcome of each is not comparable with the other. However the outcome in terms of number of Clusters and number of Regions for each image when different algorithms are applied may be compared.

**Table 4.2: Experiment 1 Regions for Histogram**

Image Data	Number of Regions		
	Image	$G_{2 \times 2}$	$G_{3 \times 3}$
MRI	12	11	22
CT-Scan	22	21	22
Ultra Sound	23	18	18
Mammogram	24	22	22

**Table 4.3: Experiment 2 Regions for RM**

Image Data	Number of Regions		
	Image	$G_{2 \times 2}$	$G_{3 \times 3}$
MRI	23	25	24
CT-Scan	23	24	23
Ultra Sound	20	23	21
Mammography	24	25	24

**Table 4.4: Experiment 3 Clusters for Histogram**

Image Data	Number of Clusters		
	Image	$G_{2 \times 2}$	$G_{3 \times 3}$
MRI	68	57	50
CT-Scan	50	52	60
Ultra Sound	129	102	102
Mammography	68	70	82

**Table 4.5: Experiment 4 Clusters for RM**

Image Data	Number of Clusters		
	Image	$G_{2 \times 2}$	$G_{3 \times 3}$
MRI	50	48	38
CT-Scan	40	41	47
Ultra Sound	117	102	119
Mammography	89	82	88

### 4.2.3 Comparison

In the experiments, number of Clusters and number of Regions are evaluated with the help of four different medical images. There are no significant changes in the values of the regions and the clusters for Histogram and RM. There are some observations from the experiment tables; Regions for CT-Scan of the base algorithm and the granulated image  $G_{3 \times 3}$  for histogram and RM have been providing the same data value, region for Mammogram image of Histogram based experiment and for RM based experiment are giving same result.

The concept of granulation for medical images has future aspect as it gives the relatively similar result in terms of clusters and region, but in terms of visualization it is presenting clear view and region of interest of the area or object. Medical practitioner had empirically observed the medical images, where the  $T_1$  weighted axial MRI (Anatomy) image of brain have been able to show visual area of gray matter and white matter and other important part of brain, sagittal reconstruction of non-contrast CT-Scan of leg showing irregular sclerotic lesion with lytic centroid focus in the metadaiphysis of tibia, Image of uterus in the ultrasound able to show grown up fetus, mammogram of breast also showing well defined high density mass.

## CHAPTER 5

---

### CONCLUSION AND FUTURE WORK

#### 5.1 Conclusion

Based on the analysis of experiment results in this study, concept of granulation in term of windows as granules is successfully implemented. Application is developed successfully in C language. There are no significant differences in the experiment results in terms of number of clusters and number of regions, that have been observed from the experiment using Roughness Measure and Granulation based approach for medical image segmentation. Regions are enhanced by coloring, so that visual analysis of the medical images has been possible.

The visual observations of the proposed algorithm have been able to distinguish better between gray matter and white matter of  $T_1$  Weighted Axial in MRI of brain image. Sagittal reconstruction of non-contrast CT-Scan of the leg had been showing irregular sclerotic lesion with the lytic centroid focus in the metadiaphysis of tibia, which is clearly observed. Fetal Ultra sound image has been able to identify the grown up fetus in the uterus. In the mammogram of the breast, the high density mass was clearly visible.

By the use of the Granular computing based medical image segmentation the computation load on the execution of algorithm can be significantly reduced, in comparison to Roughness Measure based approach for segmentation. The Granular computing based segmentation of  $G_{2 \times 2}$  could reduce data of the image matrix using the average intensity value in the ration of 4:1 information and for the window in the  $G_{3 \times 3}$  ratio is 9:1. It is enhancement of the algorithm in terms of medical image processing for image segmentation.

## 5.2 Future Work

In this dissertation medical images have been used for Granular computing based medical image segmentation. Some future extensions of this work have been mentioned below:

- 1) There are possibilities to using granulation through  $G_{n \times n}$  also for color images, satellite images image etc.
- 2) This approach may also be useful for the object detection problem is the image data or also focus on some region of interest.
- 3) In this dissertation for image segmentation only regular size of windows  $n \times n$  have been used, whereas  $m \times n$  size of windowing or supervised granulation may be explored.
- 4) Smoothing technique can be applied on the peaks of the image after finding histogram (graph) of granulated modified image.

# **APPENDIX A**

---

## A1: Procedure for Computing the Histogram

```
/* Histogram */  
  
Procedure createHistogram(Image[Row][Column])  
Begin  
  For intensity = 0 to 255  
    Begin  
      For r = 0 to Row  
        Begin  
          Initialize pixels_at_intensity = 0;  
          For c = 0 to Column  
            Begin  
              /* Dirac Impulse/Delta Function */  
              Result = !(Image[r][c] - intensity);  
              pixels_at_intensity = pixels_at_intensity + Result;  
            End  
          End  
          histogram[intensity] = pixels_at_intensity;  
        End  
      End  
    End  
  End  
End
```

## A2: Procedure for calculating new matrix X of size M x N

```
Procedure calculateExpanse(Image[Row][Column])
```

```
Begin
```

```
  Var X[Row][Column];
```

```
  For r = 0 to Row
```

```
    Begin
```

```
      For c = 0 to Column
```

```
        Begin
```

```
          Initialize totalDistance = 0, distance = 0;
```

```
          For each neighbor [x,y] of current pixel
```

```
            Begin
```

```
              ir = Image[r][c] - Image[y][x];
```

```
              ig = Image[r][c] - Image[y][x];
```

```
              ib = Image[r][c] - Image[y][x];
```

```
            End
```

```
          /* The Euclidean distance between two pixels */
```

```
            distance = sqrt((ir*ir)+(ig*ig)+(ib*ib));
```

```
            totalDistance = totalDistance + distance;
```

```
            if totalDistance < ExpanseThreshold
```

```
              then
```

```
                X[r][c] = 1;
```

```
            else
```

```
                X[r][c] = 0;
```

```
          End
```



### A3: Procedure for calculating the Histon

```
Procedure createHiston(Image[Row][Column])
Begin
  X = calculateExpanse(Image);
  For intensity = 0 to 255
  Begin
    For r = 0 to Row
    Begin
      Initialize pixels_at_intensity = 0;
      For c = 0 to Column
      Begin
        Result = (1 + X[r][c]) * (Image[r][c] - intensity);
        pixels_at_intensity = pixels_at_intensity + Result;
      End
    End
    histon[intensity] = pixels_at_intensity;
  End
End
```

## A4: Procedure for calculating the Roughness Measure

```
/* Roughness Measure */  
  
Procedure measureRoughness(Histogram[256], Histon[256])  
Begin  
  Var roughness[256];  
  For intensity = 0 to 255  
    Begin  
      If Histon[intensity] = 0  
        then  
          roughness[intensity] = 0;  
        else  
          roughness[intensity] =  
            1 - (Histogram[intensity]/Histon[intensity]);  
        End  
      Return roughness;  
    End  
  End
```

## A5: Procedure to Find out Significant Peaks and Valleys

```
Procedure findPeakValley(Roughness[256])
Begin

  initialize:
  PEAK = 1
  VALLEY = -1
  PLANE = 0

  initialize area[256] = 0;

  if Roughness[0] > Roughness[1] then
    area[0] = PEAK;

  if Roughness[255] > Roughness[254] then
    area[255] = PEAK;

  for i = 1 to 254
  Begin
    if Roughness[i] > Roughness[i-1] and Roughness[i] > Roughness[i+1] then
      area[i] = PEAK;
    if Roughness[i] < Roughness[i-1] and Roughness[i] < Roughness[i+1] then
      area[i] = VALLEY;
  End
  return area;
End
```

```
Procedure SignificantPeak(Roughness[256], area[256])
Begin

  initialize:
  GAP = 10
  HEIGHT = 20 /* % of Peak Height - Threshold */
  total_roughness = 0
```

```

for i = 0 to 255 step 10
  Begin
    total_roughness = total_roughness + Roughness[i]
  End

  avg_roughness = total_roughness/256;
  peak_threshold = (avg_roughness*HEIGHT)/100;

  for i = 0 to 255 step 10
    Begin
      startLimit = i;
      endLimit = i+10;
      if endLimit >= 255 then
        endLimit = 255;

      max_peak = 0;
      max_peak_index = -1;
      for j = startLimit to endLimit
        Begin
          if area[j] = PEAK then
            if Roughness[j] < peak_threshold then
              area[j] = PLANE;

          if area[j] = PEAK then
            if Roughness[j] > max_peak then
              if max_peak_index != -1
                area[max_peak_index] = PLANE;
              max_peak = Roughness[j];
              max_peak_index = j;
            else
              area[max_peak_index] = PLANE;

        End
      End
    End
  End

```

## A6: 8-Connected component Label based technique

```
Procedure CreateCluster(Region[R][C])
Begin /* create Clusters form Region Matrix */
    initialize Cluster [R][C] = 0;
    initialize Cluster_List[R*C] = 0;
    /* First Pass */ /* Generating Cluster*/
    label = 1;      /* Cluster label */
    for row = 0 to R-1
    Begin
        for col = 0 to C-1
        Begin
            least_label = least label of Top and Left neighbors in same region as
            Region[row][column];
            neighbor_count = no. of neighbors in same region as Region[row][column];
            if neighbor_count > 0 then
                for each neighbor found with label lb
                Begin
                    if least_label < Cluster_list[lb] then
                        Cluster_list[lb] = least_label;
                End
            Cluster [row][cloumn] = least_label;
        else
            Cluster [row][column] = label; /* no neighbor found, so assign new label */
            Cluster_List[label] = label
        End
    End
End
```

```

        label = label + 1;

    End

End

/* Updating Cluster_list - Assigning least Cluster value to each Cluster entry */

    for Cluster = label-1 to 1 step -1

Begin

    index = Cluster;

    loop while Cluster != Cluster_List[Cluster]

Begin

        Cluster = Cluster_List[Cluster];

    End

    Cluster_List[index] = Cluster;

End

/* Second Pass */

/* Updating Cluster Matrix */

for row = 0 to R-1

Begin

    for col = 0 to C-1

Begin

        Cluster [row][column] = Cluster_List[Cluster [row][column]];

    End

End

return Cluster

End

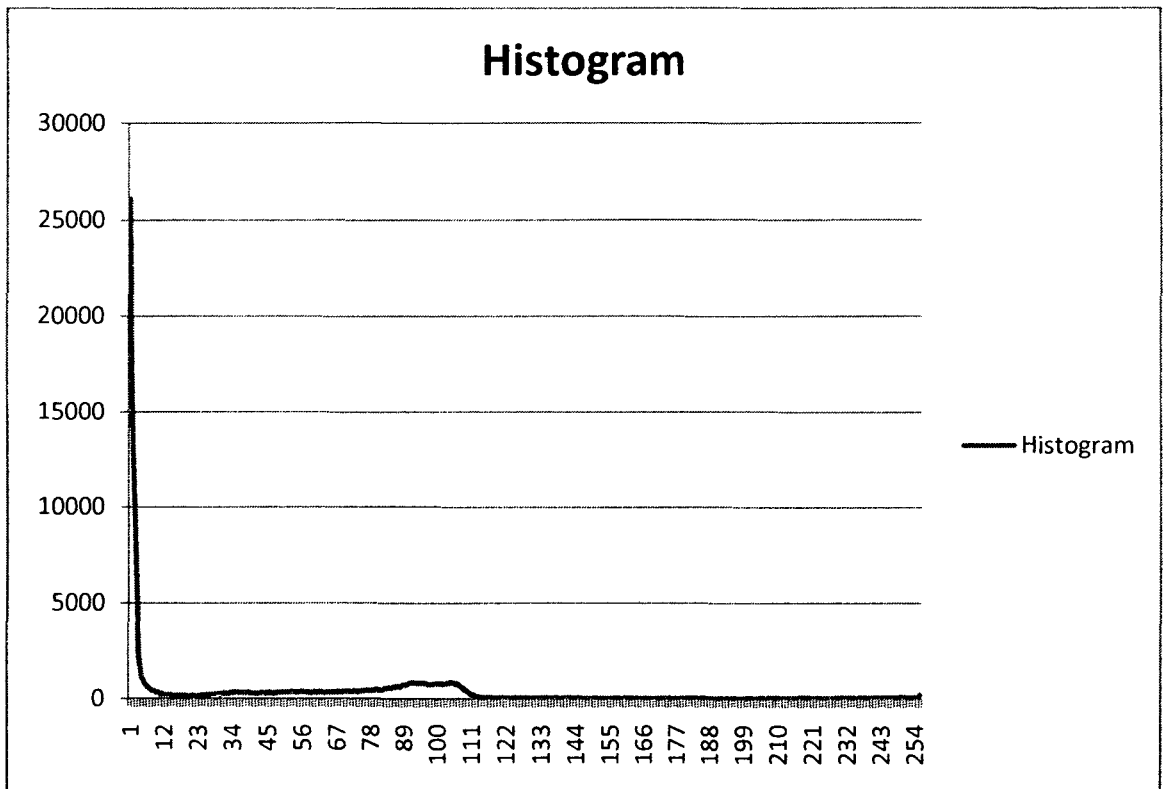
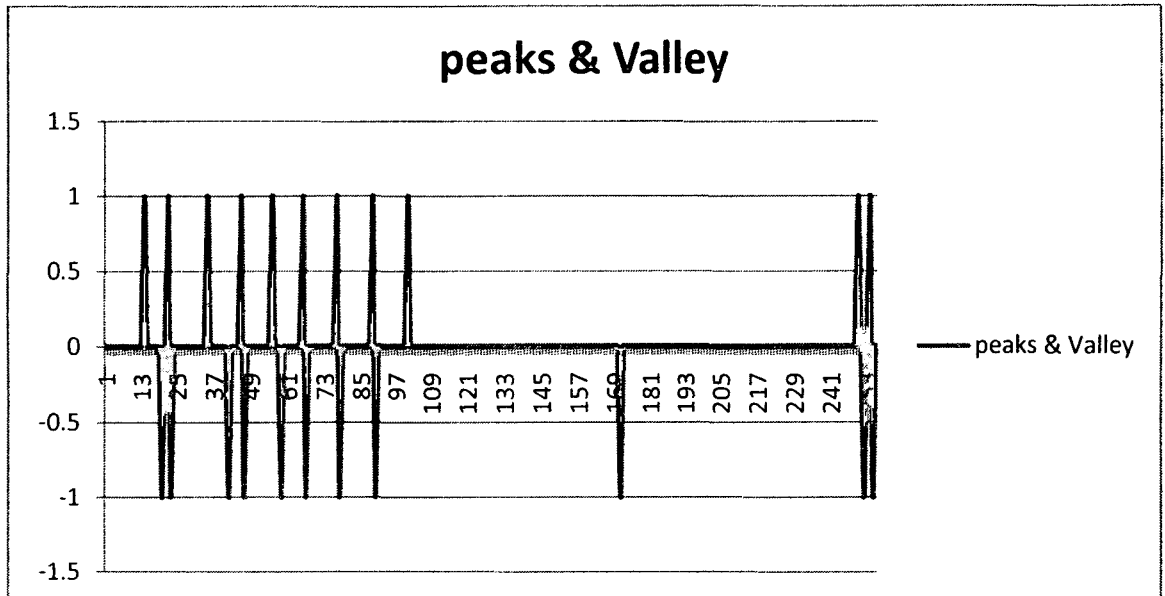
```

# **APPENDIX B**

---

# B1: Medical Image: MRI (Histogram, $G_{2 \times 2}$ , $G_{3 \times 3}$ )

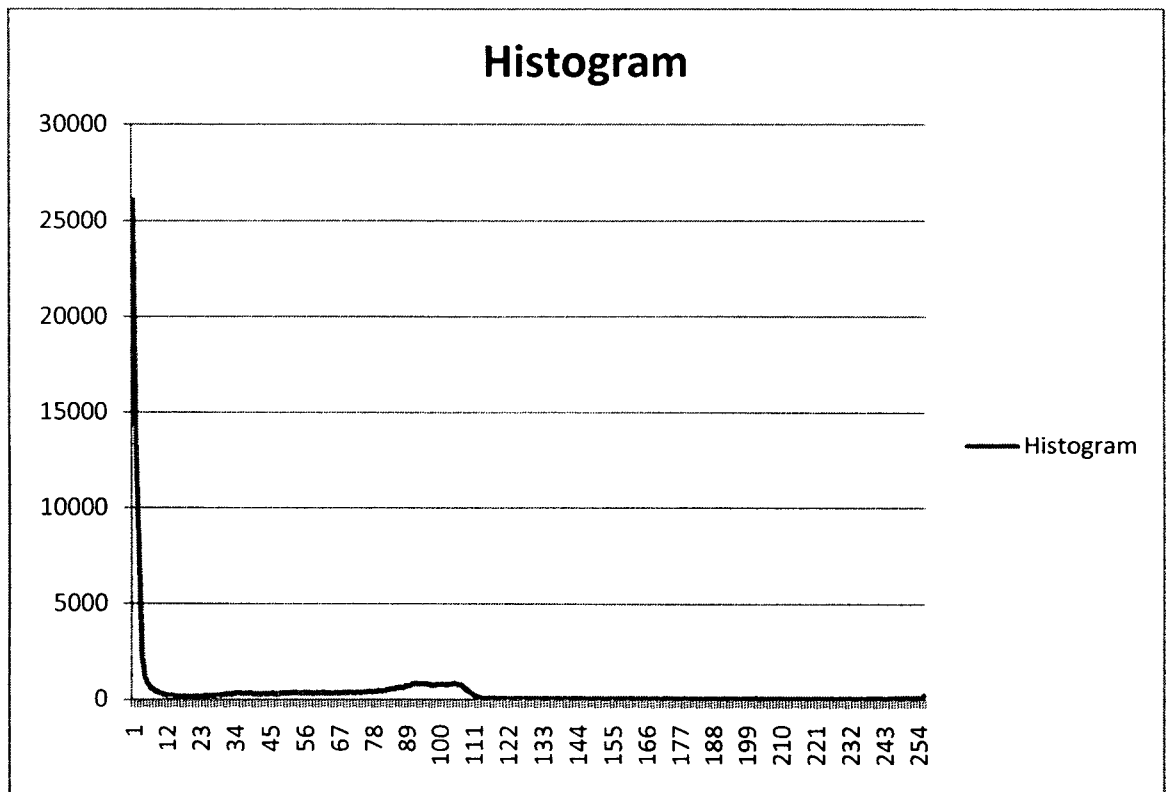
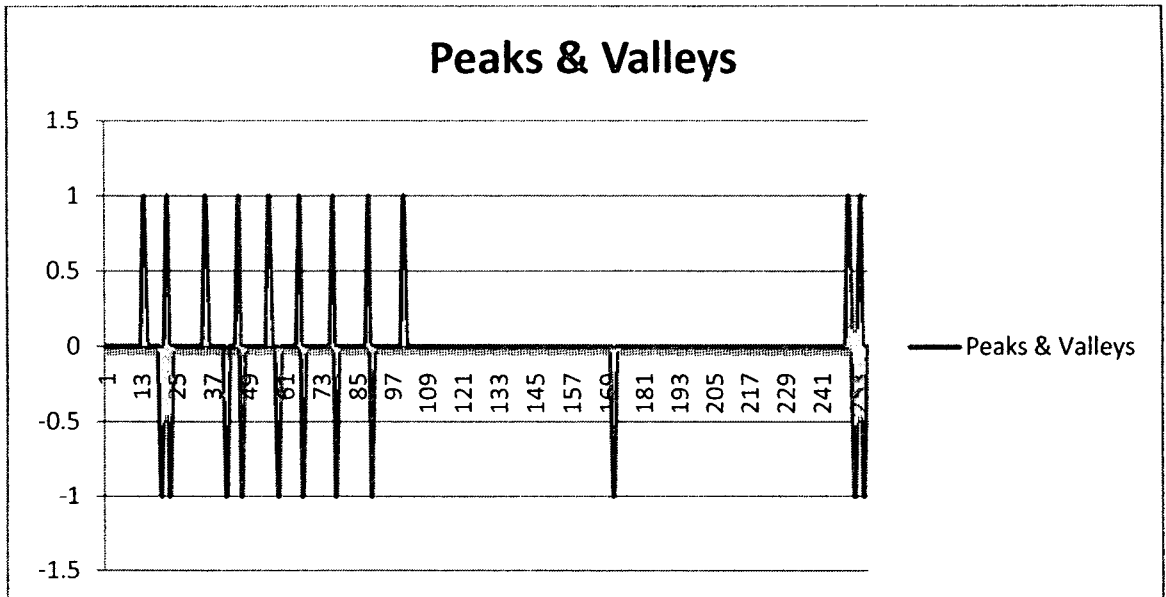
Original Histogram





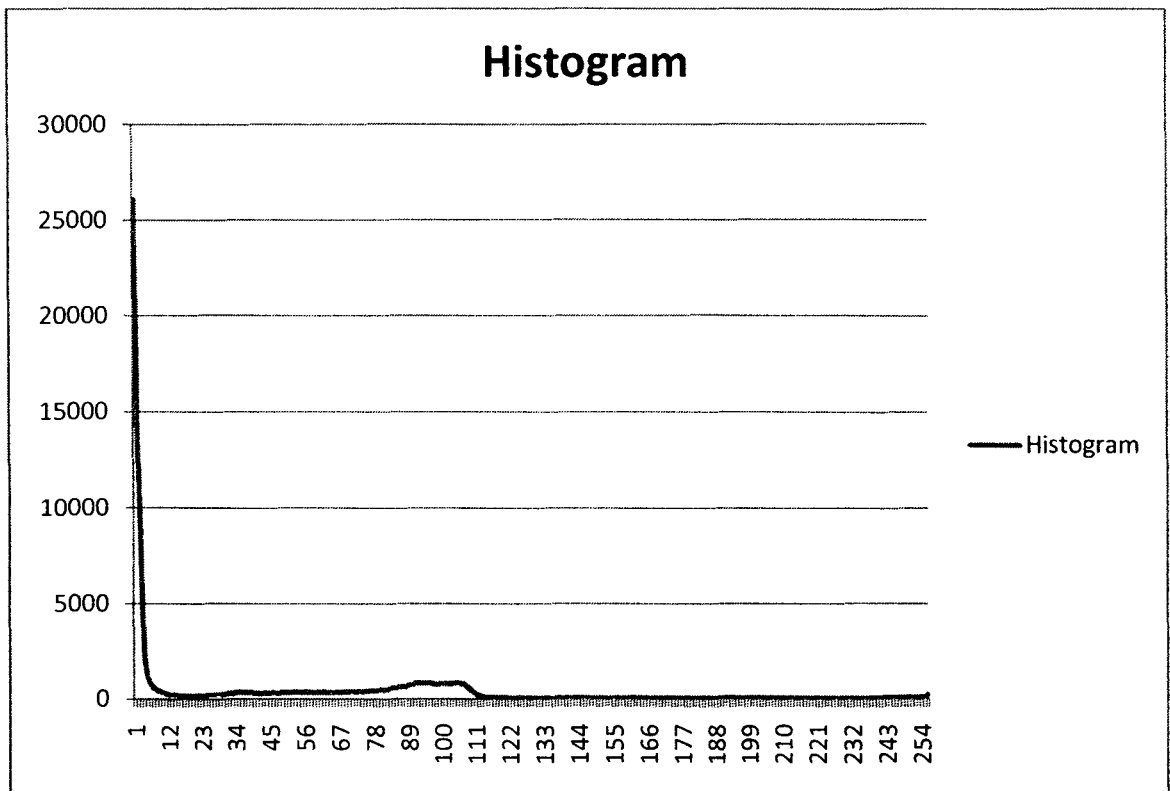
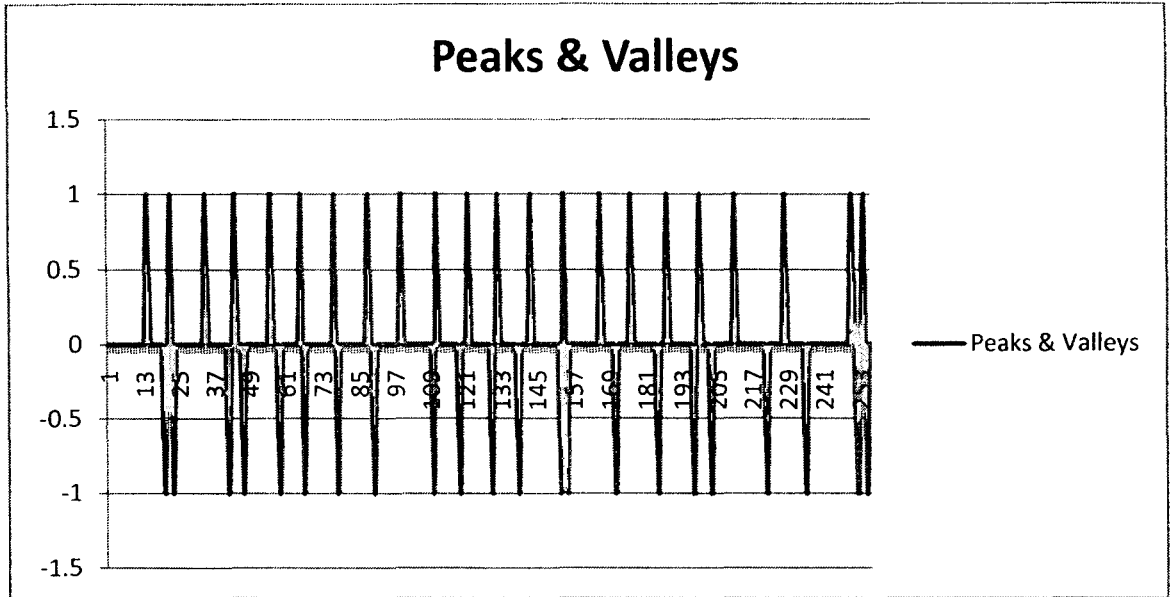
# Medical Image: MRI

## Histogram with 2x2 Granule



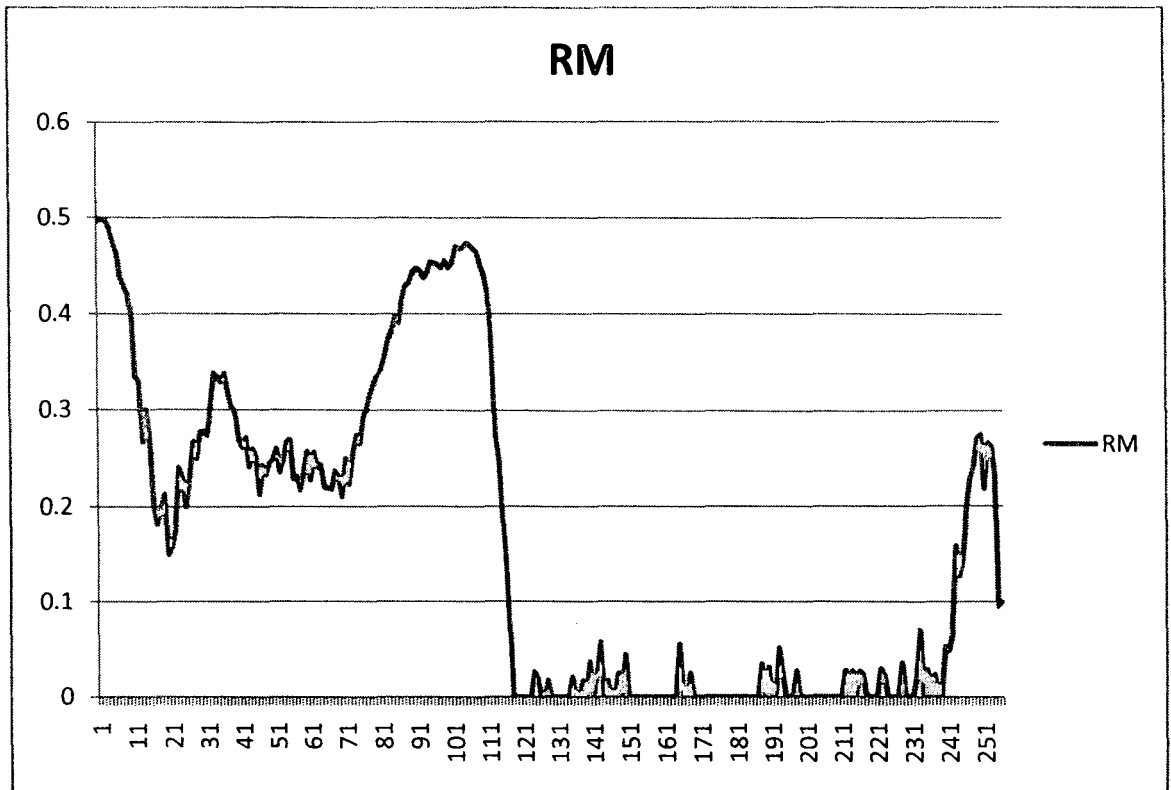
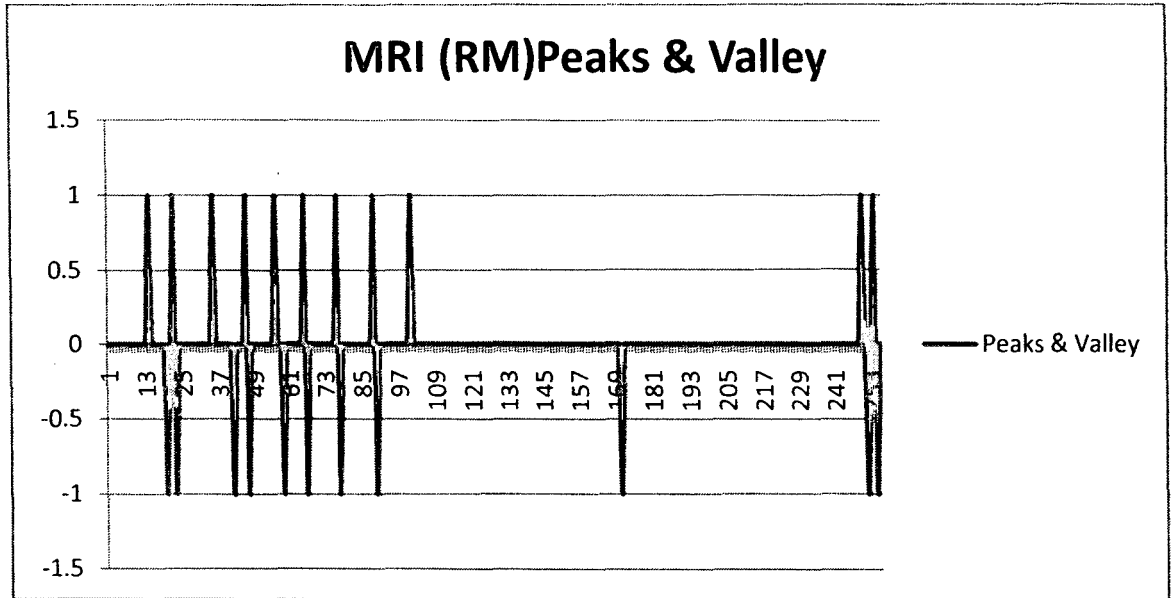
# Medical Image: MRI

## Histogram with 3x3 granule



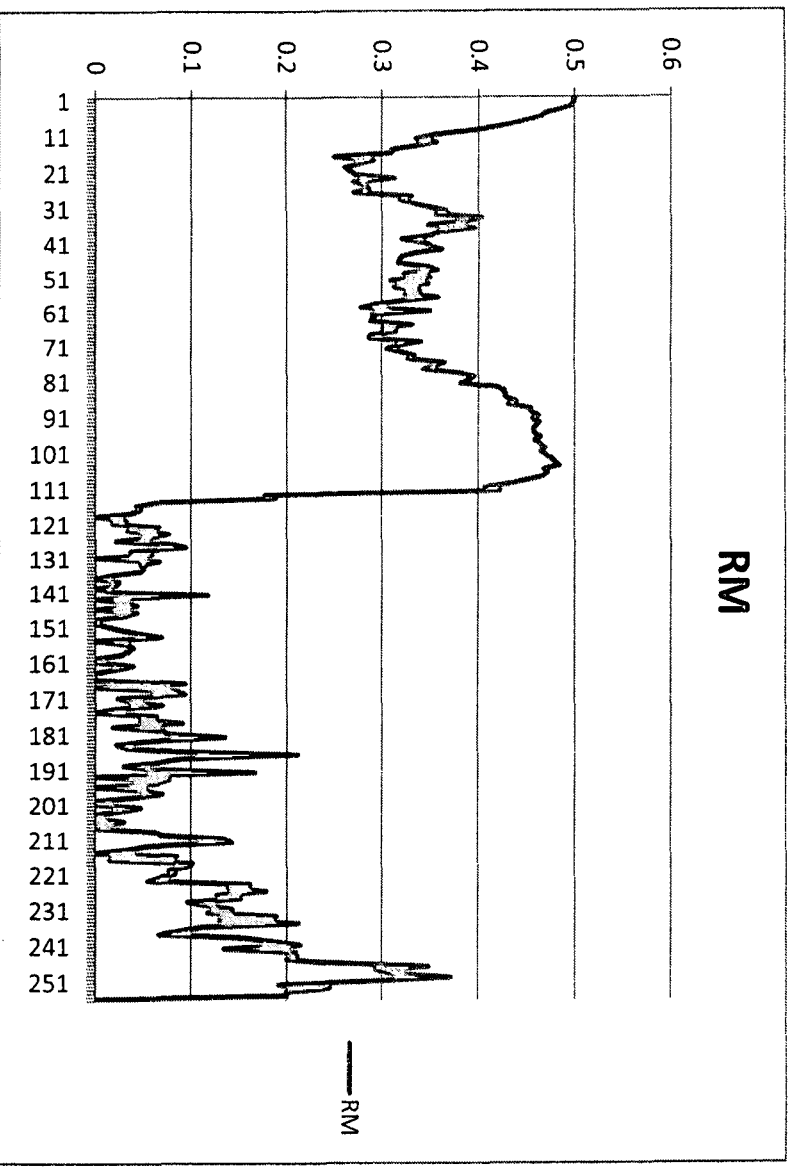
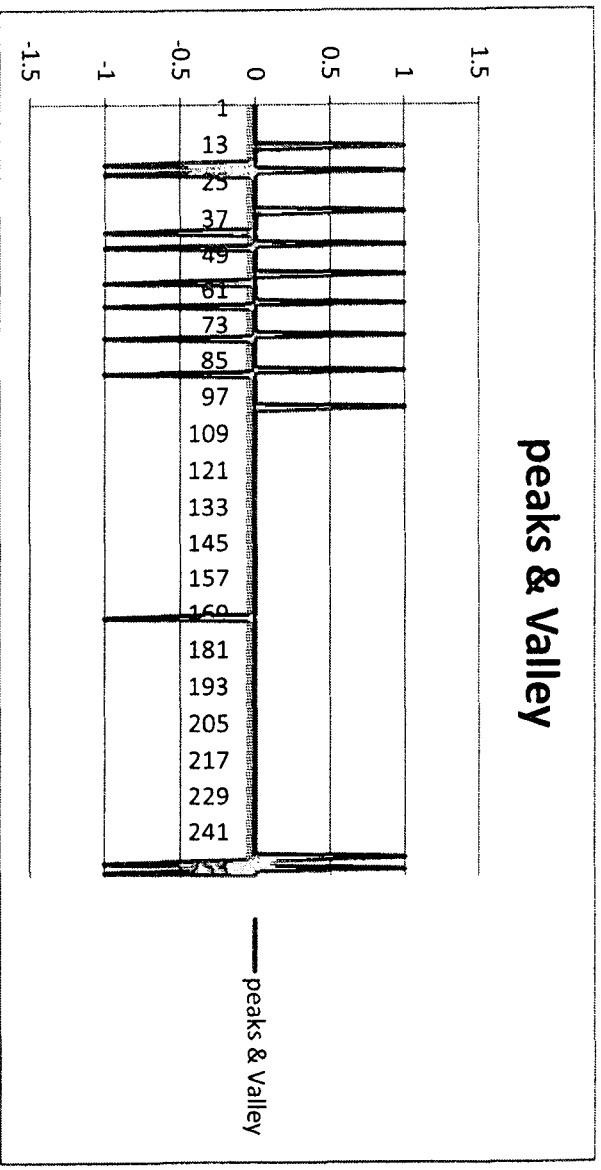
# Medical Image: MRI

## Original RM



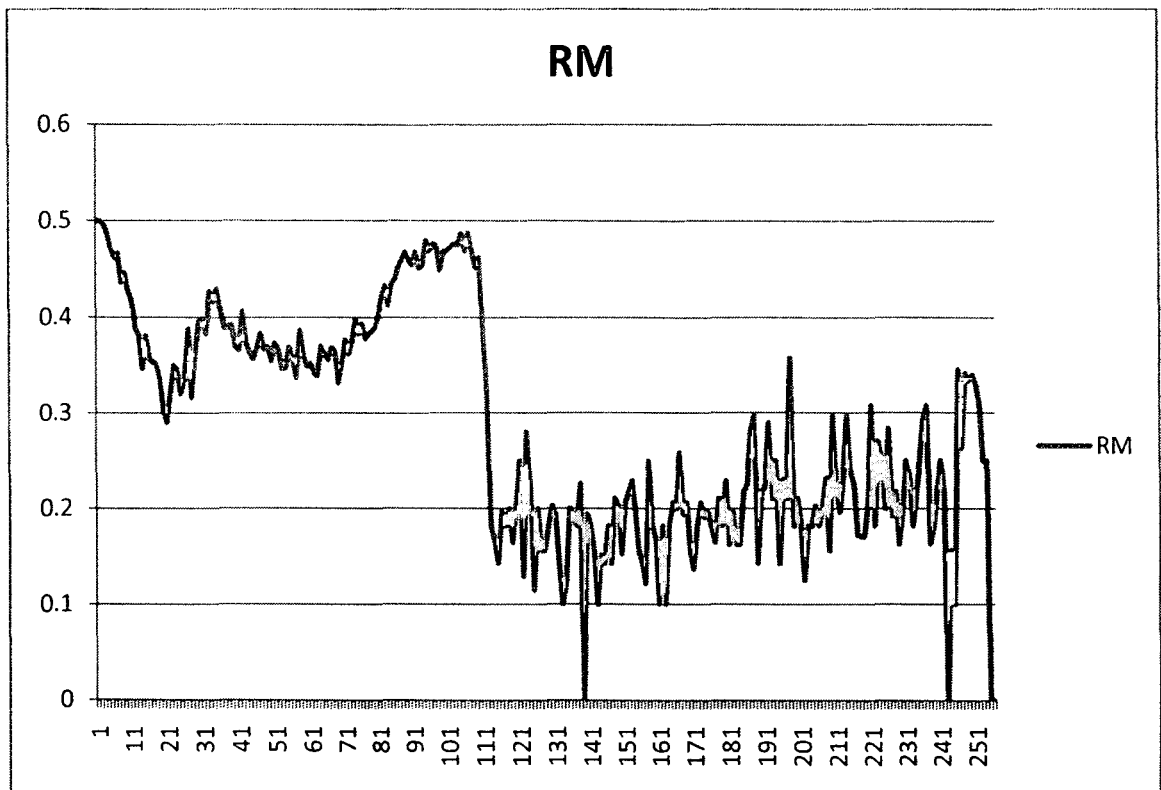
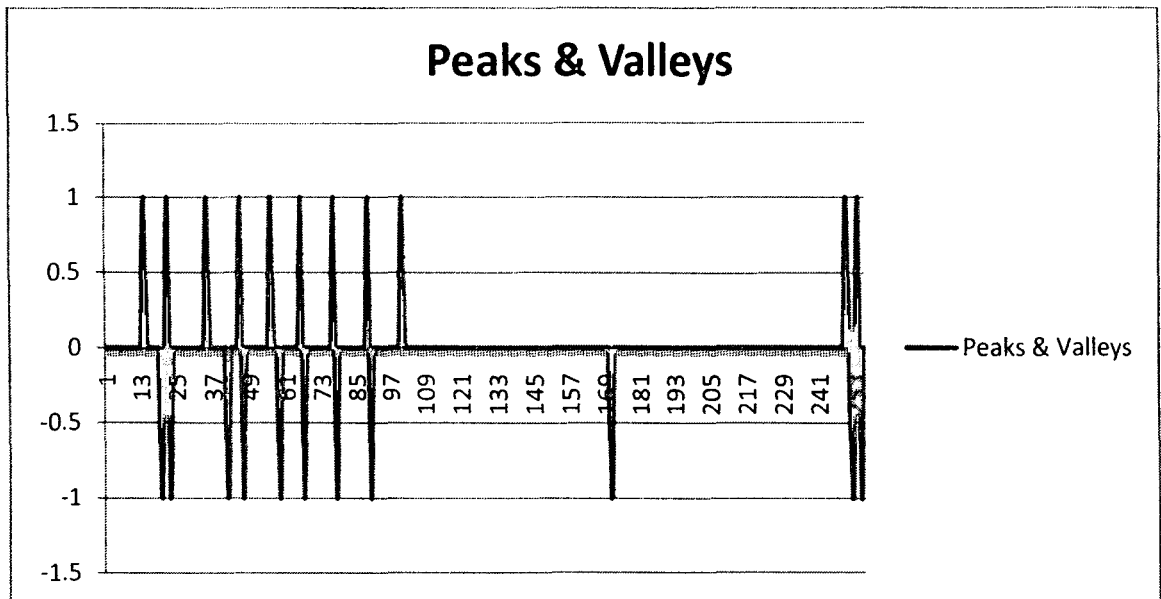
# Medical Image: MRI

RM with 2x2 granule



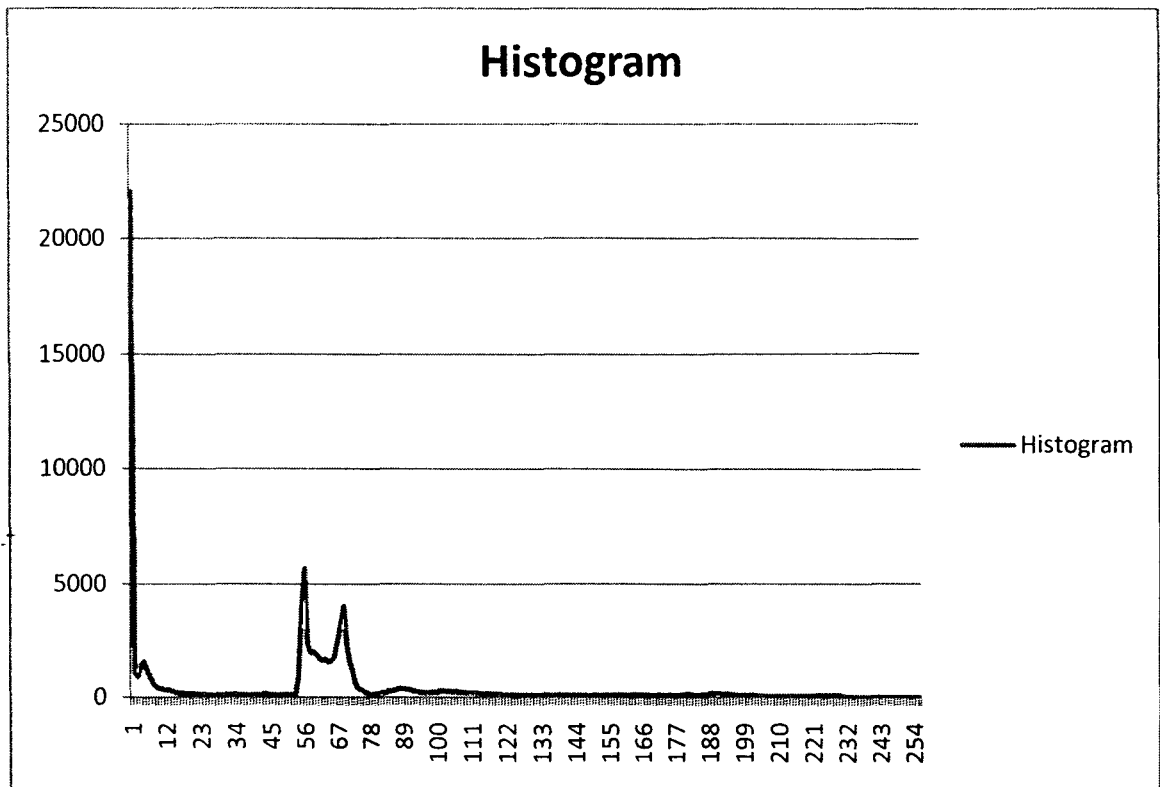
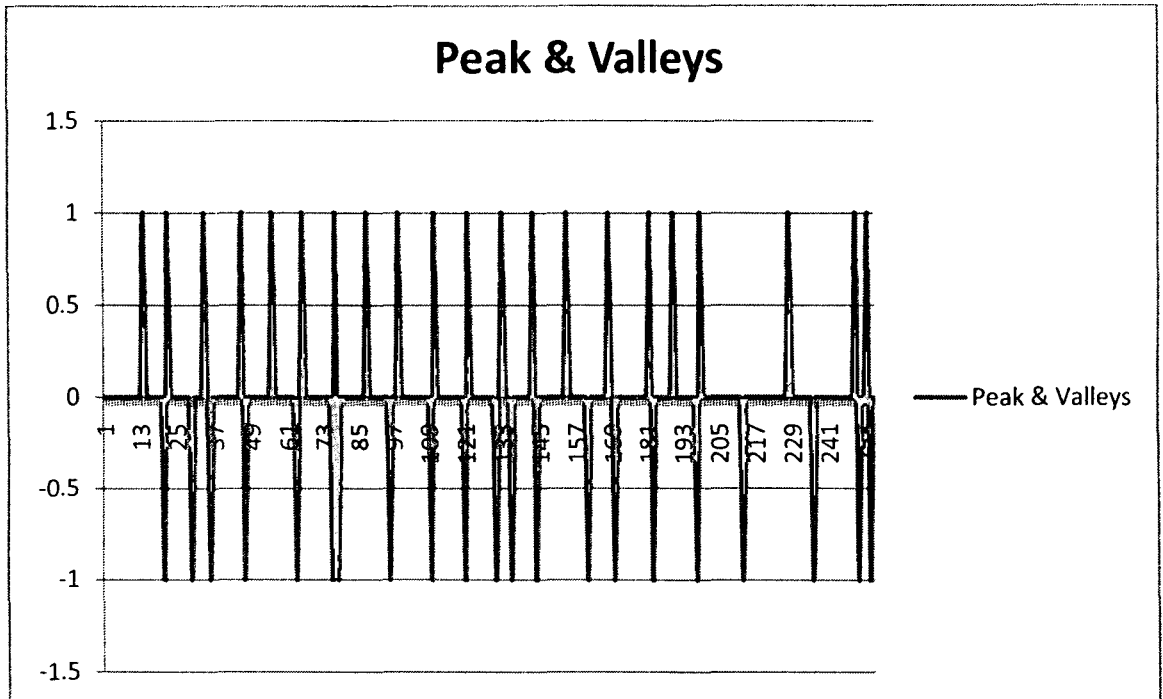
# Medical Image: MRI

RM with 3x3 granule



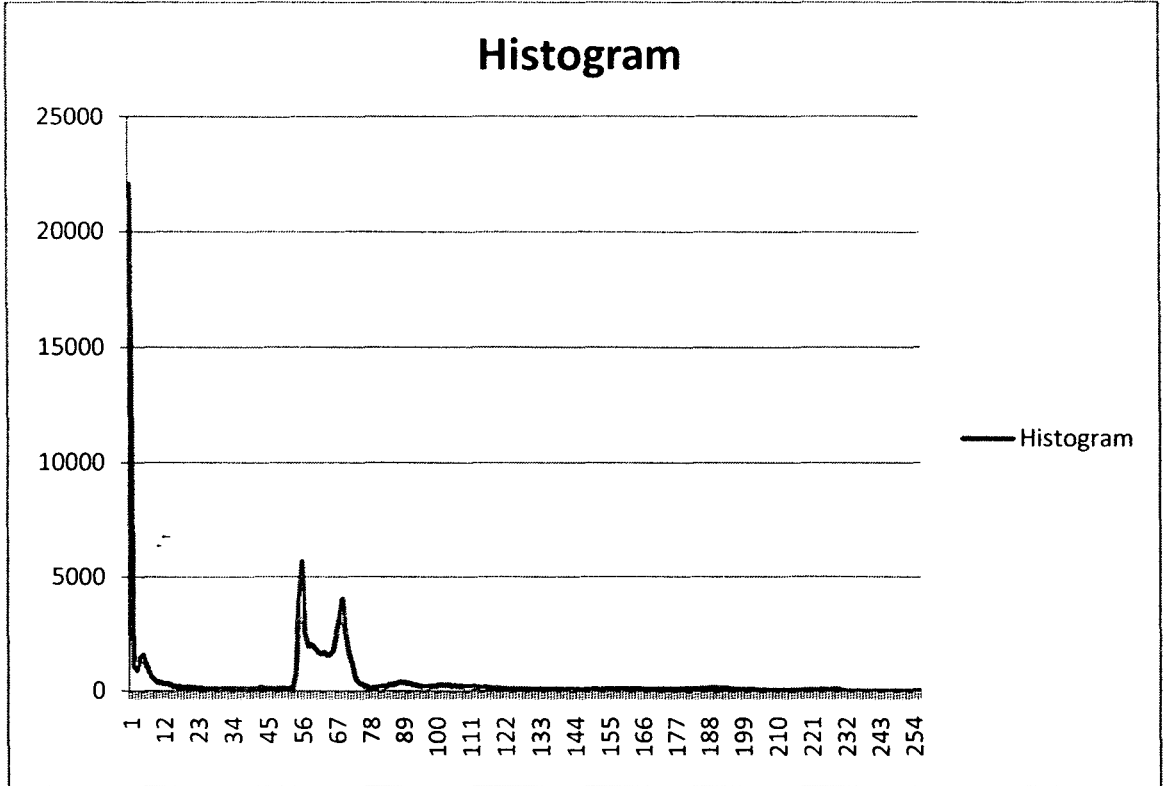
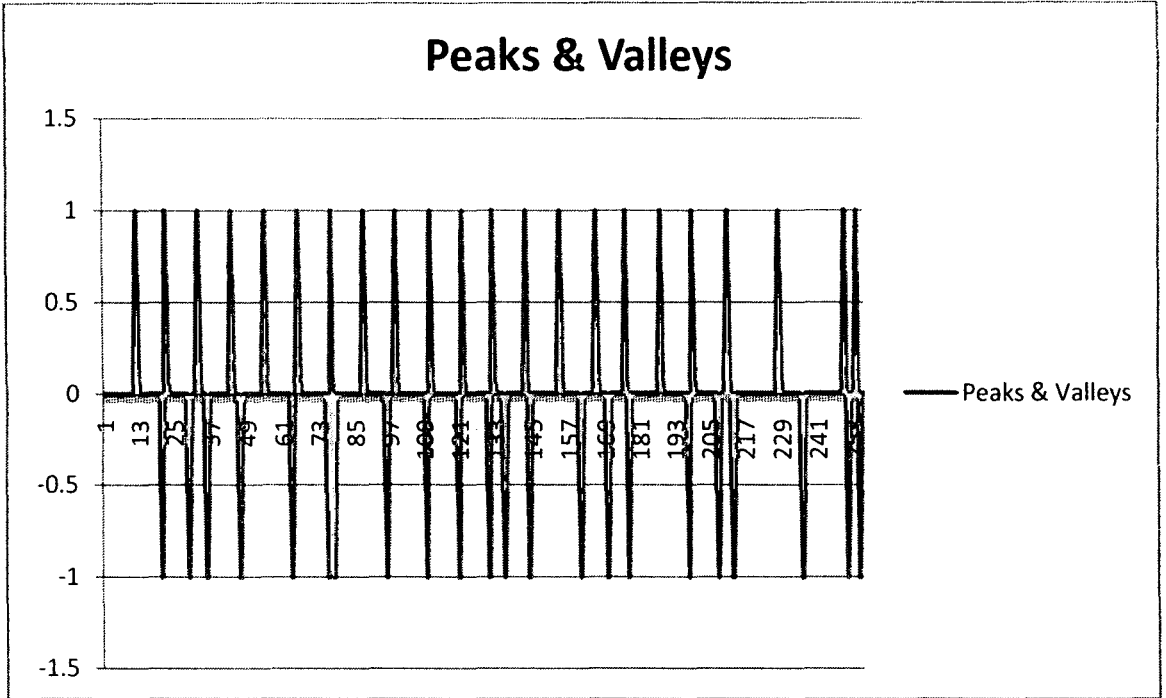
## B2: Medical Image: CT-Scan (Histogram, $G_{2 \times 2}$ , $G_{3 \times 3}$ )

Original Histogram



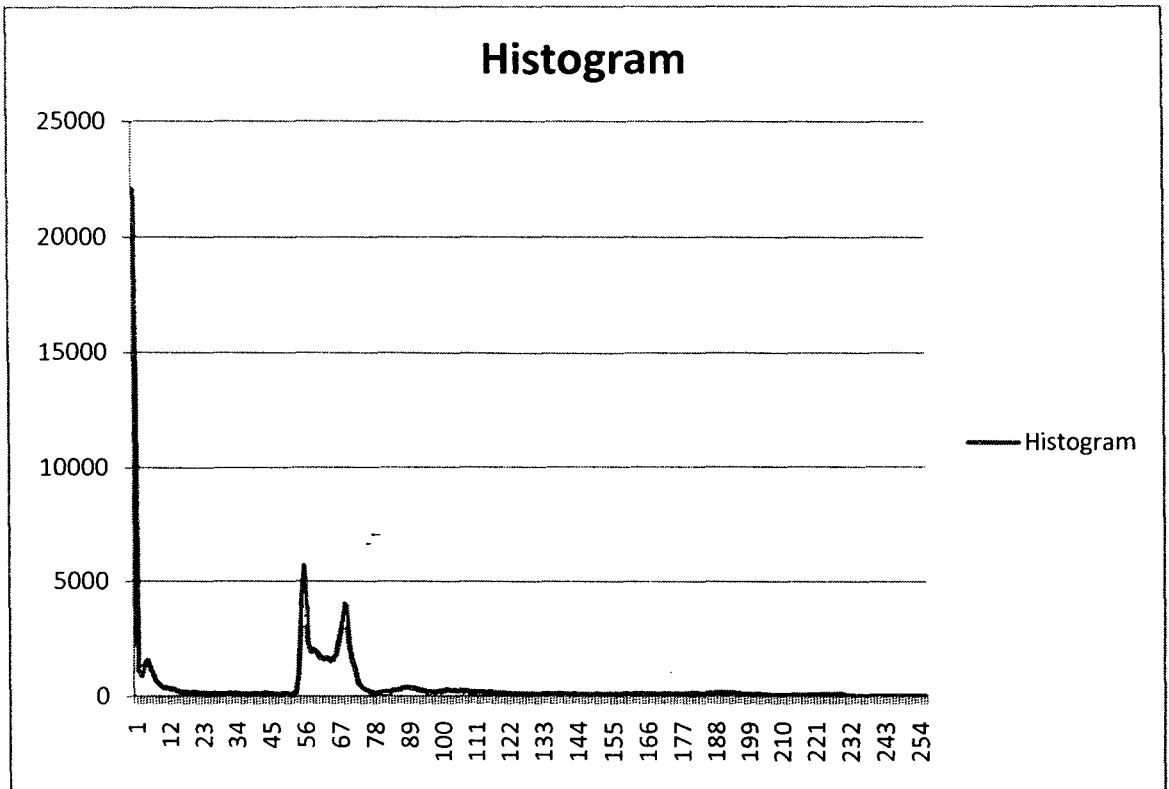
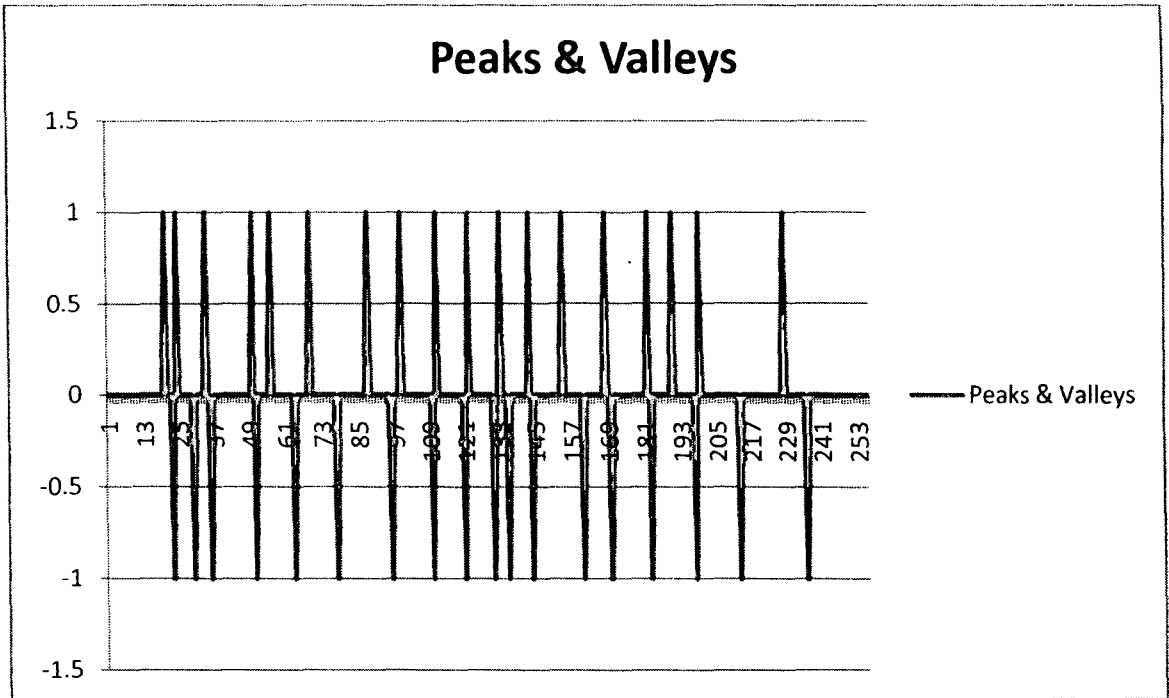
# Medical Image: CT-Scan

## Histogram with 2x2 Granule



# Medical Image: CT-Scan

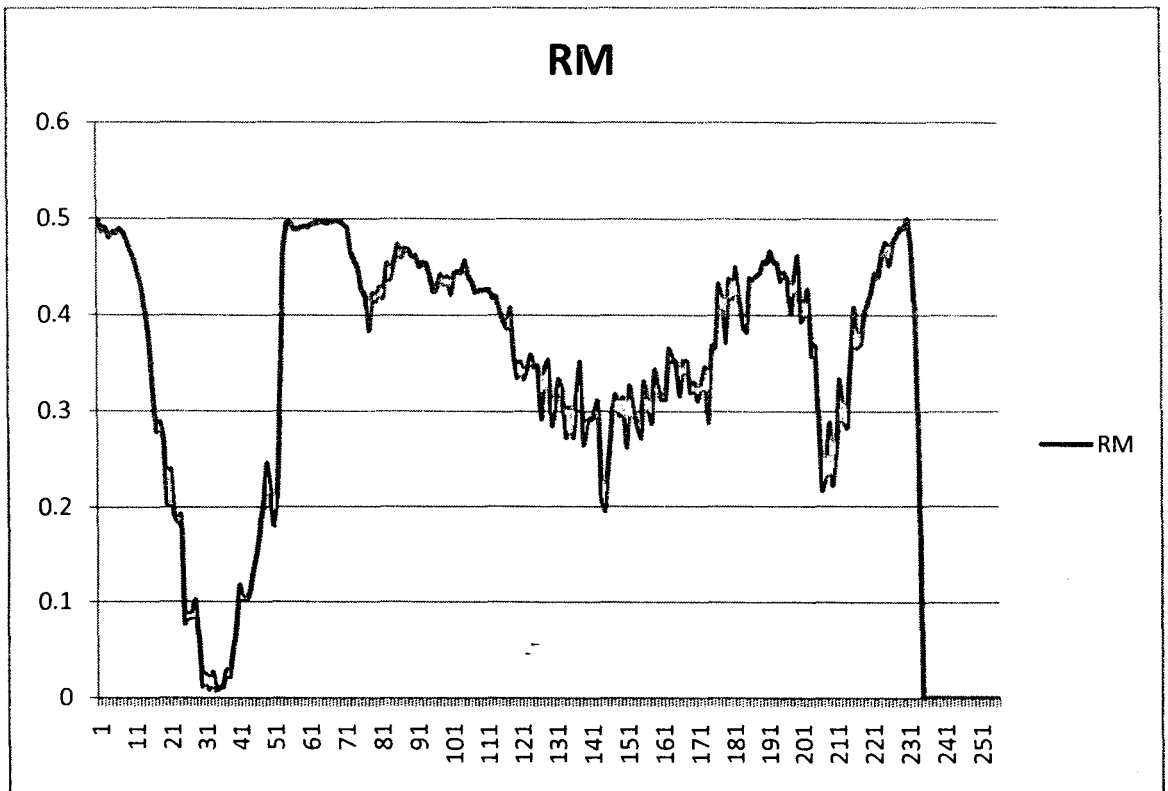
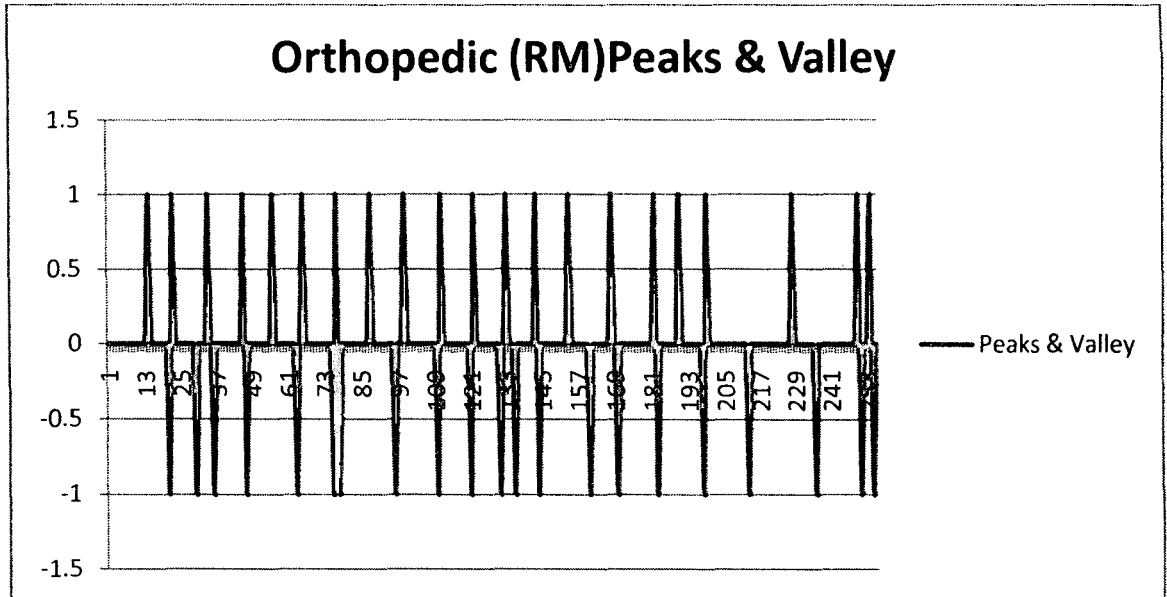
## Histogram with 3x3 Granule





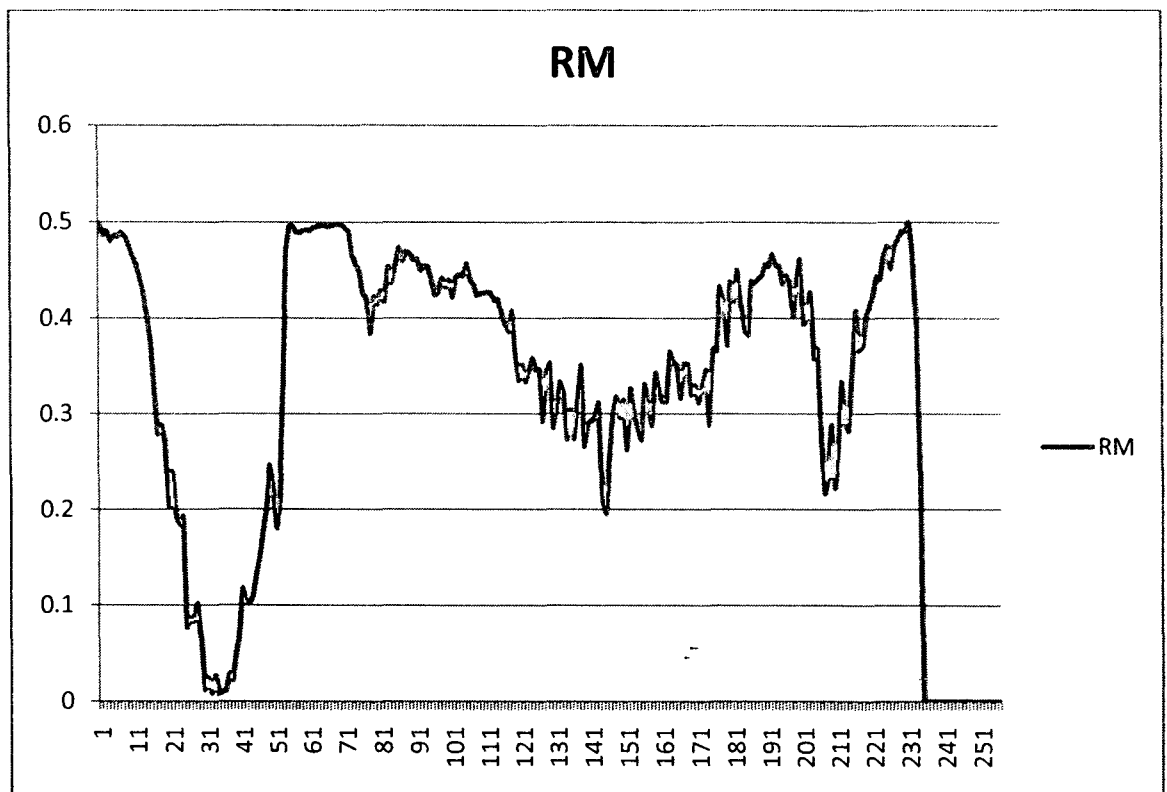
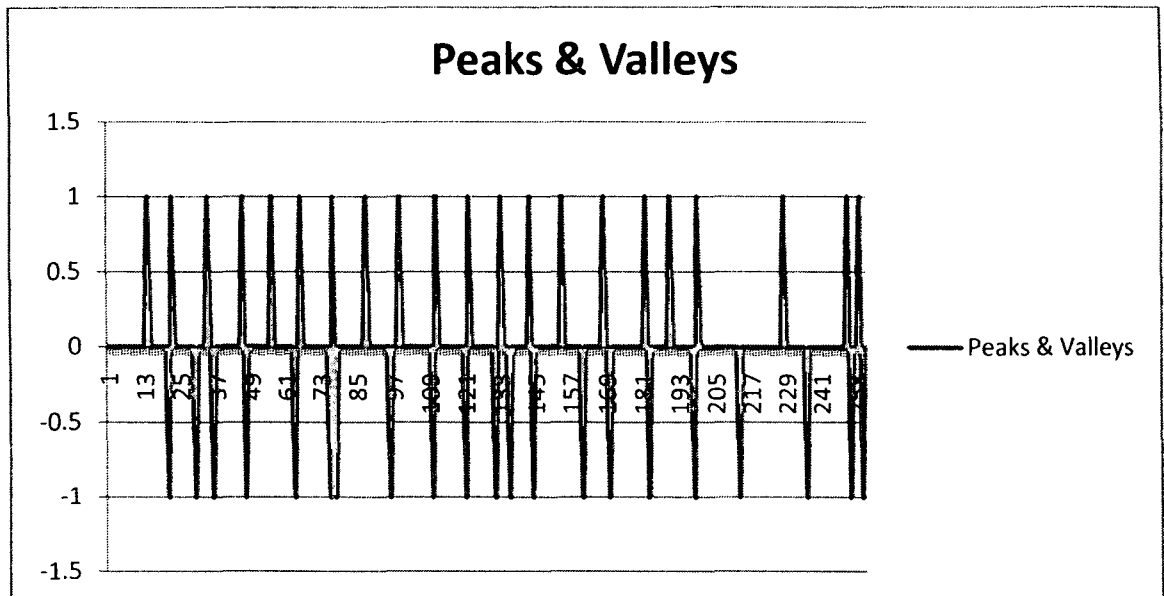
# Medical Image: CT-Scan

## Original RM



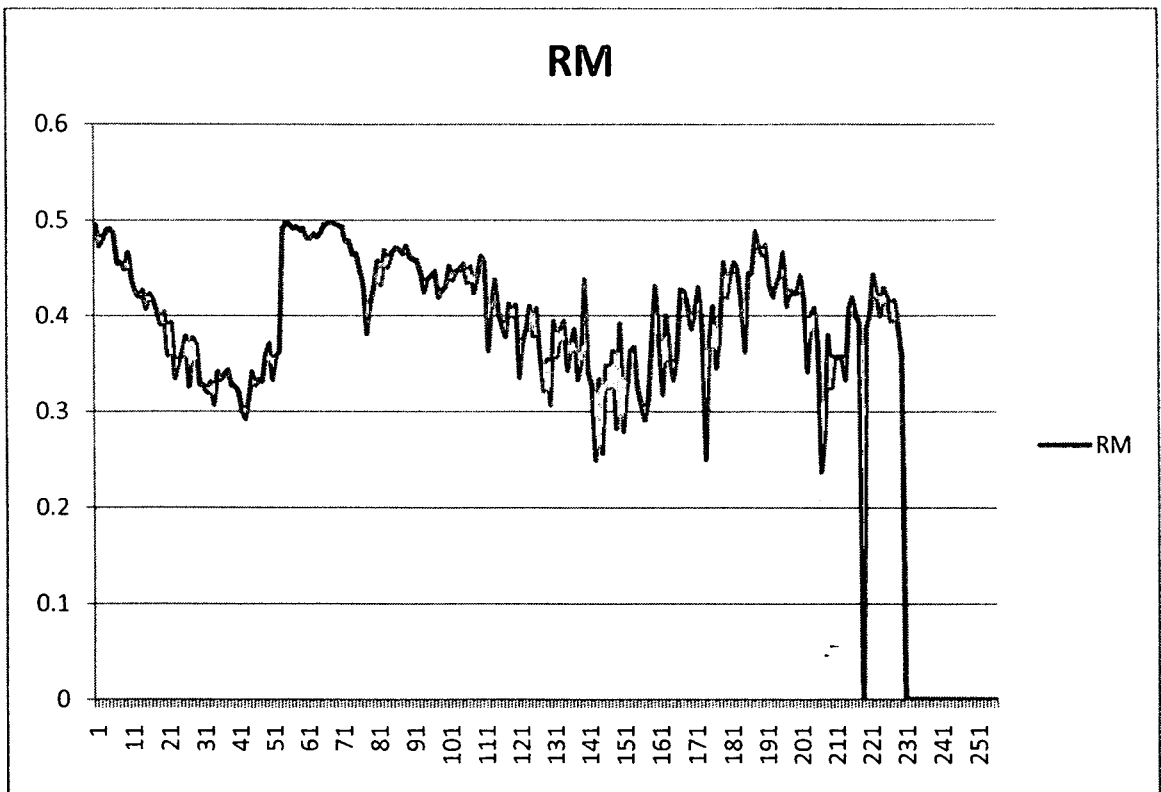
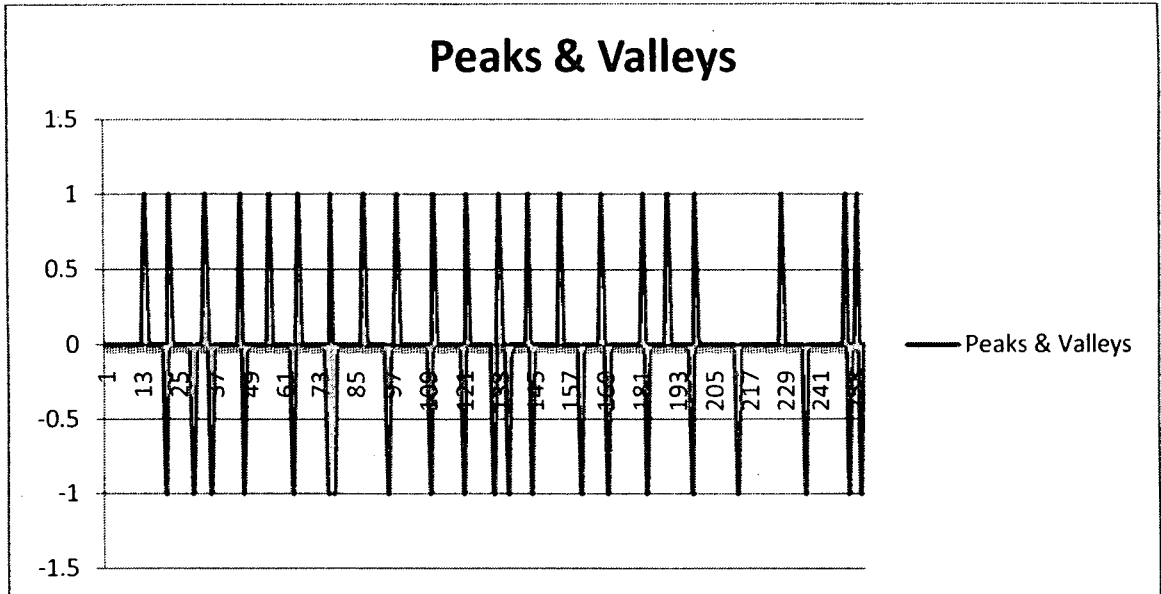
# Medical Image: CT-Scan

RM with 2x2 Granule



# Medical Image: CT-Scan

RM with 3x3 Granule

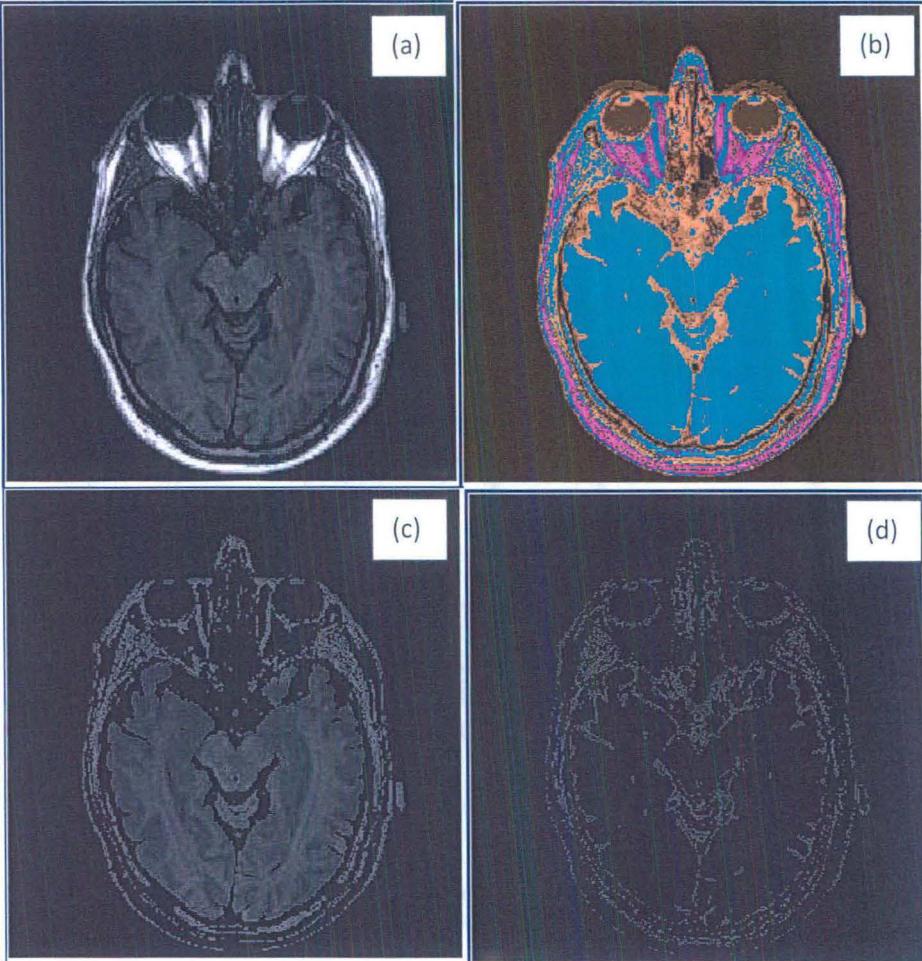


# **APPENDIX C**

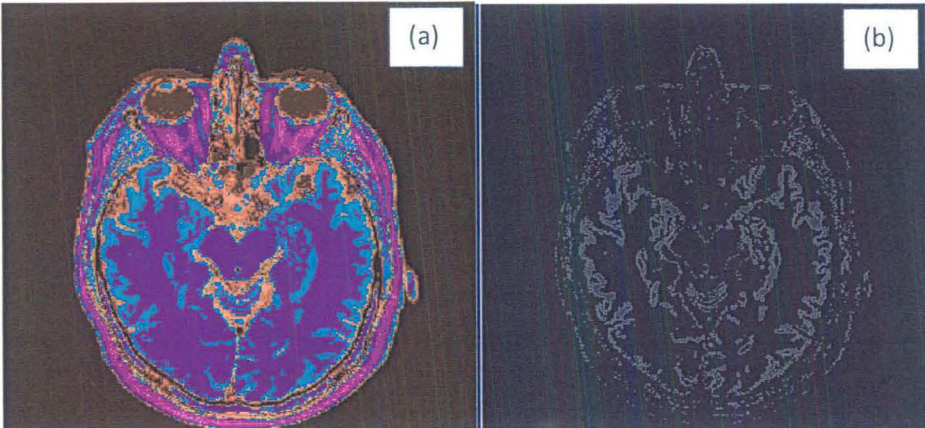
---

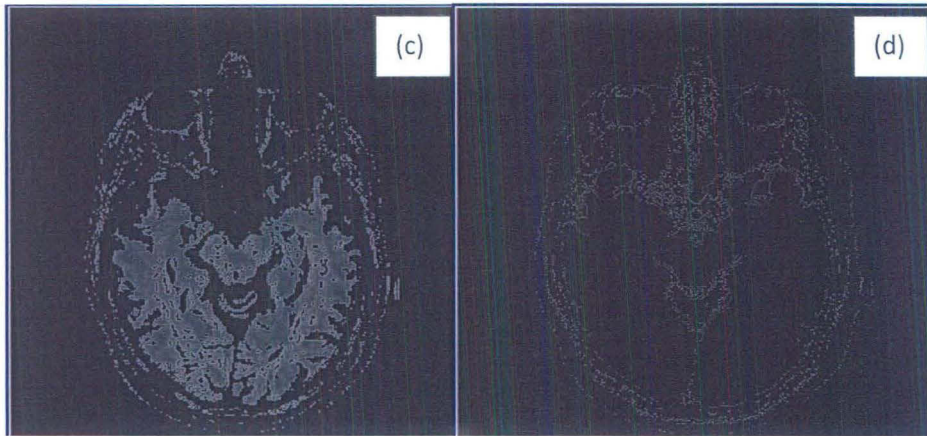
# C1: MRI (segmented regions)

C1.1 RM based (a) image (b) segmented region (c) with white matter (d) gray matter

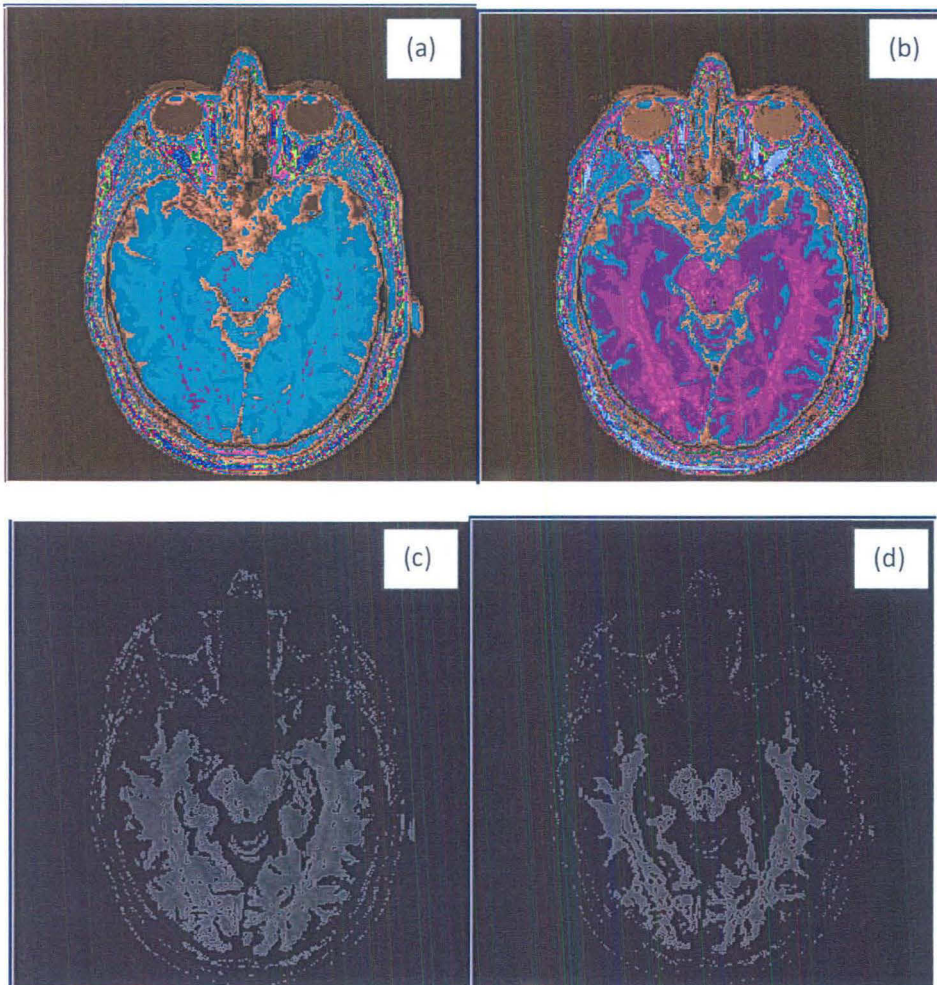


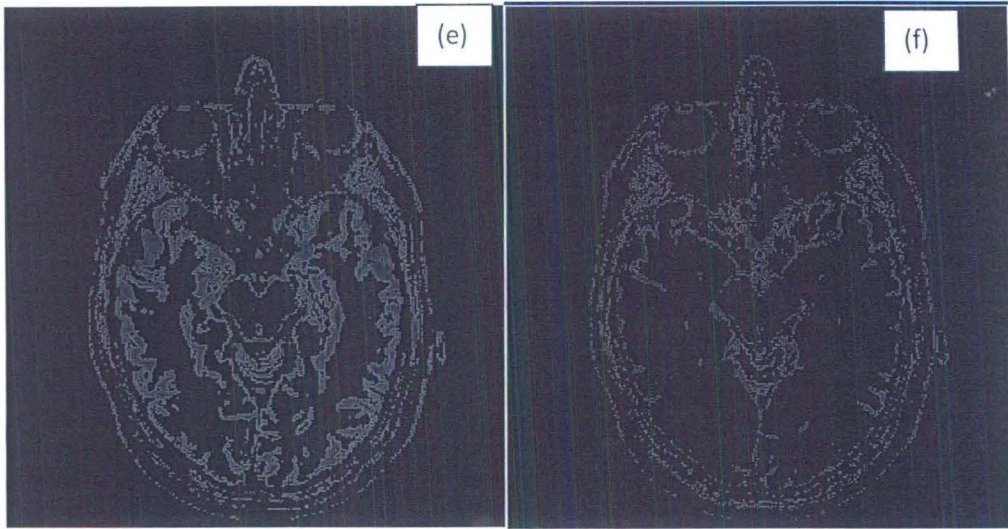
C1.2 MRI for Histogram (a)labeled region (b)with gray matter (c)with white matter (d)boundary





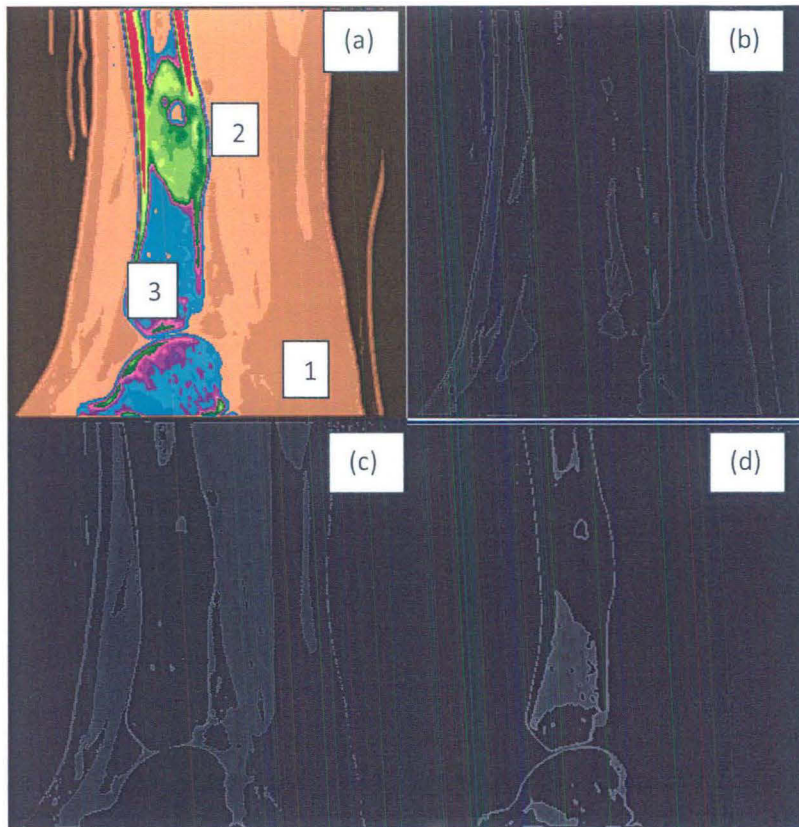
C1.3 MRI: RM with segmented region (a)  $G_{2 \times 2}$ , (b)  $G_{3 \times 3}$ , (c) and (d) white matter, (e) (f) gray matter, respectively.





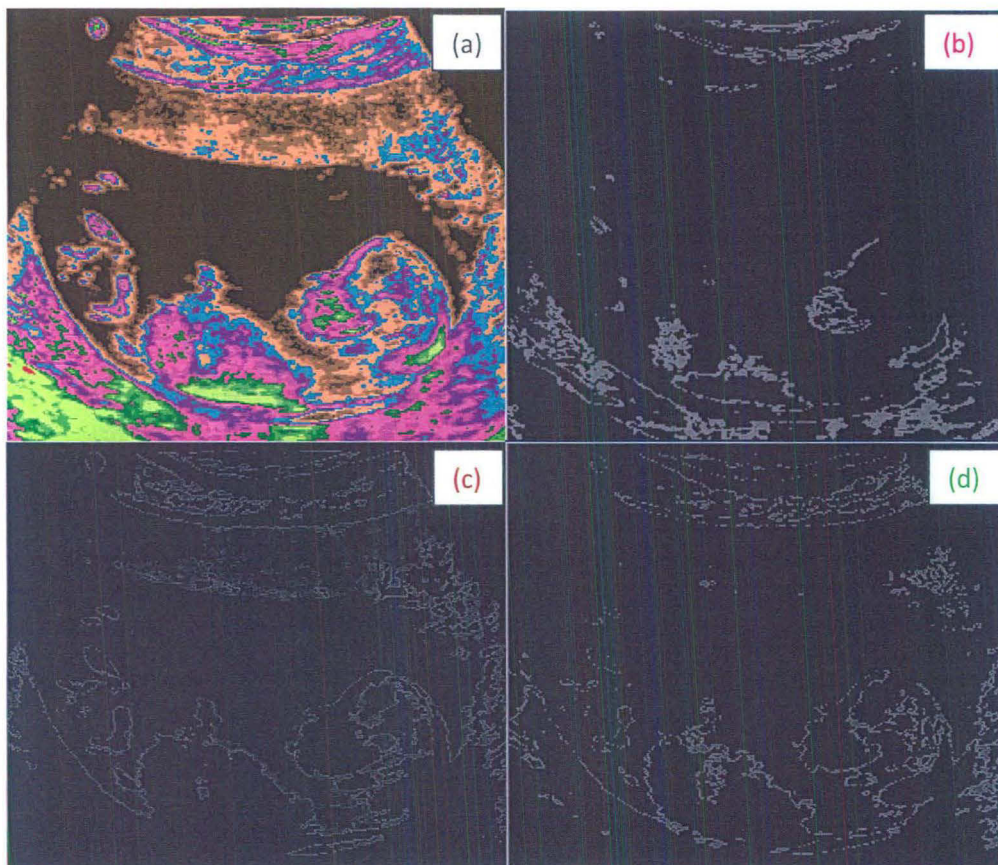
## C2: CT-Scan image (segmented regions)

C2.1 MRI for Histogram (a) labeled region (b) showing region [1], (c) region [2], (d) region [3].



### C3: Ultra Sound image (segmented regions)

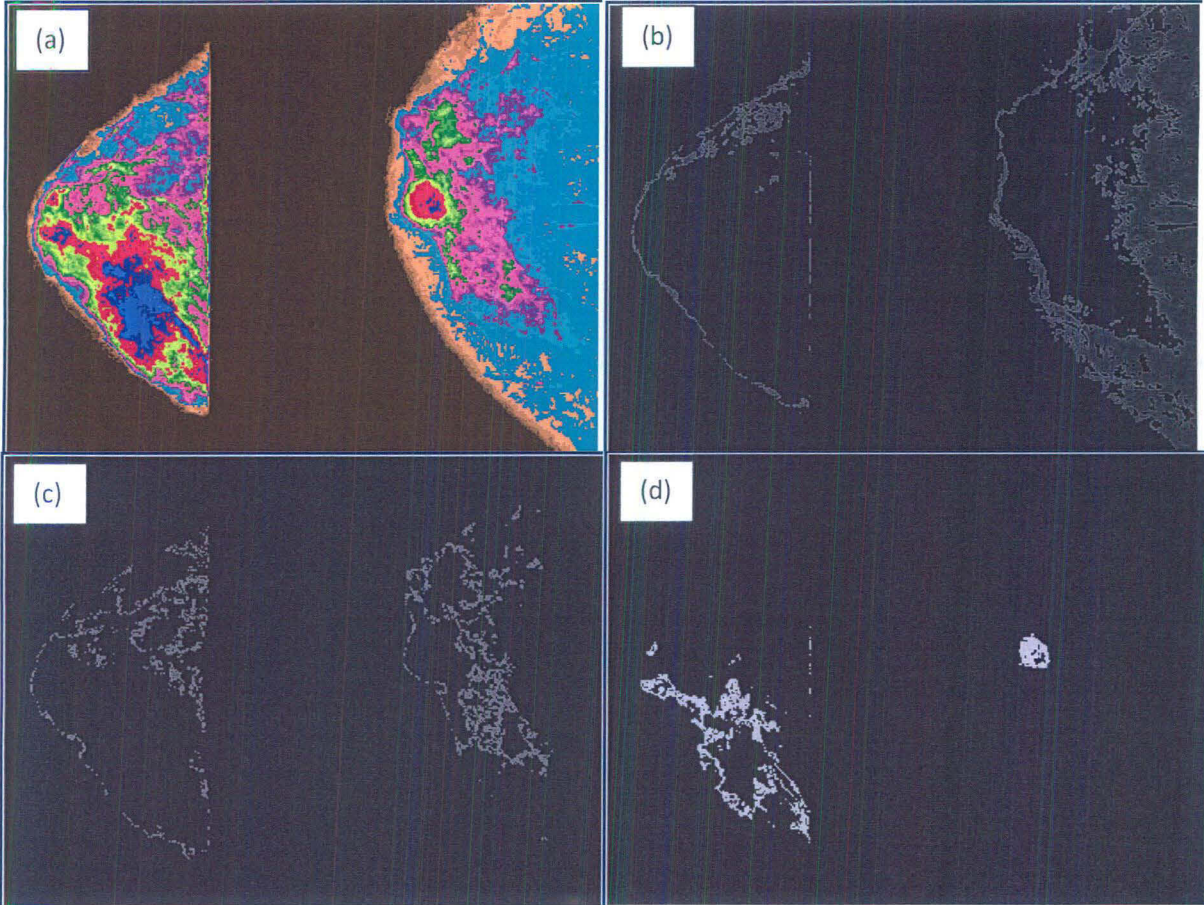
C3.1 Ultra Sound for Histogram (a) labeled region (b) showing region of color purple, (c) region of color brown , (d) region of color florescent green.





# C4: Mammogram image for Breast (segmented regions)

C4.1 Mammogram of RM (a) labeled region (b) showing region of color green, (c) region of color purple, (d) region for pink



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