TUMOR EXTRACTION FROM MRI BRAIN IMAGE AND COMPRESSION USING DWT AND NEURAL NETWORK

A project report submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted by

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CERTIFICATE

This is to certify that the project report entitled "**TUMOR EXTRACTION FROM MRI BRAIN IMAGE AND COMPRESSION USING DWT AND NEURAL NETWORK"** is a bonafide record of work carried out by **NALAM LOKHI (1210416536)** submitted in fulfilment of requirement for the award of degree of Bachelor of Technology in Electronics and Communication Engineering in the academic year 2019-2020.

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DECLARATION

I, hereby declare that the project review entitled "**TUMOR EXTRACTION FROM MRI BRAIN IMAGE AND COMPRESSION USING DWT AND NEURAL NETWORK**" is an original work done in the Department of Electrical, Electronics and Communication Engineering, GITAM Institute of Technology, GITAM (Deemed to be University) submitted in partial fulfilment of the requirements for the award of the degree of B.Tech in Electronics and Communication Engineering. The work has not been submitted to any other college or University for the award of any degree or diploma.

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ABSTRACT

Image compression is one of the most widespread techniques for applications that require storage of various types of images and transmission in database. Digital images are large in size and occupy large space. The advent of new technology, high speed internet and need for high amount of data storage, digital image processing and compression is one of the most important step in image transmission and storage and the most popular areas of research.

Image compression reduces the data from the image in either lossless or lossy way. This project provides an overview of compression techniques for image applications. The medical image is segmented using Otsu Thresholding method. In order to compress ROI (Region of Interest) , that is lossless compression, DWT (Discrete Wavelet Transform) has been implemented. Similarly, PSO optimization using ANN
(Artificial Neural Network) has been implemented for lossy compression to the NONROI region. Further, lossless and lossy decompression is applied to ROI and NON-ROI regions and are merged to obtain the result. For low power and lossless image compression, the quality will be measured by comparing certain performances parameters such as Compression Ratio, Peak Signal to Noise Ratio, Mean Square Error.

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INTRODUCTION

1.1 INTRODUCTION TO MATLAB

MATLAB in short for Matrix Laboratory is a matrix-based language that allows to

- Analyze data
- Develop algorithms
- Create models and applications

The language, apps, and built-in math functions enable to quickly multiple approaches to arrive at a solution.

Matlab is one of the best technologies available in the market for mathematical operations performed on matrices and linear algebra. It also provides the best support for faster and better algorithm design and testing.

It makes analyzing data with different algorithms and studying the changes in behaviour easy. It also provides flexibility to design new interfaces as pr ones need.

MATLAB features a family of add-on application-specific solutions called toolboxes including Image processing toolbox.

The image processing toolbox is a collection of functions that extend the capabilities of the MATLAB's numeric computing environment. It supports a wide range of image processing operations, including:

- Geometric operations
- Neighborhood and block operations
- Linear filtering and filter design
- Transforms
- Image analysis and enhancement
- Binary image operations
- Region of interest operations

MATLAB can import/ export several image formats like BMP (Microsoft Windows Bitmap), Gif (Graphics Interchange Files), HDF (Hierarchical Data Format), JPEG (Joint Photographic Experts Group), PCX (Portable Network Graphics), TIFF (Tagged Image File Format), XMD (X Window Dump), raw-data and other types of image data.

1.2 IMAGE PROCESSING

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. Image processing is one form of signal processing in which the input is a photograph or video frame; the output may be either an image or a set of characteristics or parameters related to the image.
An image contains sub-images sometimes referred as regions-of-interest, or simply regions this implies that images contain collections of objects each of which can be the basis for a region.
In image science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Image processing usually refers to digital image processing, but optical and analog image processing also are possible. The acquisition of images producing the input image in the first place is referred to as imaging.

Image processing is any form of signal processing for which the input is an, such as a photograph or video frame, the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most of the imageprocessing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

An image may be considered to contain sub-images sometimes referred to as regionsof-interest, ROIs, or simply regions. This concept reflects the fact that images frequently contain collections of objects each of which can be the basis for a region. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too.

Image processing basically includes the following three steps:

1. Importing the image with optical scanner or by digital photography.
2. Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs.
3. Output is the last stage in which result can be altered image or report that is based on image analysis.

1.2.1 What is an Image in signal processing?

Signal processing is an umbrella and image processing lies under it. The amount of light reflected by an object in the physical world (3D world) is pass through the lens of the camera and it becomes a 2D signal and hence result in image formation. This image is then digitized using methods of signal processing and then this digital image is manipulated in digital image processing.

1.2.2 Types of images

1. Binary image: A binary image contains only two pixel elements or intensities i.e 0 and 1, where 0 refers to black and 1 refers to white. This image is also known as monochrome.
2. 8 bit color format: It is the most famous image format. It has 256 different shades of colors in it and is commonly known as Grayscale image. In this format 0 stands for black and 256 stands for white, 127 stands for gray.
3. 16 bit color format: It is a color image format. It has 65,536 different colors in it. It is also known as High color format. In this format, the distribution of color is not same as Grayscale image. It is further divided into three formats which are Red, Green and Blue.

1.2.3 Image representation in MATLAB

In MATLAB workspace, most images are represented as two-dimensional arrays (matrices), in which each element of the matrix corresponds to a single pixel in the displayed image. For example, an image composed of 200 rows and 300 columns of different colored dots is stored as a 200-by-300 matrix.

Some images such as RGB, require a three-dimensional array, where the first plane in the third dimension represents the red pixel intensities, the second plane represents the green pixel intensities, and the third plane represents the blue pixel intensities. In MATLAB the start index is from 1 instead of 0. Therefore f(0,0) is written as f(1,1).

1.2.4 Phases of Image Processing

1. Acquisition: It is the creation of a digitally encoded representation of the visual characteristics of an object. The main work involves scaling and color conversion (RGB to Grayscale or vice versa).
2. Image enhancement: It is the procedure of improving the quality and information content of original data before processing and is done based on subjective image quality criteria.

3. Image restoration: It is an operation of taking a corrupt/ noisy image and estimating clean, original image. It is performed by reversing the process that blurred the image and is done either in image domain or frewuwncy domain.
4. Color image processing: The use of color in image processing is motivated by two principal factors. First, color is a powerful descriptor that often simplifies object identification and extraction from a scene.
5. Wavelets and multi-resolution processing: Multi resolution analysis is representation of an image in more than one resolution.
6. Image compression: Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level.
7. Morphological processing: Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.
8. Segmentation procedure: Image segmentation is the procedure of dividing a digital image into a multiple set of pixels. The prior goal of the segmentation is to make things simpler and transform the representation of medical images into a meaningful subject.
9. Representation and description: It follows output of segmentation stage, choosing a representation is only the part of solution for transforming raw data into processed data.
10. Object detection and recognition: It is a process that assigns a label to an object based on its descriptor.

1.2.5 Components of Image processing system

Image Processing System is the combination of different elements involved in digital image processing. Digital image processing uses different computer algorithms to perform image processing on digital images. Structure of a Digital image processing system is shown in the figure.

The various components of image processing system are mentioned below:

1. Image sensors: Image sensors sense the intensity, amplitude, co-ordinates and other features of the images and passes the result to the image processing hardware. It includes the problem domain.

2. Image processing hardware: The dedicated hardware that is used to process the instructions obtained from the image sensors. It passes the result to general purpose computer.

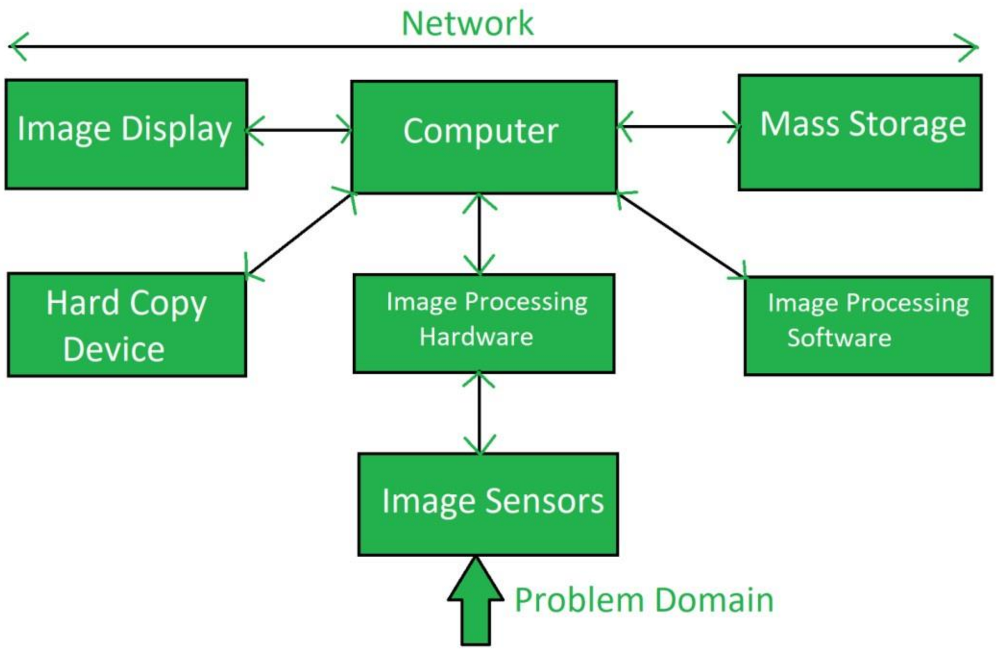


Fig 1.1: Components of Digital Image Processing system

3. Computer: Computer used in the image processing system is the general purpose computer that is used by us in our daily life.
4. Image processing software: Image processing software is the software that includes all the mechanisms and algorithms that are used in image processing system.
5. Mass storage: Mass storage stores the pixels of the images during the processing.
6. Hard copy device: Once the image is processed, it is stored in the hard copy device. It can be a pen drive or any external ROM device.
7. Image display: It includes the monitor or display screen that displays the processed images.
8. Network: Network is the connection of all the above elements of the image processing system.

1.3 IMAGE SEGMENTATION[1]

Image segmentation is the process of partitioning a digital image into multiple parts or segments, generally a set of pixels based on the characteristics of the pixels.

It could involve seperating foreground from background, or clustering regions of pixels based on similarities in color or shape.

Image segmentation plays an essential role in medical imaging field, including computer-aid diagnosis (CAD), medical image analysis, image fusion, image fusion, image-guided theraphy, image annotation and image retrieval.

In computer vision, image segmentation is the process of partitioning a 2D/3D image into multiple segments. The goal is to simplify or change the representation of an image into something more meaningful and easy to understand and analyse.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as colour, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions.

1.3.1 Image segmentation with MATLAB

MATLAB is a platform that helps perform tasks such as:

- Use apps to interactively explore different segementation techniques
- Simplify image analysis workflows using built-in image segmentation algorithms
- Perform deep learning for image segmentation

Segmentation could either be manually initailised, semi automated, or fully automated. Current advances in the field of image processing seek the full automation of segmentation techniques in order to optimise the process and refrain from manual intervention, which is time consuming and error prone as well.

Segmentation processes are subdivided into four classes according to the use of a type of region definition as shown in figure 1.2.

Type 1: Pixel-based techniques

Type 2: Area-based techniques

Type 3: Edge-based techniques

Type 4: Physics-based techniques

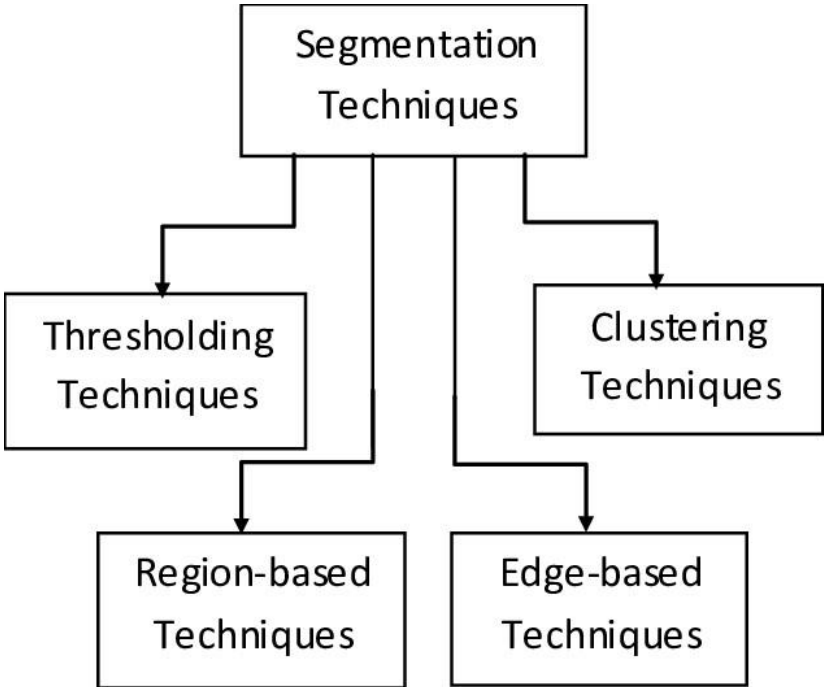


Fig 1.2: Image segmentation techniques

1.3.2 Cluster- based segmentation

Clustering is the undertaking of collection an arrangement of articles such that items in similar gathering (called a cluster) are more comparative (in some sense or another) to each other than to those in dissimilar gatherings (groups).

This type is further divided into exclusive clustering, overlapping clustering, hierarchical clustering. The clustering methods such as k means, improved K mean, fuzzy C mean (FCM) and improved fuzzy c mean algorithm (IFCM) have been proposed. K means clustering is one of the popular method because of its simplicity and computational efficiency.

1.3.3 Area/ Region- based segmentation

Region- based segmentation algorithms operate iteratively by grouping together pixels which are neighbors and have similar values and splitting groups of pixels which are dissimilar in value.

This may be regarded as spatial clustering:

- clustering in the sense that pixels with similar values are grouped together
- spatial in the sense that pixels in the same category also form a single connected component

Region- based methods can be categorized into:

- those which merge pixels
- those which split the image into regions
- those which both split-and –merge in an iterative search scheme

1.3.4 Edge-based segmentation

An edge filter is applied to the image, pixels are classified as edge or non-edge depending on the filter output, and pixels which are not seperated by an edge are allocated to the same category.

1.3.5 Physics-based segmentation

Segmentation techniques in which physical models in color space are used for division of an image into regions that correspond to surfaces and/or objects at object borders and not at shadows or specular highlights in the image are called physics-based segmentation techniques. A highlight can be segmented as separate region in the image or the surface area of a bent object can be sub divided into many regions on the basis of intensity changes caused by shading. These techniques facilitate the segmentation of real images on the basis of physical models for image formation.

1.4 IMAGE THRESHOLDING

Thresholding is the simplest method of segmenting images. It is a way to create a binary image from a grayscale or full-color image. This is done to sepearate "object" or foreground pixels from the background pixels to aid image processing. It is most effctive in images with high levels of contrast.

The input of a thresholding operation is usually a gray scale or color image. In a grayscale image, the black pixels correspond to background and the white pixels correspond to foreground. Each pixel is compared with a threshold value. If the pixel's intensity is higher than the threshold, it forms the foregriund, else it forms the background.

There are three types of thresholding algorithms:

- Global thresholding
- Local or regional thresholding
- Adaptive thresholding

1.4.1 Global thresholding

Global thresholding is applicable when the intensity distribution of objects and background pixels sre sufficiently distinct. In this method, a single threshold value is used in the whole image.

Choose a threshold ‘T’ that seperates object from background as shown in figure.

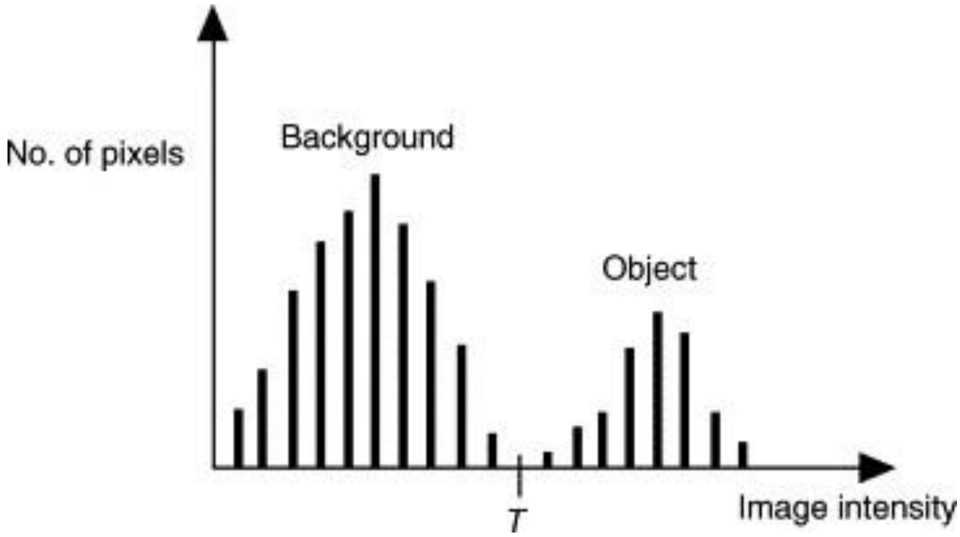


Fig 1.3: Selection of threshold ‘T’ from Histogram of an image

If g(x,y) is a threshold version of f(x,y) at some global threshold T,

$$g(x, y) = \begin{cases} 1, & \text{if } f(x, y) > T \\ 0, & \text{if } f(x, y) \leq T \end{cases}$$

There are a number of thresholding techniques such as: Otsu, Optimal thresholding, histogram analysis, iterative thresholding, maximum correlation thresholding, clustering, multispectral and multithresholding.

Threshold selection based on Histogram

A image histogram is a type of histogram that acts as a graphical representation of the tonal distribution of an image. For a 8-bit grayscale image there are 256 different possible intensities, and so the histogram wil graphically display 256 numbers showing the distribution of pixels amongst those grayscale values.
Histograms can also be taken for color images – either individual histograms of red, green and blue channels can be taken or a 3D histogram can be produced, with the three

axes representing the red, blue and green channels, and brightness at each point representing pixel count.

Let P1 and P2 be the gray value of the peaks of the histogram. The threshold value ‘T’ is given by:

T= (P1 + P2)/2

Or T maybe the gray level at the minimum between the two peaks

T= min H(u)

U € *P1,P2+, where H(u) is the histogram value at gray level between P1 and P2.
The histogram value based technique is dependent on the success of estimating the threshold value that seperates the two homogenous region of the object and background of the image.

Some factors affect the suitability of histogram for guiding the choice of the threshold:

- The seperation between peaks
- The noise content in the image
- The relative size of objects and background
- The uniformity of the illumination’the uniformity of the reflectance

Threshold Selection based on iterative techniques

Iterative methods give better result comapred to histogram and in cases where histogram doesn’t clearly define a valley point. The procedure to find threshold ‘T’ is as follows:

- Segment the image using ‘T’. This will produce two groups of pixels.
- G1 consisting of all pixels with gray level values >T and G2 consisting of pixels with values <=T.
- Compute the average gray level values mean1 and mean2 for pixels in regions in G1 and G2.
- Compute a new threshold value T= (1/2)(mean1 + mean2)
- Repeat previous 2 steps until difference in T in successive iterations is smaller than a predefined parameter.

Threshold selection based on Otsu's method

Otsu's thresholding is used to overcome the drawback of iterative thresholding i.e., calculating mean after each step. In this method, optimal threshold is identified by making use of the histogram of the image. Otsu's method is aimed ain finding the optimal value for the global threshold.

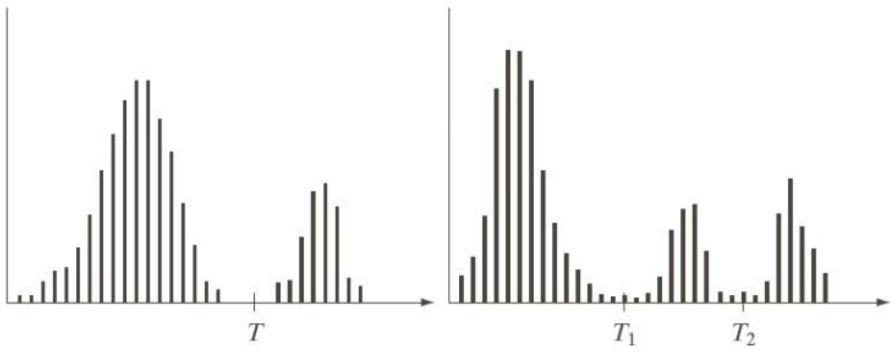


Fig 1.4: Comparison of Histograms of two images, the second histogram having multiple thresholds

The main drawback of Otsu's method of threshold selection is that it assumes the histogram is bimodal. A histogram with 2 peaks is called a bimodal histogram. This method fails if two classes are of different sizes and also variable illumination. This method will be discussed ellaboarately in upcoming sections.

Multithresholding and multiple thresholding methods

Multilevel thresholding is a process that segments a gray-level image into several distinct portions. This technique determines more than one threshold for the given image and segments the image into certain brightness regions, which correspond to one background and several objects. Similarly, multiple thresholding involves selection of multiple thresholds for different parts of an image.

This method works very well for objects with colored or complex backgrounds, on which bi-level thresholding fails to produce satisfactory results.

The output equation is as follows:

$$g(x, y) = \begin{cases} a, & \text{if } f(x, y) > T_2 \\ b, & \text{if } T_1 < f(x, y) \leq T_2 \\ c, & \text{if } f(x, y) \leq T_1 \end{cases}$$

1.4.2 Variable thresholding

In this kind of thresholding, a threshold is calculated for each pixel, baseed on some local characterictics and statistics such as range, variance, or surface-fitting parameters of the neighborhood cells. It can be approached in different ways such as background subtraction, waterflow model, mean and standard deviation of pixel value, local image contrast.

 Local or regional thresholding, if T depends on a neighborhood of (x,y). Adaptive thresholding, if T is a function of (x,y).

Some drawbacks of local adpative thresholding techniques are region size dependent, individual image characteristics and time consuming.

1.5 IMAGE COMPRESSION

A typical image produced by technologies such as Computed Tomography (CT), X-ray, Magnetic Resonance Imaging (MRI), Ultrasound have sizes ranging from 512×512×8 bit up to 1024×1024×12 bit with a size of 5-6 MB. Such large image sizes pose a challenge to limited bandwidth and storage capacity. This can be solved by image compression techniques.

Image is a function that signifies a measure of characteristics such as illumination or color or viewed sight. Digital compressions has several benefits such as faster and cheap processing cost, easy storing and communication, immediate quality assessment, multiple copying with reserving the quality, fast and cheap reproduction and adaptable manipulation.

The compression can be done either by lossy or lossless compression techniques. The main goal of these methods is to reduce the file size while achieving high quality of decompressed image.

Lossy compression methods are irreversible in nature, where the decompressed image is reasonably close to the original image. They provide a compression ratio as high as 10:1 at the cost of image quality degradation.

Lossless compression is reversible methods where the reconstructed image is almost similar to original image and the compression ratio obtained could be as low as 2:1.

A 3D medical data set is a collection of 2D images, henceforth called slices. The most important drawback of 3D based approaches in ROI based compression is twofold.

First, the image quality along the three principal 3D axes is not uniform, i.e. the resolution between the slices is much less than the resolution within each slice. Second, the ROI does not necessarily lie in a 3D primitive shape such as a cube. As a consequence, a primitive 3D ROI would occupy a big portion of the data, thereby deviating from our initial objective of high compression rate. To address these problems, a 2D ROI based scheme is explored in this paper.

1.6 REGION BASED COMPRESSION

Region based coding is a form of selective image compression. The medical image is divided into regions based on their diagnostic importance. Region of interest (ROI) is thr diagnostically significant information i.e. the affected part of the image used for analysis, which is located over very small regions, nearly about 5-10% of the total area of the image. The rest of the image is termed as NON-ROI. An illustration of ROI and NON-ROI in MRI image of brain with a tumor is shown below.

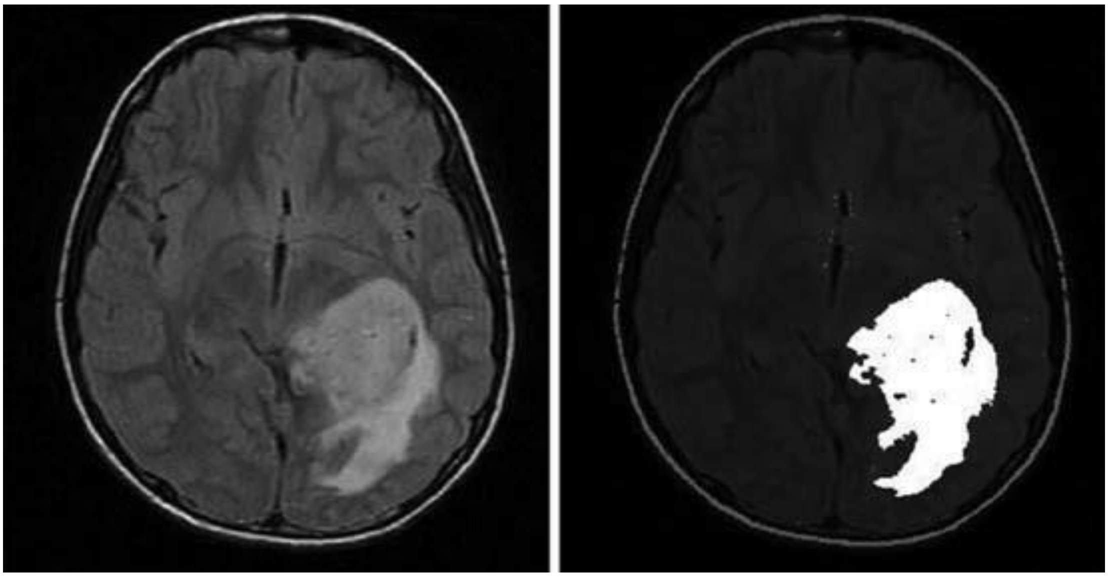


Fig 1.5: ROI and NON-ROI of MRI Scan of human brain with tumor

As medical field cannot afford loss of information, lossless compression of medical images is under intensive interest over the past few years. However, a low compression ratio is obtained is case of lossless compression. In order to have a balance between high quality of the reconstructed image and low use of memory, a region of interest based compression can be used.

In region based coding lossy and lossless compression techniques are combined to achieve higher compression at visually acceptable quality.

Lossless compression is used for abnormal regions that are important for diagnosis and therefore achieving high quality, while NON-ROI region undergoes lossy compression. During transmission of these images, ROI regions are transmitted first at higher priority.

The amount of image information retained by an image after compression and decompression is known as 'energy retained' and this is proportional to the sum of squares of pixel values.

1.6.1 Lossless compression technique

Lossless compression is a method of data compression in which the size of the file is reduced without sacrificing image quality. Unlike lossy compression, that will be discussed in the next section, no data is lost when this method is used. Because the data is preserved, the technique will decompress the data and restore it exactly to its original state.

However, because no quality is lost, the resulting files are typically much larger than image files compressed with lossy compression.

In lossless compression techniques, the original image can be perfectly recovered from the compressed (encoded) image. These are also called noiseless since they do not add noise to the image. It is also known as entropy coding since it uses statistics/ decomposition techniques to eliminate/ minimize redundancy.

Lossless compression is used only for a few applications with stringent requirements such as medical imaging. Following techniques are included in lossless compression:

- Run length encoding

  RLE is used in the first stage which involves decorrelation procedure which removes the spatial and interspatial redundancy. In RLE, a sequence of repeating pixels is replaced by two numbers, first being the value of pixel and second being the number of times it is repeating.
  For example, consider a screen containing plain black text on a solid white background:
  WWWWBWWWWWWAWWWWWWWBWWWB
  With RLE, the above code can be recoded as:
  4W1B6W1A7W1B3W1B
  RLE works best for binary images. As the pixel value varies the coding sequence increases.

- Huffman encoding

Huffman coding is the variable length coding which is used to compress the image. It deals with how frequently pixels of certain intensity repeat.
The pixels with maximum frequency and close intensity are replaced with pixels with mean intensity value.

- LZW coding
This algorithm is mainly used in GIF and optionally in PDF and TIFF. LZW compression works by reading a sequence of symbols, grouping the symbols into strings, and converting the strings into codes.
It is an error free approach and does not require prior knowledge of probability of occurrence of symbols to be encoded.
LZW coding is extremely effective when there are repeated patterns in the data that are widely spread.
- Area coding
Area coding is an enhanced form of run length coding, reflecting the two dimensional character of images. This is a significant advance over the other lossless methods. For coding an image it does not make too much sense to interpret it as a sequential stream, as it is in fact an array of sequences, building up a two dimensional object.
The algorithms for area coding try to find rectangular regions with the same characteristics. These regions are coded in a descriptive form as an element with two points and a certain structure. This type of coding can be highly effective but it bears the problem of a nonlinear method, which cannot be implemented in hardware.

1.6.2 Lossy compression techniques

Lossy compression methods have larger compression ratios as compared to the lossless compression techniques. Lossy compression methods include some basic considerations like speed of encoding and decoding, compression ratio and SNR ratio.

Lossy compression includes following methods:

- Block truncation coding
Initially image is divided into blocks. The window of N by N is considered as a block. The mean value of all the values of that wIndow consisting a certain number of pixles is calculated. The threshold is mormally the mean value of the pixel values of all vector. Then a bitmap of that vector is generated by replacing all pixels having values greater than or equal to the threshold by a 2.
Then for each segment in the bitmap, a value is determined which is the average of the values of corresponding pixels in the original code vector.

- Code vector quantization

The basic idea in vector quantization is to create a dictionary of vectors of constant size, called code vectors. Values of pixels composed the blocks called as code vector. A given image is then parted into non-recurring vectors called image vectors. Dictionary is made out of this information and is indexed. Further, it is used for encoding the original image. Thus, every image is then entropy coded with the help of these indices.

- Fractal coding
  The idea behind this coding is to divide image into segments by using standard points like color difference, edges, frequency and texture. It is obvious that parts of an image and other parts of the same image are usually resembling. Here, there is a dictionary which is used as a look up table called as fractal segments. The library contains codes which are compact sets of numbers. Doing an algorithm operation, fractals are operated and image is encoded. This scheme is far more effective for compressing images that are natural and textured.

- Transform coding
  In this coding, transforms like Discrete Fourier Transform (DFT) and Discrete Cosine Transform (DCT), Discrete Sine Transform are used to alter the pixel specifications from spatial domain into frequency domain. One is the energy compaction property, some few coefficients only have energy of original image signal that can be used to reproduce itself.
  Only those few significant coefficients are considered and remaining are discarded. These coefficients are given for quantisation and encoding. DCT coding has been the most commonly used in transformation of image data.

- Sub-band coding
  In this coding, quantisation and coding is applied to each of the analysed subbands from the frequency components bands. This coding is very useful because quantisation and coding is more accurately applied to sub-bands.

CHAPTER 2

OTSU'S METHOD

The initial task that we have to initiate image compression is to divide the required image, the brain tumor MRI, into Region of Interest and Non-Region of interest. This is done with the help of Otsu's method.

Otsu's method is named after its inventor Nobuyuki Otsu. It is one of the many binarization algorithms. In this method, we need to understand how the algorithm works and provides a Java implementation, which can be easily ported to other languages.

Otsu's thresholding method involves iteration of all possible threshold values and the calculation of a measure of spread for the pixel levels each side of the threshold. This means we consider the pixels that fall either in foreground or background. The whole purpose is to fund the threshold value where the sum of foreground and background spreads is at the minimum.

Let us understand the method with an example given below:

We have taken a 6*6 image and to simplify the explanation, we have used only 6 greyscale levels. The image is labeled as figure 2.2. The histogram of the image is given below as well, labeled as figure 2.1.

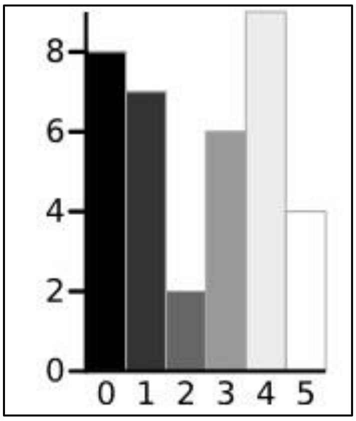


Fig 2.1: Histogram of image

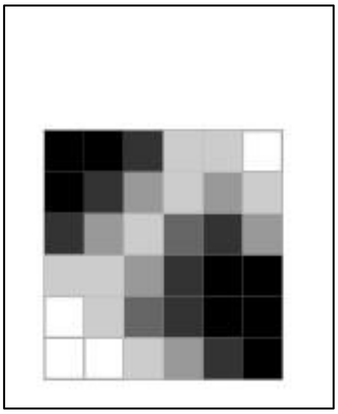


Fig 2.2: Sample image

The calculation for finding the foreground and background variance (the measure of spread) for a single threshold is to be done. Here, the chosen threshold value is 3. That is, the pixel intensities less than 3 form the background and remaining form forground.

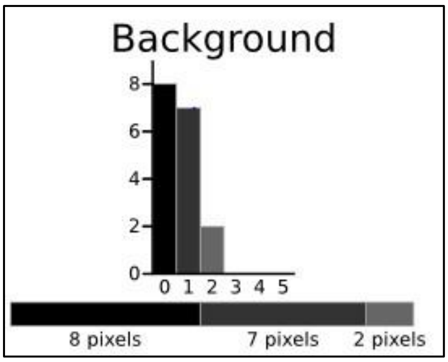


Fig 2.3: Histogram of background

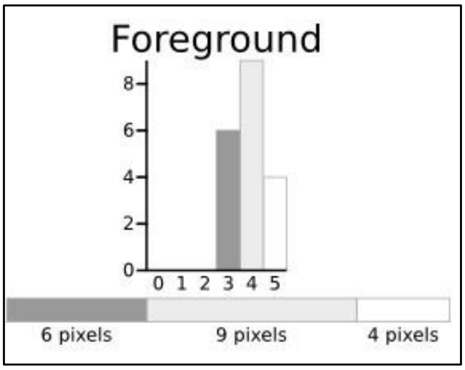


Fig 2.4: Histogram of foreground

Calculations:

Weight is calculated as the ration of the sum of pixels that form the region to total number of pixels.
Mean and Variance are also calculated for the assumed foreground and background region as shown below: Background:

$$\text{Weight} \quad W_b = \frac{8+7+2}{36} = 0.4722$$
$$\text{Mean} \quad \mu_b = \frac{(0\times 8)+(1\times 7)+(2\times 2)}{17} = 0.6471$$
$$\text{Variance} \quad \sigma_b^2 = \frac{((0-0.6471)^2\times 8)+((1-0.6471)^2\times 7)+((2-0.6471)^2\times 2)}{17}$$
$$= \frac{(0.4187\times 8)+(0.1246\times 7)+(1.8304\times 2)}{17}$$
$$= 0.4637$$

Foreground:

$$\text{Weight} \quad W_f = \frac{6+9+4}{36} = 0.5278$$
$$\text{Mean} \quad \mu_f = \frac{(3\times 6)+(4\times 9)+(5\times 4)}{19} = 3.8947$$
$$\text{Variance} \quad \sigma_f^2 = \frac{((3-3.8947)^2\times 6)+((4-3.8947)^2\times 9)+((5-3.8947)^2\times 4)}{19}$$
$$= \frac{(4.8033\times 6)+(0.0997\times 9)+(4.8864\times 4)}{19}$$
$$= 0.5152$$

Naturally to segment, we would like to have threshold which keeps the clusters as tight as possible and at the same time maximizes the separation between two clusters (to minimize the overlap).

- This keeping clusters as tight as possible is minimizing intra-class or within class variance.

- The maximization of distance between them is maximizing inter-class or between class variance.

So, we must calculate the 'Within–class Variance'. This is the sum of the two variances multiplied by their associated weights.

$$\text{Within Class Variance} \quad \sigma_W^2 = W_b\, \sigma_b^2 + W_f\, \sigma_f^2 = 0.4722 * 0.4637 + 0.5278 * 0.5152$$
$$= 0.4909$$

The final value obtained is the sum of weighted variances for the threshold value of 3.The similar set of steps or procedure is to be followed for the threshold values from 0 to 5, each time assuming a new threshold value.

The table shows the total results of all threshold values. The results of threshold 3 are highlighted in the table.

We can notice that for the threshold value 3 has the lowest sum of weighted variances. Therefore, this is the final selected threshold. All pixels with a level less than 3 are background and those equal to or greater than 3 are foreground. The result of Otsu's method is shown below:

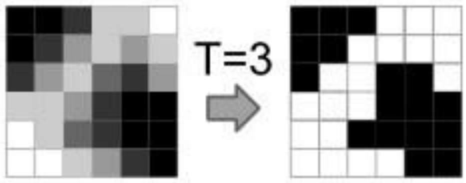
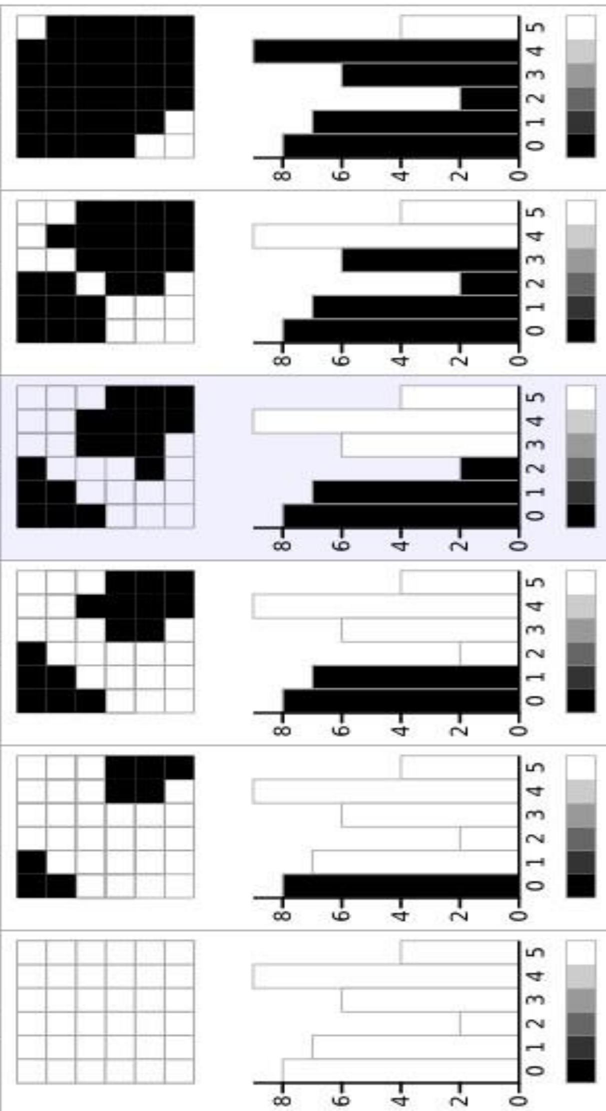


Fig 2.5: Example result of Otsu's method

This approach for calculating Otsu's threshold is useful for explaining the theory, but it is computationally intensive, especially if you have a full 8-bit greyscale.



Threshold	T=0	T=1	T=2	T=3	T=4	T=5
Weight, Background	$W_b = 0$	$W_b = 0.222$	$W_b = 0.4167$	$W_b = 0.4722$	$W_b = 0.6389$	$W_b = 0.8889$
Mean, Background	$M_b = 0$	$M_b = 0$	$M_b = 0.4667$	$M_b = 0.6471$	$M_b = 1.2609$	$M_b = 2.0313$
Variance, Background	$\sigma^2_b = 0$	$\sigma^2_b = 0$	$\sigma^2_b = 0.2489$	$\sigma^2_b = 0.4637$	$\sigma^2_b = 1.4102$	$\sigma^2_b = 2.5303$
Weight, Foreground	$W_f = 1$	$W_f = 0.7778$	$W_f = 0.5833$	$W_f = 0.5278$	$W_f = 0.3611$	$W_f = 0.1111$
Mean, Foreground	$M_f = 2.3611$	$M_f = 3.0357$	$M_f = 3.7143$	$M_f = 3.8947$	$M_f = 4.3077$	$M_f = 5.000$
Variance, Foreground	$\sigma^2_f = 3.1196$	$\sigma^2_f = 1.9639$	$\sigma^2_f = 0.7755$	$\sigma^2_f = 0.5152$	$\sigma^2_f = 0.2130$	$\sigma^2_f = 0$
Within Class Variance	$\sigma^2_W = 3.1196$	$\sigma^2_W = 1.5268$	$\sigma^2_W = 0.5561$	$\sigma^2_W = 0.4909$	$\sigma^2_W = 0.9779$	$\sigma^2_W = 2.2491$

Table 2.1 Results of example for Otsu's method

CHAPTER 3 DISCRETE WAVELET TRANSFORM

Discrete wavelet transforms is the most popular transformation technique adopted for image compression. Complexity of DWT is always high due to large number of arithmetic

operations. Two-dimensional image transforms are extremely important areas of study in image processing. The image output in the transformed space may be analyzed, interpreted, and further processed for implementing diverse image processing tasks.
These transformations are widely used, since by using these transformations, it is possible to express an image as a combination of a set of basic signals, known as the basic functions.

Now, that we have segmented the ROI and NON-ROI of an image, let us move to the next step of compressing ROI (Region of Interest) which is lossless compression. ROI comprises the most important information in the image and has to hold the information appreciably. To do this, we are using Discrete Wavelet Transfor.

The Discrete Wavelet Transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT), or its implementation for the discrete time series sometimes called discrete-time continuous wavelet transform (DT-CWT).

The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere e. g. the dilation equation.

$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(Sx - k).$$

where S is a scaling factor. Moreover, the area between the function must be normalized and scaling function must be ortogonal to its integer translates e. g.

$$\int_{-\infty}^{\infty} \phi(x)\phi(x+l)dx = \delta_{0,l}$$

After introducing some more conditions (as the resstrictions above soes not produce unique solution) we can obtain results of all this equations, e. g. finite set of coefficients a_k which define the scaling function and also the wavelet. The wavelet is obtained from the scaling function as:

$$\psi(x) = \sum_{k=-\infty}^{\infty} (-1)^k a_{N-1-k} \psi(2x - k)$$

where N is an even integer. The set of wavelets than forms an orthonormal basis which we use to decompose signal. Note that usually only few of the coefficients a_k are nonzero which simplifies the calculations.

3.1 THE WAVELET TRANSFORM

A wavelet is defined as a "small wave" that has its energy concentrated in time to provide a tool for the analysis of transient, non-stationary, or time-varying phenomena. It has the oscillating Wave-like properties but also has the ability to allow simultaneous time and frequency analysis. Wavelet Transform has emerged as a powerful mathematical tool in many areas of science and engineering, more so in the field of audio and data compression.

In Fourier transform domain, we completely lose information about the localization of the features of an audio signal. Quantization error on one coefficient can affect the quality of the entire audio file. The wavelet expansion allows a more accurate local description and separation of signal characteristics.

A wavelet expansion coefficient represents a component that is itself local and is easier to interpret. The Fourier basis functions have infinite support in that a single point in the Fourier domain contains information from everywhere in the signal. Wavelets, on the other hand, have compact or finite support and this enables different parts of a signal to be represented at different resolution.

A wavelet function Ψ(t) has two main properties,

$$\int_{-\infty}^{0} \Psi(t)dt = 0;$$

That is, the function is oscillatory or has wavy appearance.

$$\int_{-\infty}^{0} \left|\Psi(t)\right|^2 dt < \infty;$$

That is, the most of the energy in Ψ(t) is confined to a finite duration.

Wavelets are adjustable and adaptable and can therefore by designed for adaptive systems that adjust themselves to suit the signal. Fourier Transform, however, is suitable only if the signal consists of a few stationary components. Also, the amplitude spectrum does not provide any idea how the frequency evolve with time. All wavelets tend to zero at infinity, which is already better than the Fourier series function. Furthermore, wavelets can be made to tend to zero as fast as possible. It is this property that makes wavelets so effective in signal and audio compression.

3.2 DWT ARCHITECTURE

Image consists of pixels that are arranged in two dimensional matrix, each pixel represents the digital equivalent of image intensity. In spatial domain adjacent pixel values are highly correlated and hence redundant. In order to compress images, these redundancies existing among pixels needs to be eliminated. DWT processor transforms the spatial domain pixels into frequency domain information that are represented in multiple sub-bands, representing different time scale and frequency points.

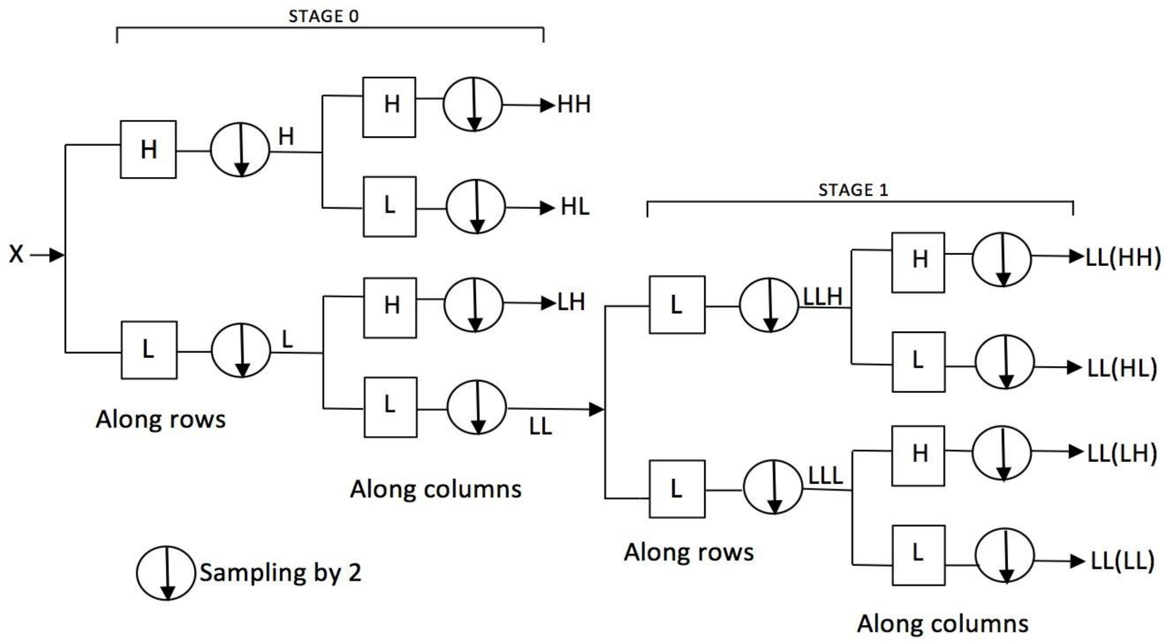


Fig 3.1: DWT Architecture

Human visual system is very much sensitive to low frequency and hence, the decomposed data available in the lower sub-band region and is selected and transmitted, information in the higher sub-bands regions are rejected depending upon required information content.

As shown in the figure, input image consisting rows and columns are transformed using high pass and low pass filters. The filter coefficients are predefined and depend upon the wavelets selected.

First stage computes the DWT output along the rows, the second stage computes the DWT along the column achieving first level decomposition. Low frequency sub-bands from the first level decomposition is passed through the second level and third level of filters to obtain multiple level decomposition.

3.3 COMPRESSION STEPS

- Digitize the source image into a signal s, which is a string of numbers.
- Decompose the signal into a sequence of wavelet coefficients w.
- Use threshold to modify the wavelet coefficients from w to w’.
- Use quantization to convert w’ to a sequence q.
- Entropy encoding is applied to convert q into a sequence e.

Digitation

The image is digitized first. The digitized image can be characterized by its intensity levels, or scales of gray which range from 0(black) to 255(white), and its resolution, or how many pixels per square inch.

Thresholding

In certain signals, many of the wavelet coefficients are close or equal to zero. Through threshold these coefficients are modified so that the sequence of wavelet coefficients contains long strings of zeros. In hard threshold ,a threshold is selected. Any wavelet whose absolute value falls below the tolerance is set to zero with the goal to introduce many zeros without losing a great amount of detail.

Quantization

Quantization converts a sequence of floating numbers w’ to a sequence of integers q. The simplest form is to round to the nearest integer. Another method is to multiply each number in w’ by a constant k, and then round to the nearest integer. Quantization is called lossy because it introduces error into the process, since the conversion of w’ to q is not one to one function.

Entropy Coding

With this method, a integer sequence q is changed into a shorter sequence e, with the numbers in e being 8 bit integers. The conversion is made by an entropy encoding table. Strings of zeros are coded by numbers 1 through 100,105 and 106, while the non-zero integers in q are coded by 101 through 104 and 107 through 254.

3.4 ONE LEVEL OF TRANSFORM

The DWT of a signal *x* is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response *g* resulting in a convolution of the two:

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

The signal is also decomposed simultaneously using a high-pass filter *h*. The outputs give the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter. The impulse response of low-pass filter is represented by *g* and impulse response of high-pass filter is represented by *h*.

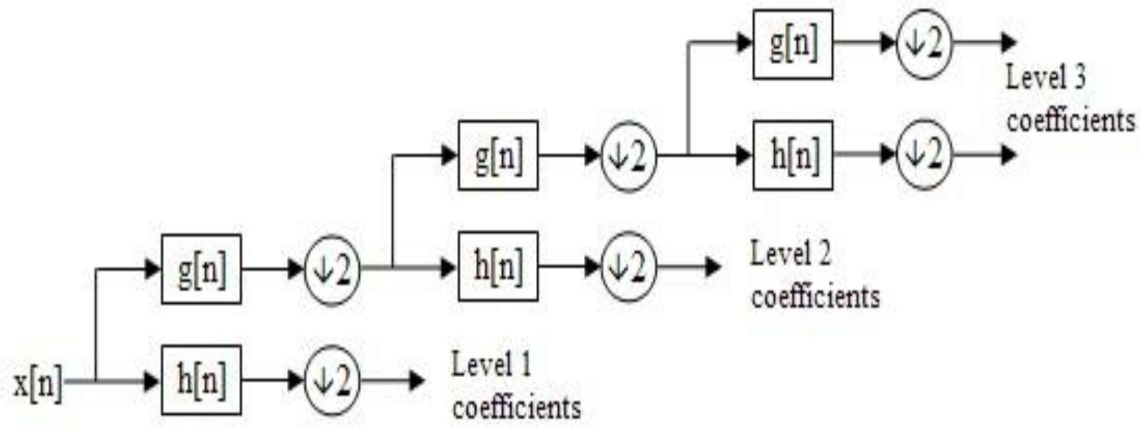


Fig 3.2: Block diagram of level wise DWT: Filter analysis

However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule.

The filter output of the low-pass filter *g* in the diagram above is then subsampled by 2 and further processed by passing it again through a new low- pass filter *g* and a high-pass filter *h* with half the cut-off frequency of the previous one, as given in the next equations.

$$y_{\text{low}}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]$$

$$y_{\text{high}}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k]$$

CHAPTER 4 PSO OPTIMIZATION

The particle swarm optimization (PSO) algorithm was proposed by Kennedy and Eberhart. PSO algorithm is based on the concept of swarm intelligence capable of solving complex mathematics problems. In real life, some animals belonging to a certain group, that is, birds such as swans and fishes, are able to share information among theie group, and such capability confers these animals to stay together and is a great survival advantage. The authors derived this algorithm from a similar concept. This optimization technique can be used to implement lossy compression on Non- ROI.

4.1 INTENT OF PSO

The objective of optimization is to seek values for a set of parameters that maximize or minimize objective functions subject to certain constraints. A choice of values for the set of parameters that satisfy all constraints is called a feasible solution. Feasible solutions

with objective function value(s) as good as the values of any other feasible solutions are called optimal solutions.
An example of an optimization problem is the arrangement of the transistors in a computer chip in such a way that the resulting layout occupies the smallest area and that as few as possible components are used. Optimization techniques are used on a daily base for industrial planning, resource allocation, scheduling, decision making, etc. Furthermore, optimization techniques are widely used in many fields such as business, industry, engineering and computer science.

Research in the optimization field is very active and new optimization methods are being developed regularly. Optimization encompasses both maximization and minimization problems.
Any maximization problem can be converted into a minimization problem by taking the negative of the objective function, and vice versa. Hence, the terms optimization, maximization and minimization are used interchangeably in this thesis. In general, the problems tackled in this thesis are minimization problems.

In a PSO system, a swarm of individuals (called particles) fly through the search space. Each particle represents a candidate solution to the optimization problem. The position of a particle is influenced by the best position visited by itself (i.e. its own experience) and the position of the best particle in its neighborhood (i.e. the experience of neighboring particles).

The initial intent of the particle swarm concept was to graphically simulate the graceful and unpredictable choreography of a bird flock, with the aim of discovering patterns that govern the ability of birds to fly synchronously, and to suddenly change direction with a regrouping in an optimal formation. From this initial objective, the concept evolved into a simple and efficient optimization algorithm.

In PSO, individuals, referred to as particles, are “flown” through hyper dimensional search space. Changes to the position of particles within the search space are based on the social psychological tendency of individuals to emulate the success of other Individuals. The changes to a particle within the swarm are therefore influenced by the experience, or knowledge, of its neighbours.
The search behaviour of a particle is thus affected by that of other particles within the swarm (PSO is therefore a kind of symbiotic cooperative algorithm). The consequence of modelling this social behaviour is that the search process is such that particles stochastically return toward previously successful regions in the search space. Particle Swarm has two primary operators:

- Velocity update
- Position update

A swarm of birds flying over a place must find a point to land. The location and destination of the birds is illustrated in the image. Each animal would most likely land at a different point and different time and hence finding the point is complex. The movement of the flock only happens if all the members of the swarm are able to share information among themselves. The birds encounter the best point, in terms of latitude, longitute and maximal survival condition, only until it is found by one of the swarm's members. Each member of he swarm balances its individual according to the swarm knowledge experience.

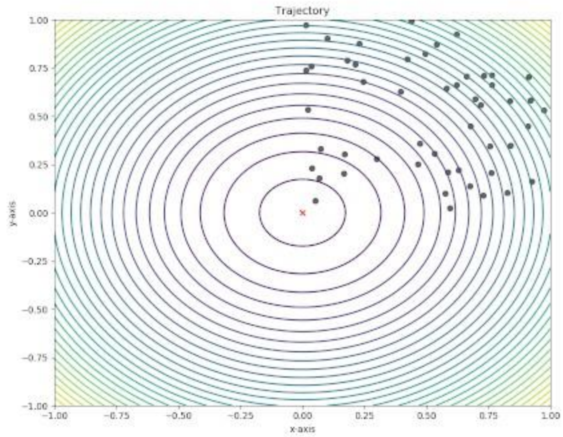


Fig 4.1: Location of swarm of birds and the optimum/ best location

4.2 PSO algorithm

The initial population (swarm) of size N and dimension D is denoted as X = [X1, X2, ..., XN]^T , where 'T' denotes the transpose operator.

Each individual (particle) X_i (i = 1; 2; ...;N) is given as X_i =[$X_{i,1}$; $X_{i,2}$; ...; $X_{i,D}$]. Also, the initial velocity of the population is denoted as V = [V_1 ,V_2 ,...,V_N]^T .

Thus, the velocity of each particle X_i (i = 1; 2; ...; N) is given as V_i =[$V_{i,1}$; $V_{i,2}$; ...; $V_{i,D}$].

The index I varies from 1 to N, whereas the index j varies from 1 to D. The detailed algorithms of various methods are described below for completeness.

$$V_{i,j}^{k+1} = w \times V_{i,j}^{k} + c_1 \times r_1 \times (Pbest_{i,j}^{k} - X_{i,j}^{k}) + c_2 \times r_2 \times (Gbest_{j}^{k} - X_{i,j}^{k}) \quad (1)$$

$$X_{i,j}^{k+1} = X_{i,j}^{k} + V_{i,j}^{k+1} \quad (2)$$

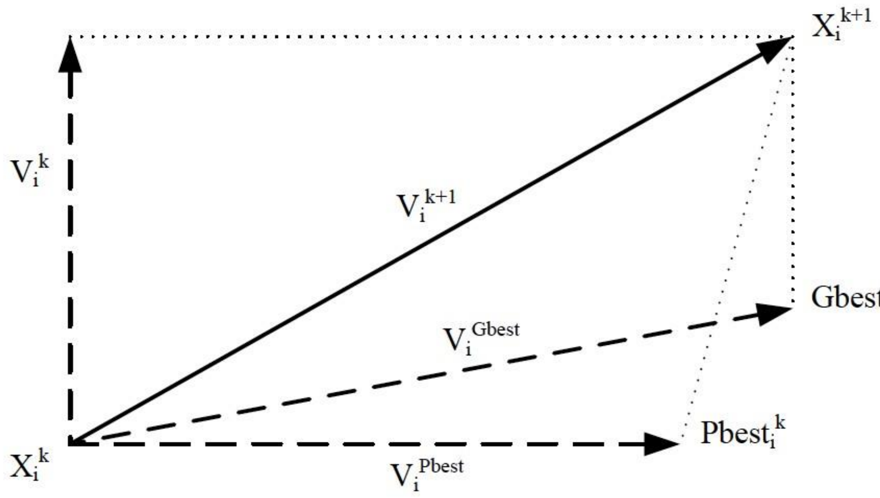


Fig 4.2: PSO search mechanism in multidimensional search space

In equation (1) P*best*$^{k}_{i;j}$ represents personal best j^{th} component of i^{th} individual, whereas G*best*$^{k}_{j}$ represents j^{th} component of the best individual of population upto iteration k . Figure shows the search mechanism of PSO in multidimensional search space with respect to the above algorithm terms.

The different step is PSO are as follows:

1. Set parameter w_{min}, w_{max}, c_1 and c_2 of PSO
2. Initialize population of particles having positions $\mathbf{X}$ and velocities $\mathbf{V}$
3. Set iteration $k = 1$
4. Calculate fitness of particles $F_i^k = f(\mathbf{X}_i^k), \forall i$ and find the index of the best particle b
5. Select $\mathbf{Pbest}_i^k = \mathbf{X}_i^k, \forall i$ and $\mathbf{Gbest}^k = \mathbf{X}_b^k$
6. $w = w_{max} - k \times (w_{max} - w_{min})/Maxite$
7. Update velocity and position of particles
   $V_{i,j}^{k+1} = w \times V_{i,j}^k + c_1 \times rand() \times (Pbest_{i,j}^k - X_{i,j}^k) + c_2 \times rand() \times (Gbest_j^k - X_{i,j}^k)$; $\forall j$ and $\forall i$
   $X_{i,j}^{k+1} = X_{i,j}^k + V_{i,j}^{k+1}$; $\forall j$ and $\forall i$
8. Evaluate fitness $F_i^{k+1} = f(\mathbf{X}_i^{k+1}), \forall i$ and find the index of the best particle $b1$
9. Update Pbest of population $\forall i$
   If $F_i^{k+1} < F_i^k$ then $\mathbf{Pbest}_i^{k+1} = \mathbf{X}_i^{k+1}$ else $\mathbf{Pbest}_i^{k+1} = \mathbf{Pbest}_i^k$
10. Update Gbest of population
    If $F_{b1}^{k+1} < F_b^k$ then $\mathbf{Gbest}^{k+1} = \mathbf{Pbest}_{b1}^{k+1}$ and set $b = b1$ else $\mathbf{Gbest}^{k+1} = \mathbf{Gbest}^k$
11. If $k < Maxite$ then $k = k + 1$ and goto step 6 else goto step 12
12. Print optimum solution as $\mathbf{Gbest}^k$

A detailed flowchart of PSO is shown in the figure:

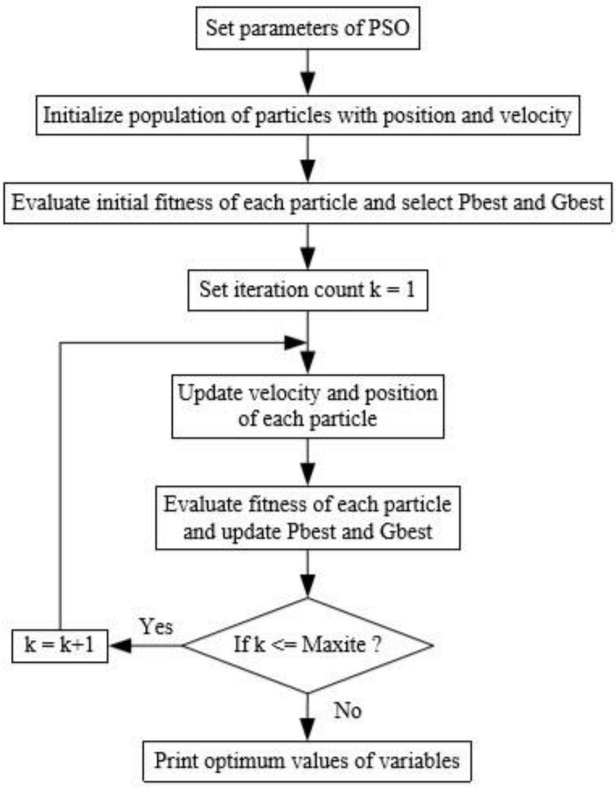


Fig 4.3: Flowchart of PSO

4.3 GLOBAL BEST PSO

When the neighborhood of a particle is the entire swarm, the best position in the neighborhood is referred to as the global best particle, and the resulting algorithm is referred to as a gbest PSO.
When smaller neighborhoods are used, the algorithm is generally referred to as a lbest PSO. The performance of each particle (i.e. how close the particle is from the global optimum) is measured using a fitness function that varies depending on the optimization problem.

Each particle in the swarm is represented by the following characteristics:
x_i: The current position of the particle; v_i: The
current velocity of the particle; y_i: The personal
best position of the particle; ÿ$_i$: The neighborhood
best position of the particle.

The personal best position of particle i is the best position (i.e. the one resulting in the best fitness value) visited by particle i so far. Let ‘f’ denote the objective function. Then the personal best of a particle at time step ‘t’ is updated as:

$$\boldsymbol{y}_i(t+1) = \begin{cases} \boldsymbol{y}_i(t) & \text{if } f(\boldsymbol{x}_i(t+1)) \geq f(\boldsymbol{y}_i(t)) \\ \boldsymbol{x}_i(t+1) & \text{if } f(\boldsymbol{x}_i(t+1)) < f(\boldsymbol{y}_i(t)) \end{cases}$$

For the gbest model, the best particle is determined from the entire swarm by selecting the best personal best position. If the position of the global best particle is denoted by the vector ÿ, then

$$\hat{\boldsymbol{y}}(t) \in \{\boldsymbol{y}_0, \boldsymbol{y}_1, \ldots, \boldsymbol{y}_s\} = \min\{f(\boldsymbol{y}_0(t)), f(\boldsymbol{y}_1(t)), \ldots, f(\boldsymbol{y}_s(t))\}$$

eqn (1)

where s denotes the size of the swarm.

The velocity update step is specified for each dimension j ∈ 1,…,N_d, hence, vi,j represents the j^{th} element of the velocity vector of the i^{th} particle. Thus the velocity of particle ‘i ‘is updated using the following equation:

$$v_{i,j}(t+1) = wv_{i,j}(t) + c_1 r_{1,j}(t)(y_{i,j}(t) - x_{i,j}(t)) + c_2 r_{2,j}(t)(\hat{y}_j(t) - x_{i,j}(t))$$

eqn (2)

In the above equation, w is the inertia weight, c_1 and c_2 are the acceleration constants, and $r_{1,j}(t)$, $r_{2,j}(t)$ ~ U(0,1).

The components in the equation are:

- The inertia weight term ‘w’ was first introduced by Shi and Eberhart. This term serves as a memory of previous velocities. The inertia weight controls the impact of the previous velocity: a large inertia weight favors exploration, while a small inertia weight favors exploitation.
- The cognitive component, $y_i(t) - x_i$, represents the particle's own experience as to where the best solution is.
- The social component, $\ddot{y}(t) - x_i(t)$, represents the belief of the entire swarm as to where the best solution is.

4.4 FLOW CHART OF PSO ALGORITHM

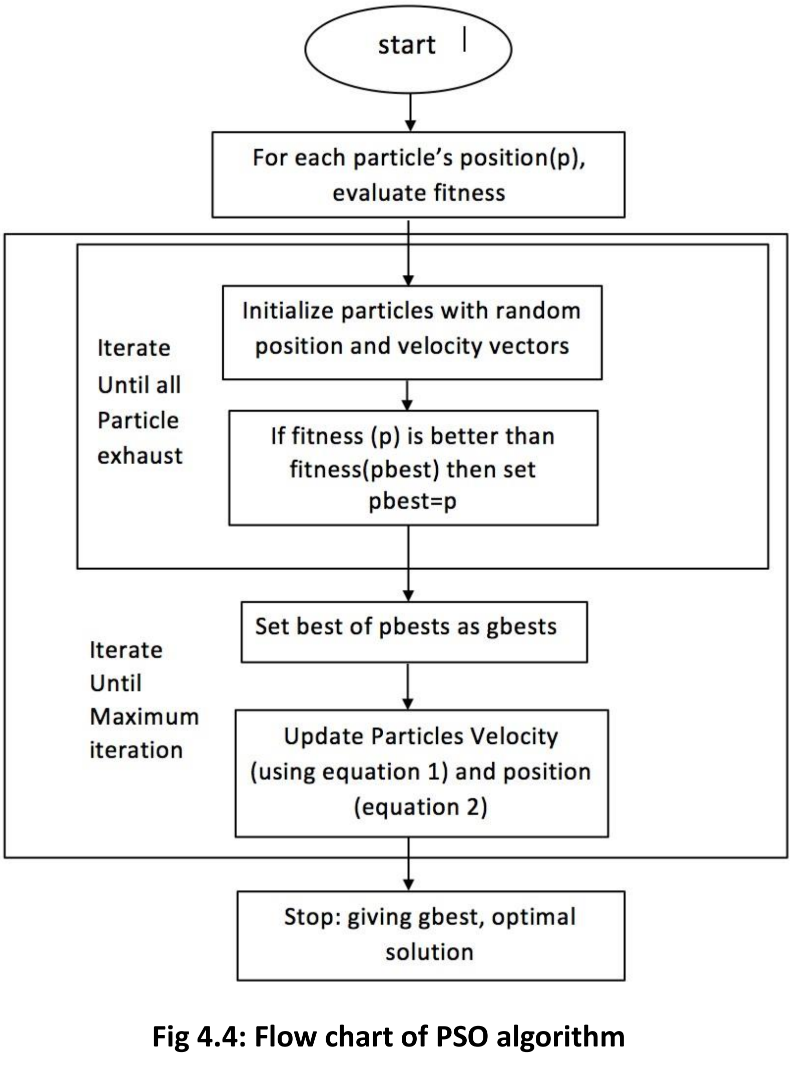


Fig 4.4: Flow chart of PSO algorithm

4.5 LOCAL BEST PSO

The local best PSO, or lbest PSO, uses a ring social network topology where smaller neighbourhoods are defined for each particle. The social component reflects information exchanged within the neighbourhood of the particle, reflecting local knowledge of the environment.
With reference to the velocity equation, the social contribution to particle velocity is proportional to the distance between a particle and the best position found by the neighbourhood of particles.

4.6 PSO ALGORITHM APPLICATION IN IMAGE SEGMENTATION

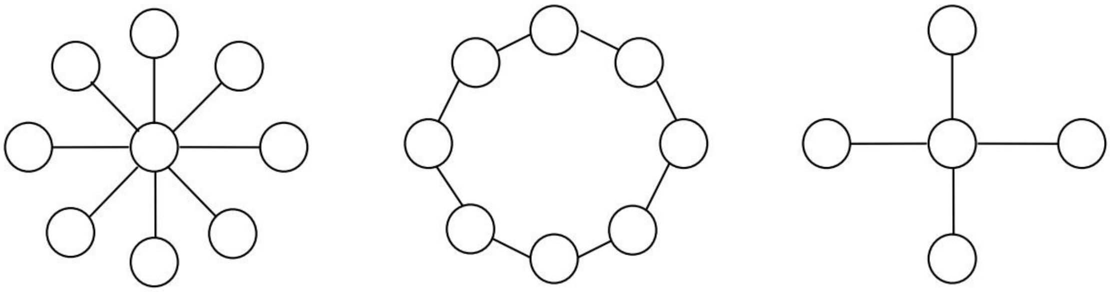
The application of this algorithm to the image segmentation problem can be sequenced in the following manner:

Step 1: Read the input image to be segmented.
Step 2: Select PSO method to be applied on that image with a particular threshold level.
Step 3: For each particle in the population do update particle's fitness in the search space and update particle's best in the search space move particle in the population . Step 4: For each particle do if swarm gets better then reward the swarm spawn the particle: extend the swarm/particle life.
Step5: For each particle do if swarm is not improving its performance then punish swarm: delete the swarm/particle: or reduce the swarm life.
Step 6: Extend the swarm to spawn (the swarm is considered for next iteration) Step 7: Delete the "failed" swarms (the swarm will never come into search space) and Reset threshold counter.

4.7 PSO NEIGHBORHOOD TOPOLOGIES

Different neighborhood topologies have been investigated. Two common neighborhood topologies are the star (or wheel) and ring (or circle) topologies. For the star topology one particle is selected as a hub, which is connected to all other particles in the swarm. However, all the other particles are only connected to the hub. For the ring topology, particles are arranged in a ring.

Each particle has some number of particles to its right and left as its neighborhood.



(a) Star topology (b) Ring Topology (c) Von Neumann Topology

Fig 4.5: Diagrammatic representation of neighborhood topologies

The choice of neighborhood topology has a profound effect on the propagation of the best solution found by the swarm. Using the gbest model the propagation is very fast (i.e. all the particles in the swarm will be affected by the best solution found in iteration t, immediately in iteration t+1).

4.8 PSEUDO CODE FOR PSO PROCEDURE

For each particle
    Initialize particle
End

Do
    For each particle
        Calculate fitness value
        If the fitness value is better than the best fitness value (pBest) in history set current value as the new pBest
End

Choose the particle with the best fitness value of all the particles as the gBest

For each particle
    Calculate particle velocity
    Update particle position
End

CHAPTER 5

ARTIFICIAL NEURAL NETWORKS

Neural networks are a set of algorithms, modeled on the basis of working and transfer of message by the human brain, that are designed to recognize patterns. The basic idea behind a neural network is to simulate lots of densely interconnected brain cells inside a computer and make it learn, recognize patterns and make decisions in a humanlike way.

The human brain consists of nearly 10 billion nerve cells called neurons. These neurons communicate via electrical signals or short impulses in the voltage of the cell wall or membrane. The interneuron connections are mediated by electrochemical junctions called synapses which are located on branches of the cell referred to as dendrites. Each neuron constantly receives a multitude of incoming signals from other neurons which are summed or integrated together. If the resulting signal exceeds a certain threshold level, the neuron will generate a voltage impulse or response. The signal is then transmitted to other neurons via a branching fiber called axon.

5.1 STRUCTURE OF NEURAL NETWORKS

A typical neural network consists of millions of artificial neurons called units arranged in a series of layers, each of which connects to the layers on the other side.Some units are input units and are designed to receive information. Other units called output units sit on the opposite side of the network and signal how it responds to the information. In between iput and output units are more layers of nits called hidden units which form the majorty of the artificial brain.

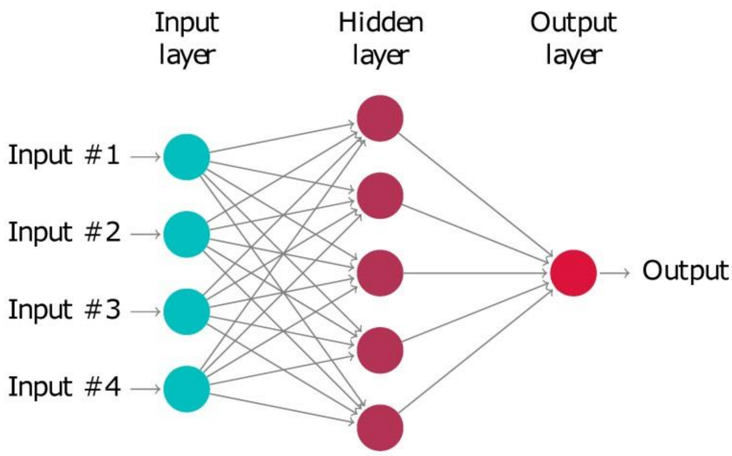


Fig 5.1: Basic diagram of Neural Network

It is in the hidden layers where all the processing happens through a system of connections characterised by weights and biases as shown in the figure. A neural network is an adaptive system and the adaptive parameters are called weights.

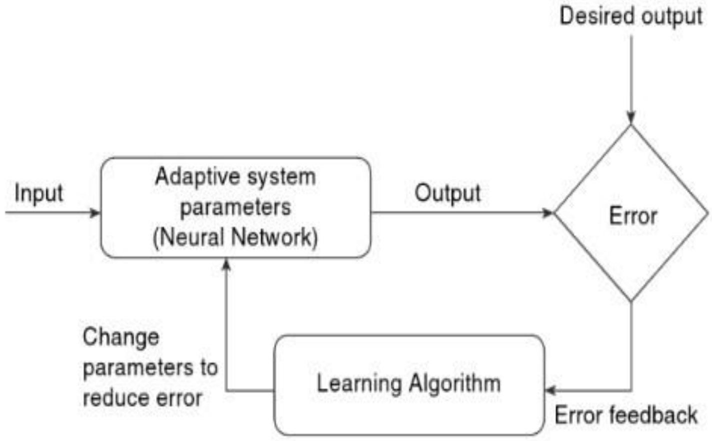


Fig 5.2: Basic diagram of adaptive system

When an input is released, the neuron calculates a weighted sum adding the bias and according to the result and a pre-set activation function, it decides whether it should be 'fired' or activated. The figure below shows the summation of inputs in the process. Then, the neuron transmits the information downstream to other connected neurons in a process called 'forward pass'. At the end of the process, the last hidden layer is linked to the output layer which has one neuron layer for each possible desired output.

A neural network has the ability to learn from inputs in order to perform intelligent tasks. The primary application of neural networks is in areas where problems are illdefined, data is incomplete or noisy in nature or dynamic. Typical applications include signal enhancement, noise cancellation, clustering, classification, pattern recognition, system identification, time series prediction and control.

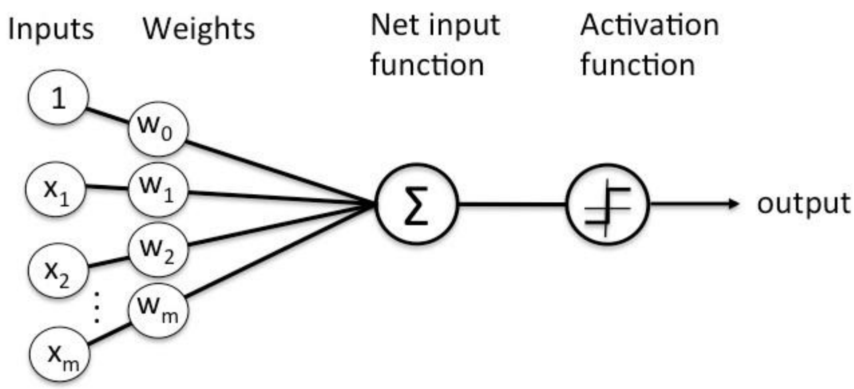


Fig 5.3: Summation of inputs for learning and output generation in NN

The input presented to the system is processed internally to generate an output which is then compared with a desired output to estimate the error. The error estimate is provided to a learning algorithm which first estimates and then makes appropriate incremental changes to the system parameters in order to reduce the error on the current input. Input is a vector of numbers which the network processes to generate a set of output vectors. Weights undergo changes in their values in accordance with a learning algorithm.

5.2 IMAGE PROCESSING USING NEURAL NETWORKS

Image processing using artificial neural networks has een successfully used in various fields such as medical, geotechnics, civil engineering, mechanics, industrial surveillance, defence department, automatics and transport. Image processing, data reduction, segmentation and recognitionare the processes used in managing images with ANN.

An image can be represented as a matrix, each element of the matrix containing color information for a pixel. The matrix is used as input data for the neural network. The small dimensions of the images, to quickly and easily help learning, establish the size of vector and number of input vectors.

The image is a function defined on a spatial domain, it has a limited scale of numeric values (natural numbers, real numbers or complex numbers), values which can be used to form a matrix.

Depending on the type of data in the matrix, the images are divided into images of intensity scale and indexed (each component having a unique number, a scalar) and vector images (eachcompnent being a vector, vector number that splits into a number of parts). Scalar image intensity is an image where each pixel value is considered a measure of luminous intensity. Scalar indexed image is an image in which the value of a pixel is an indx where information can be associated with the color of the pixel.

An image can be represented as a matrix $M_{m \times n}$, each element of the array containing information of color for a pixel. Each color can be represented as a combination of three basic colors: red, blue and green. The array is used as input to the neural networks that are aimed at identifying images or grading. Each input neuron represents color information in the image, and each output neuron corresponds to an image. All images will be scaled to the same size and small to be easy and quick to learn.

Processing of images with ANN involves different processes, such as:

1. Image preprocessing, an operation which shows a picture (contrast enhancement, noise reduction) with the same dimensions as the original image. The objective of

images preprocessing with ANN consists in improvising, restoring or rebuilding images.

2. Data reduction or fature extractioninvolves extracting a number of features smaller than the number of pixels in input window. The operationconsists in compressing the image followed by extracting geometric characteristics (edges, corners, joints), facial features, etc.

3. Segmentation is the process of dividing of image into regions.

4. Recognition involves the determination of objects in an image and their classification.

5.3 METHODOLOGY

Now that lossless and lossy compression is done, image has to be reconstructed as per the following flowchart:

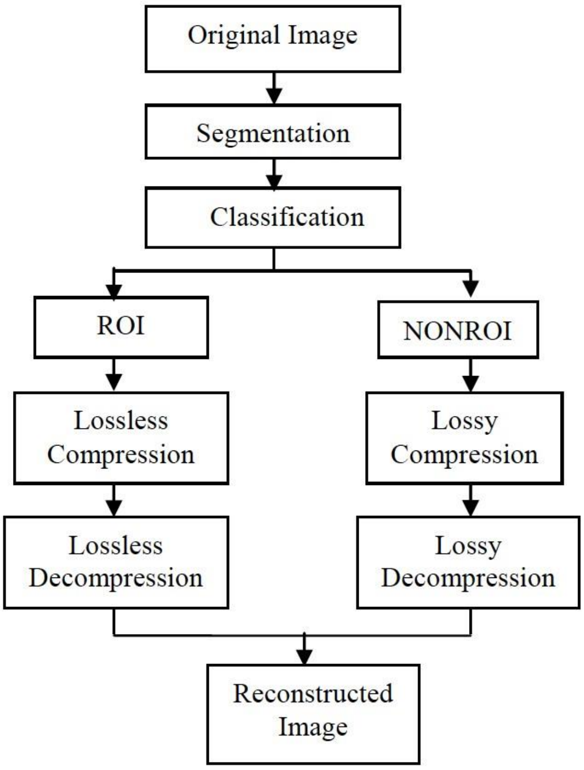


Fig 5.4: Flow of methodology

CHAPTER 6

OBSERVATIONS AND RESULTS

6.1 PERFORMANCE PARAMETERS

6.1.1 PSNR (Peak Signal to Noise Ratio)

It is defined as the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. This ratio measures the quality between the original and a compressed image. The higher value of PSNR represents the best quality of the compressed image.

$$\text{PSNR}= 10 \log_{10}(Imax^2/MSE)\ \text{dB}$$

where I_{max} is the intensity value of each pixel which is equal to 255 for 8 bit grayscale images.

6.1.2 MSE (Mean Square Error)

It is defined as the average squared difference between a reference image and a distorted image. The smaller the MSE, the more efficient the image steganography technique. MSE is computed pixel-by-pixel by adding up the squared differences of all the pixels and dividing by the total pixel count.

$$\text{MSE} = (1/(\text{MN}))\sum_{i=1}^{M}\sum_{j=1}^{N}[(X_{i,j}-Y_{i,j})^{\wedge}2]$$

where M and N denote the total number of pixels in the horizontal and the vertical dimensions of the image Xi, j represents the pixels in the original image and Yi, j, represents the pixels of the stego image.

6.1.3 Compression Ratio

The compression ratio is used to measure the ability of data compression by comparing the size of the image being compressed to the size of the original image.
The greater the compression ratio means the better the wavelet function.

6.2 RESULTS:

Fig 6.1: Original Image

OTSU METHOD RESULTS:

Region of Interest:

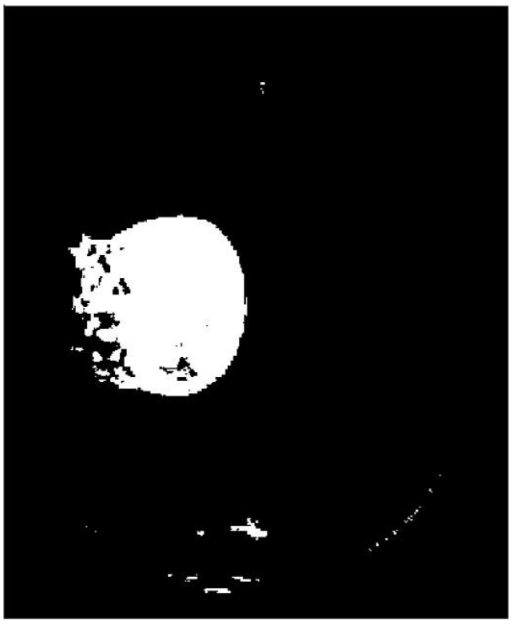


Fig 6.2: Identifying the Region of Interest

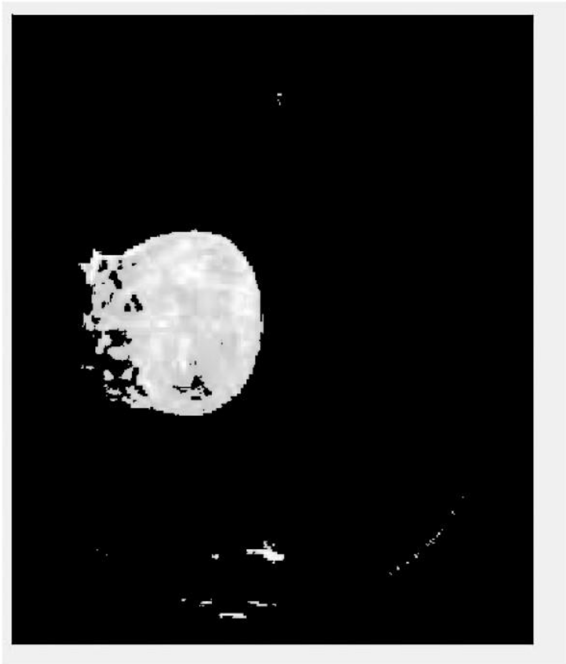


Fig 6.3: Replacing identified ROI with original pixels

Non- Region of Interest:

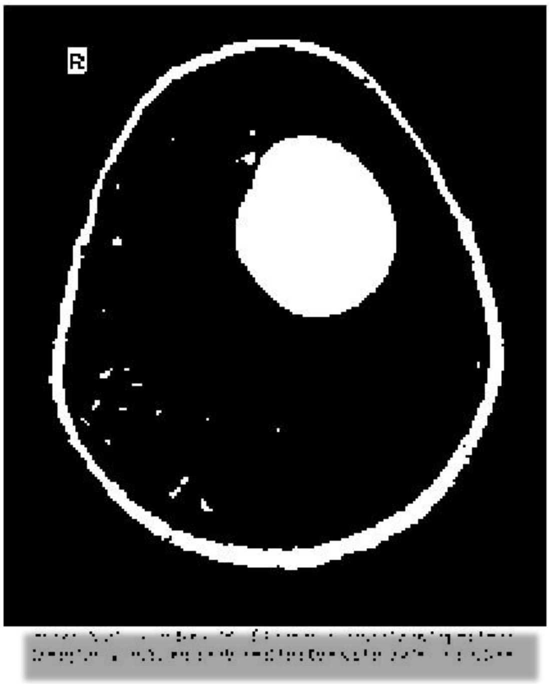


Fig 6.4: Identifying the Non- Region of Interest

Fig 6.5: Replacing identified NON-ROI with original pixels

DISCRETE WAVELET TRANSFORM RESULTS:

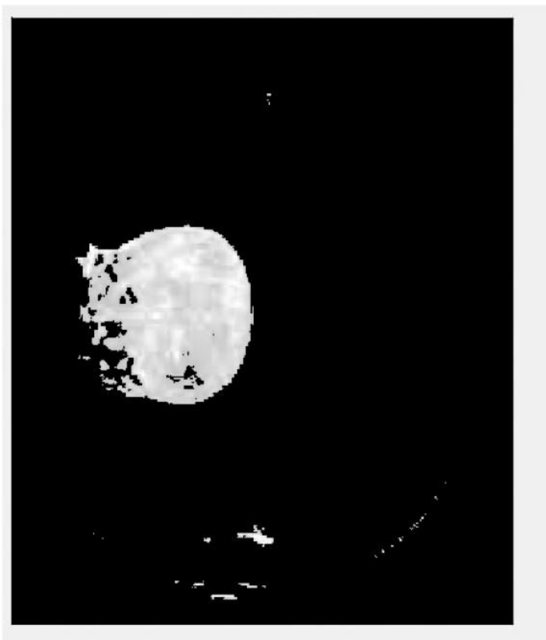


Fig 6.6: Input image for DWT

Fig 6.7: Output image for DWT

PSO RESULTS:

Fig 6.8: Input image for PSO

Fig 6.9: Output image for PSO

REFERENCES

[1] Region based hybrid compression for medical images by Preethi V. Joshi & C. D. Rawat

[2] https://www.wikipedia.org/