A New Approach for Digital Watermarking In Medical Images

Thesis submitted in partial fulfilment of the requirement for the degree of
Bachelor of Computer Science and Engineering
Under the Supervision of
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Declaration

We hereby declare that this thesis is based on results obtained from our own work. Due acknowledgement has been made in the text to all other material used. This thesis, neither in whole nor in part, has been previously submitted to any other University or Institute for the award of any degree or diploma.

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Abbreviations

CC	Correlation Coefficient
DWT	Discrete Wavelet Transform
EPR	Electronic Patient Report
IDWT	Inverse Discrete Wavelet Transform
MQU	Mean Quantization Unit
MRI	Magnetic resonance imaging
MSE	Mean Squared Error
PSNR	Peak-Signal-to-Noise-Ratio
SMQT	Successive Mean Quantization Transform

Abstract

Security and hiding personal data of medical image is very critical issue in transferring medical image data from one medical center to another .In this paper, a new approach for Digital Watermarking on Medical images is proposed which worked on various requirements such as robustness and imperceptibility. In this model, image enhancement was done by SMQT based on OTSU, segmentation of the image is performed by OTSU thresholding. Then Discrete Wavelet Transform (DWT) and IDWT is used to embed and extract the watermark on and from the host image. To evaluate the performance of the proposed model, numerous attacks were performed and measured using PSNR, MSE, and CC.

CHAPTER 01: Introduction

Nowadays, medical images are transmitted over electronic networks for improved health care as well as for clinical interpretation such as telediagnosis, teleconferences among clinicians, distant learning of medical personnel etc. Digital medical imaging facilities have become so reliable and less costly that film-based imaging technology has transferred to filmless technology for generating digital images on devices instead of creating hardcopies. With the emerge of this technology, privacy and security of the patient information became the most critical issue. Digital Watermarking appeared to be a solution to protect the privacy and security of the medical images. Our aim is to develop a digital watermarking model which will ensure confidentiality as well as will be robust to attacks for example, salt and pepper, shear attack, rotation, median attacks.

1.1 Motivation

Exchanging medical images between clinicians, specialists, and radiologists provides a platform for discussing and consulting diagnostic and therapeutic measures. In this case, the electronic patient report (EPR) and medical images are sent separately to the destination. Using watermarking techniques and integrating the EPR into the medical images will not only guarantee the confidentiality and security of the sent data but also the integrity of the medical images. In addition to the basic requirements of a typical watermarking system, various specific features such as imperceptibility, reversibility, that is, one should be able to exactly recover the original image after extracting the watermark and authentication, on other words, identification of the image source and verification that the image belongs to the correct patient [1] are needed for the medical image watermarking system.

The above discussed feature makes the watermarking in medical images more challenging and sophisticated. Therefore, finding and developing new watermarking models to satisfy these requirements is an important and relevant research area.

1.2 Contribution Summary

Digital watermarking is relatively a new research field of image processing. Extensive research is going on to find better schemes for watermarking because there is no single scheme which can be termed as best. Besides this, watermarking in medical images is more challenging since medical images needs to be more robust, personal information should be hidden, the host or original image should be reversible. Moreover, robustness and imperceptibility are the factors a medical image must have but increasing quality of one of the factors adversely affect the other. Therefore, maintaining balance of these factor is very difficult. This gave us the incentive to perform a research to propose a model which will perform better than the existing models on the above mentioned issue.

1.3 Thesis Outline

- Chapter 2 discusses the Literature Review of related works in this field
- Chapter 3 provides the Background study in details including the algorithms and techniques used in the system
- Chapter 4 describes the proposed model along with implementation details
- Chapter 5 presents the results of the experiment along with performance analysis and comparisons
- Chapter 6 concludes the paper specifying the limitations and challenges while planning future development of the project

CHAPTER 02: Literature Review

Digital Watermarking in Medical Images is a solution for security and privacy of personal data and medical information. Image enhancement is a technique which converts the image to a form which is more suitable for analysis by a machine or human. In general there is still no general theory of image enhancing technique since no common standard of image quality which can be used as design criterion for an image enhancement processor. The effect of image enhancement directly determines the quality of the subsequent image analysis work. Therefore, how to improve the effect of image enhancement is obviously very important [10]. There are various techniques that are used to enhance image for example, Histogram Equalization Method, Improved Adaptive Immune Genetic Algorithm, Successive Mean Quantization Transform (SMQT) etc. which have many shortcomings when they work individually.

Over the years, scholars home and abroad have put forward a variety of excellent image enhancement algorithms. Among them, the histogram equalization method is one of the most classical and commonly used algorithms for its simple principle, small amount of computation and remarkable effect. However, it is easy to produce noise, lose details. And the phenomenon of over saturation and distortion often appears [11]. A modified adaptive immune genetic algorithm was proposed [10], which overcomes the shortcomings of the previous method, such as the loss of details, the low contrast and the poor universality. Thus the algorithm improves the efficiency and the convergence rate of the algorithm, but it does not work with light intensity and shooting at the same time.

A mathematical model of a histogram equalization optimization was established [13], which was better than the traditional histogram equalization on experimental results. However, because the parameter adjustment in the model needs a lot of work, the automatic enhancement of image cannot be realized automatically. Mikael et al [12] proposed a successive mean quantization transform (SMQT) algorithm, which used the point of view of set theory to analyze the function and performance of the transformed image enhancement. The enhanced image can maintain the basic shape of the original histogram by performing a nonlinear stretch. So, it can reveal the underlying structure in data, and decompose the details of information in the image. But in the algorithm, the mean value is selected as a threshold to segment image, which results in a very bright enhanced image with weak contrast, much noise, and some stiff details.

2.1. Digital Watermarking in Medical Image

Digital Watermarking is a process by which additional data as a 'watermark' into a digital media such as digital image , audio, video etc. in a way that the 'watermark' can be detected afterwards. The fundamental and most attractive property of watermarking is data-hiding capability [2, 3]. Maximum privacy can be maintained by hiding the personal information into the images. Keeping necessary medical information (e.g., EPR including demographic data, diagnostic results, treatment procedures, etc.) hidden in medical images may provide a better security against malicious tampering, assuming medical images would not be of people's interest without the patient information [4]. As pointed out in a survey paper written by Navas et al. [5], the objectives of medical image watermarking (MIW) can be divided into two parts:

1. To control integrity and authentication
2. To hide the electronic patient record (EPR) information.

Another paper [6] divided medical image watermarking methods into three separate categories according to their application: authentication, data hiding, and both authentication and data hiding combined.

2.2. Discrete Wavelet Transform (DWT)

There are many frequency domain methods. DWT is one of them that analyze signal at multiple resolution or level. DWT is based on mathematical implement for ordered decomposition of an image into a set of basis functions, known as wavelets. A two dimensional image is transformed into single DWT, image is decomposed into four parts, one part is a low frequency of original image, the one bottom left is vertical details of the original image, the top right contains horizontal detail of the image , the bottom right block contains high frequency of original image.

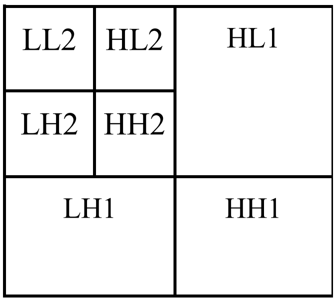
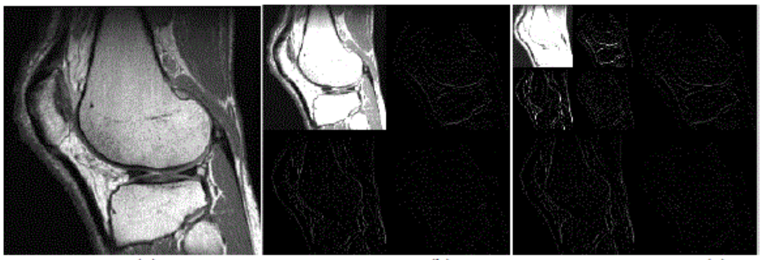


Figure 1. 2-level DWT decomposition

Again we compute second level DWT of the low frequency coefficient [7]. The low frequency coefficient contains most information of the original image, so it is more robust to embed watermark in this position. Watermark must be robust against compression so it is necessary to choose the low frequency of DWT to embed watermark.



(a) (b) (c)

(a) MRI image (b) First Level Wavelet Transform (c) Second Level Wavelet Transform

Figure 2: Different Level of Discrete Wavelet Transform

2.2.1 Algorithm

The following steps are used for watermark embedding and extraction using DWT:

1. Original host image is divided into 4x4 image blocks.
2. Two-level DWT transform decomposes the image into frequency sub-bands, LL1, LH1, HL1, and HH2. Again LL1 is chosen and decomposed to sub-bands LL2, LH2, HL2, and HH2.
3. The watermark image is also processed using steps (1) and (2).
4. For embedding process, second level DWT transform of Host Image Host_LL2 is selected to embed watermark image using the following equation
   $$Watermarked\_Image = Host\_\mathrm{LL2} + 0.005 * Watermark\_\mathrm{LL2}$$
5. To recover the host image, second level Inverse Discrete Transform(IDWT) of Watermarked Image Watermarked_LL2 is selected to extract watermark image using the following equation:
   $$Recovered\_Host\_Image = (Watermarked\_\mathrm{LL2} - Watermark\_\mathrm{LL2}) * 0.005$$
6. Watermark is embedded using the coefficient matrices with respect to a *haar* wavelet filter.

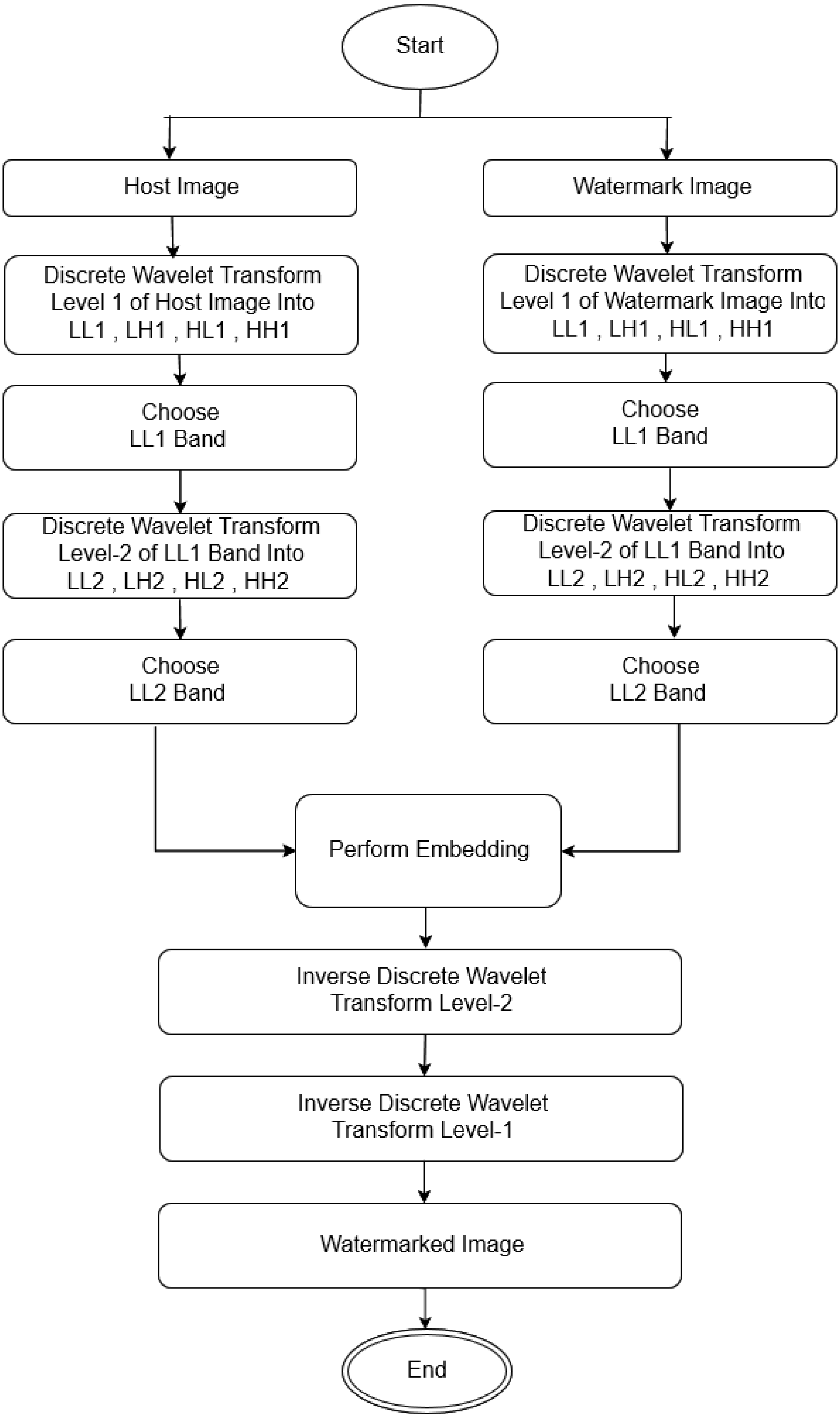


Figure 3. Flowchart of DWT for Embedding Watermark

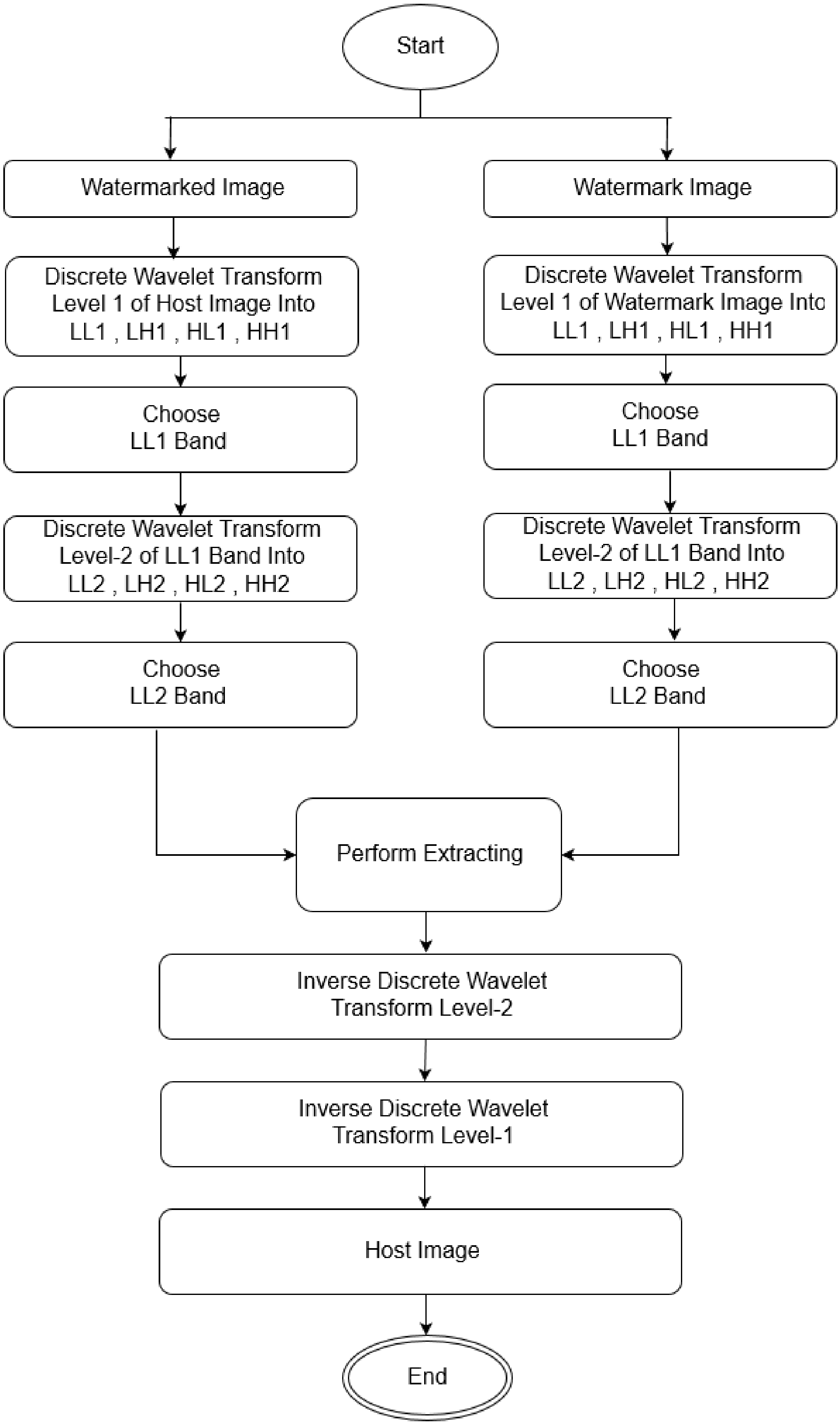


Figure 4. Flowchart of DWT for Extracting Watermark

2.3. Successive Mean Quantization Transform (SMQT)

The Successive Mean Quantization Transform is a non-linear transformation technique which unfolds the underlying structure of the data and eliminates the properties like gain [7]. The Successive Mean Quantization Transform algorithm is first proposed by Mikael Nilsson, Mattias Dahl and Ingvar Claesson [8] in 2005 which is applied for image enhancement by analyze function and performance of the enhanced image using point of view of set theory [7]. SMQT can be used in different kind of images such as RGB image, Gray image.

Successive Mean Quantization Transform algorithm mainly focuses on values like mean value, pixel value. Let x be a pixel of an image where the image is represented by D(x) and the gray value is represented by *V*(x). The input parameter of the algorithm is L and the output is represented by M(x). The size of D(x) and M(x) is same. Then the transform of level L from D(x) to M(x) can be expressed as:

$$\text{SMQT}_{\text{L}}: D\,(x) \rightarrow M\,(x) \tag{1}$$

SMQT_{L} is represented as a binary tree where all the nodes of the tree denotes mean quantization units (MQUs). Each of the MQU is divided into three steps: A mean calculation, a quantization and a split of the input set.

2.3.1 Mean Calculation

In the first step of the MQU finds the mean of the data pixels which is expressed as $\overline{V}\,(x)$. The following expression denotes $\overline{V}\,(x)$.

$$\overline{V}\,(x) = \frac{1}{|D|} \sum_{x\,\epsilon\,D} V\,(x) \tag{2}$$

2.3.2 Quantization

Quantization is the second step and in this step the quantization of the values of the data points into {0, 1} is done using the mean value when y ∈ *D*. The comparison function is expressed as

$$\xi\left(V(y), \overline{V}(y)\right) = \begin{cases} 1, & if V(y) > \overline{V}(x) \\ 0, & else. \end{cases} \tag{3}$$

Let ⊗express as concatenation of the two matrix $\overline{V}\,(x)$ and *V*(*y*), then

$$u(x) = \bigotimes_{y \in D} \xi(V(y), \overline{V}(x)) \tag{4}$$

This is the mean quantized set. The set $u(x)$ denotes the main output from MQU.

2.3.3. Split of the Input Set

In the final step the inputs are spited into two subsets:

$$D_0(x) = \{V(x) \leq \bar{V}(x), \forall x \epsilon D\} \quad (5)$$

$$D_1(x) = \{V(x) > \bar{V}(x), \forall x \epsilon D\} \quad (6)$$

Where $D_0(x)$ denotes the left and $D_1(x)$ denotes the right of the binary tree. The binary tree is shown in figure 5.

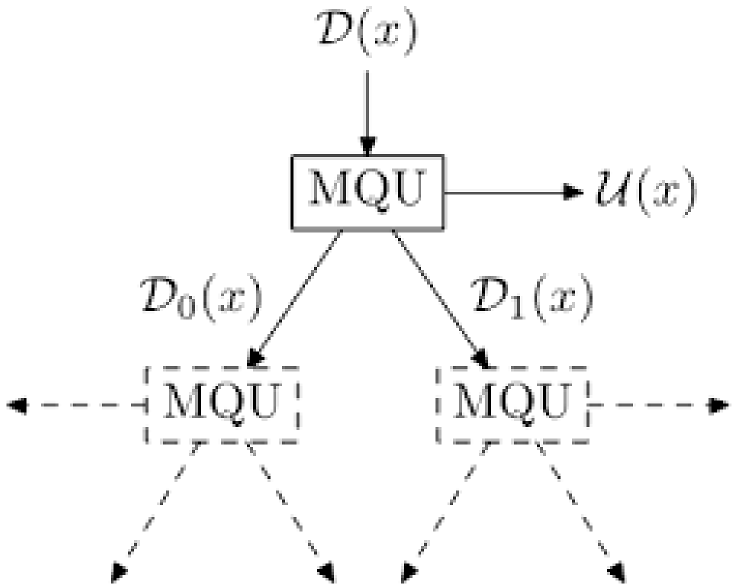


Figure 5: The operation of one Mean Quantization Unit (MQU)

The output set $u(x)$ from MQU is not a value or a similarity coefficient as in the linear transforms. For this reason, the output set $u(x)$ can be defined as the structure of $D_1(x)$. The MQU is independent of input's gain and bias adjustment.

The MQU does the main computing for SMQT. Based on the output of a single MQU the first level transform, $SMQT_L$ is done, where $u(x)$ is the output set at the root node. Extended notation are needed for the output in the binary tree. The output set from one MQU in the tree is expressed as $u_{(l,n)}$, where l= 1, 2, ….. , L is the current level, and n = 1, 2… $2^{(l-1)}$ is the number of the output for the MQU at level l which is shown in figure 6.

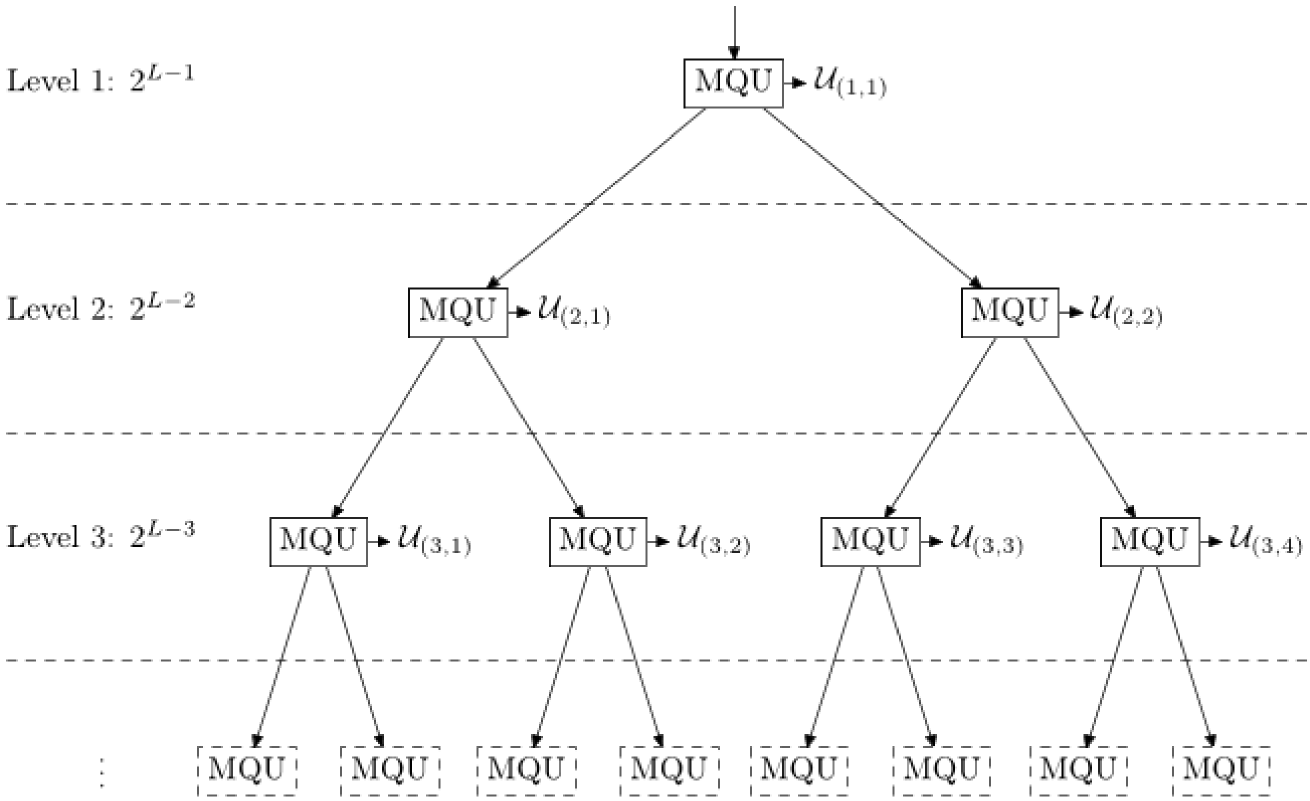


Figure 6: The Successive Mean Quantization Transform (SMQT) as a binary tree of Mean Quantization Units (MQUs)

Weighting of the data points values in the $u_{(l,n)}$ sets is performed and the $SMQT_L$ is found by adding the result. The weighting is done by 2^{L-1} at each level l. Hence, the final result for the

$$M(x) = \left\{ x | V(x) = \sum_{l=1}^{L} \sum_{n=1}^{2^{l-1}} V(u_{(l,n)}) \cdot 2^{L-1}, \forall x \in M, \forall u_{(n,l)} \in u_{(l,n)} \right\} \tag{7}$$

$SMQT_L$ can be found by the following equation [8]. As a result of this weighting, the quantization level number which is denoted by Q_L, for a structure of level L will $Q_L=2^L$. But since the main aim of this algorithm is to produce low dynamic range image the most common choice is L=8.

2.4. OTSU Thresholding Methods

OTSU's method [16] is a class variance method which is very famous global automatic thresholding technique. OTSU is based on the variance of pixel intensity [15]. The method was presented by Nobuyunki Otsu in 1979. Nobuyunki Otsu proposed this method to make calculations, consistency and effectiveness easy to calculate. This method is one of the effective processes for finding the threshold as well as its rare time consumption [15].

2.4.1 OTSU'S THRESHOLDING

OTSU's thresholding method includes the iteration between all the possible threshold values and evaluates a standard layout for the whole pixel level that fill ups every side of the threshold [19]. The main objective is to calculate the threshold value for those position where the foreground and background addition expands is minimally possible. Initially a grey level histogram is required for Otsu's thresholding, but it does not give the expected result for one dimensional surface[18]. However Otsu's method is effective for selecting threshold for gray and real time images with respect to different shape and uniform measures.

2.4.2 OTSU'S Method

Otsu's method is utilized using many image processing application for executing histogram image thresholding or transforming image from gray to binary.[17]. Assuming an image is expressed in L gray levels [0, 1,...., L-1]. Pixel at level i is represented by n_i, and the total number of pixels are represented by N=n_1 +n_2 +..... +n_L. The gray level i probability is expressed by [15]

$$p_i = n_i/N, p_i \geq 0, \sum_{0}^{L-1} p_i = 1 \tag{8}$$

In binary level thresholding, the image pixels are divided into C_1 class with gray levels [0, 1,....., t] and C_2 class with gray levels[t+1, …, L-1] by the threshold t. In order to find the class variance first, the probability of gray level distributions for C_1 and C_2 need to be calculated using equation (9) and equation (10).

$$w_1 = \Pr(C_1) = \sum_{i=0}^{t} p_i \tag{9}$$

$$w_2 = \Pr(C_2) = \sum_{i=t+1}^{L-1} p_i \tag{10}$$

After finding the probability of gray level, the mean values should be calculated. Mean values for C_1 and C_2 class are

$$u_1 = \sum_{i=0}^{t} ip_i/w_1 \tag{11}$$

$$u_2 = \sum_{i=t+1}^{L-1} ip_i / w_1 \tag{12}$$

The total mean of grey levels is expressed by u_T

$$u_T = w_1 u_1 + w_2 u_2 \tag{13}$$

The class variances σ_1 and σ_2 are

$$\sigma_1^2 = \sum_{i=0}^{t} (i - u_1)^2 \, p_i / w_1 \tag{14}$$

$$\sigma_2^2 = \sum_{i=t+1}^{L-1} (i - u_2)^2 \, p_i / w_2 \tag{15}$$

After finding the class variances the within-class variance need to be found. The within-class variance σ_w is

$$\sigma_W^2 = \sum_{k=1}^{M} w_k \, \sigma_k^2 \tag{16}$$

The between-class variance σ_B is

$$\sigma_B^2 = w_1 (u_1 - u_T)^2 + w_2 (u_2 - u_T)^2 \tag{17}$$

By adding the within-class variance and between-class variance the total variance of gray levels σ_T is found.

$$\sigma_T^2 = \sigma_w^2 + \sigma_B^2 \tag{18}$$

By Otsu method, the optimal threshold *t* is chosen by maximizing the between-class variance, which is equivalent to minimizing the within-class variance, because for different partitions, the total variance (addition of the within-class variance and the between-class variance) is constant.

$$t = arg \left\{ \max_{0 \le t \le L-1} \left\{ \sigma_B^2 (t) \right\} \right\} = arg \left\{ \min_{0 \le t \le L-1} \left\{ \sigma_W^2 (t) \right\} \right\} \tag{19}$$

Otsu method can be extended to multilevel thresholding method. Assuming there are M-1 thresholds $[t_1, t_2, ..., t_M]$ which divides the image pixels in the M classes $\{C_1, C_2, ... C_M\}$.

$$\left\{ t_1, t_2, ... t_{M-1} \right\} = arg \left\{ \max_{0 \le t \le L-1} \left\{ \sigma_B^2 \left(t_1, t_2, ... t_{M-1} \right) \right\} \right\} = arg \left\{ \min_{0 \le t \le L-1} \left\{ \sigma_W^2 \left(t_1, t_2, ... t_{M-1} \right) \right\} \right\} \tag{20}$$

Where w_j is the probability of the gray level distribution

$$w_j = \sum_{i=t_{j-1}+1}^{t_j} p_i \tag{21}$$

The mean value denotes by u_j

$$u_j = \sum_{i=t_{j-1}+1}^{t_j} ip_i / w_j \tag{22}$$

σ_j denotes the class variance

$$\sigma_j^2 = \sum_{i=t_{j-1}+1}^{t_j} (i - u_j)^2 \, p_i/w_j \tag{23}$$

The between-class variance is σ_B

$$\sigma_B^2 = \sum_{j=1}^{M} w_j (u_j - u_T)^2 \tag{24}$$

The within-class variance is σ_w

$$\sigma_w^2 = \sum_{j=1}^{M} w_j \sigma_j^2 \tag{25}$$

2.4.3. Algorithm

1. For each intensity level calculate histogram and all the probabilities.
2. Initially set values of w_1 *and* u_1
3. For all possible thresholds from *t*=0,...., maximum gray level intensity for C_1
    a. Update w_1 and Compute u_1
4. For all possible thresholds from *t*=1....,maximum gray level intensity for C_2
    a. Update w_2 and Compute u_2
5. Calculate the total mean u_T using equation (13)
6. For each threshold calculate class variance σ_1 *and* σ_2 using equation (14) and (15).
7. Find the within-class variance σ_w using the equation (16) and between-class variance σ_B using equation (17).
8. Find desired threshold corresponds to the maximum σ_B or minimumσ_w .

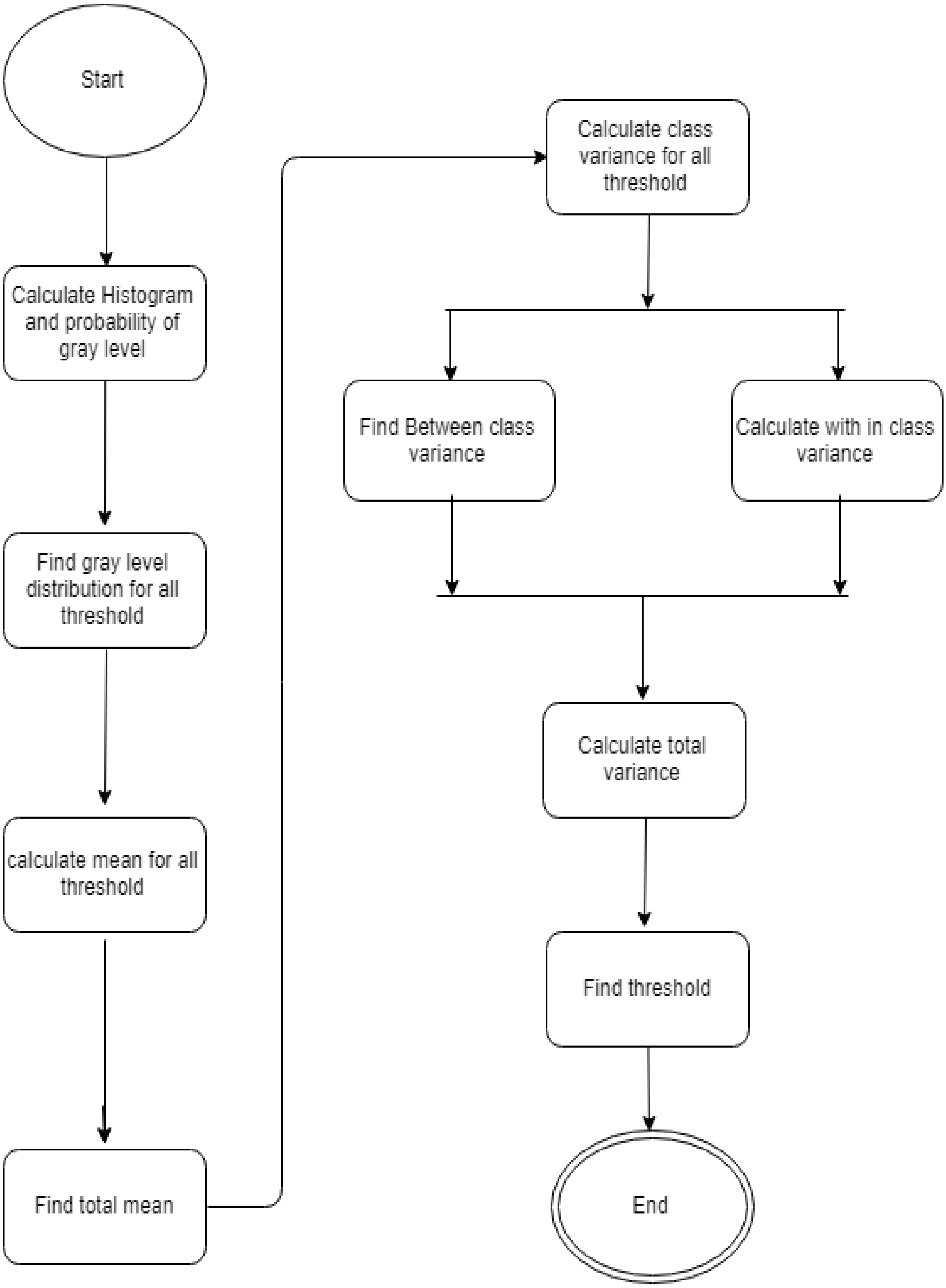


Figure 7. Flowchart of OTSU

2.5 Successive Mean Quantization Transform (SMQT) Based on Otsu Threshold

SMQT is used for image enhancement as discussed above. Its helps to enhance image by calculating the mean value for each node. But when we use only SMQT algorithm, we use mean values as threshold for segmentation which gives a very bright enhanced and noisy image with very weak contrast, various stiff details. To minimize the problem an advanced image enhancement technique has been proposed to improve SMQT algorithm utilizing the threshold value from OTSU's threshold [9].

Let x be a pixel of an image where the image is represented by $D(x)$ and the gray value is represented by $V(x)$. The input parameter of the algorithm is L and the output is represented by $M(x)$. The size of $D(x)$ and $M(x)$ is same. Then the transform of level L from $D(x)$ to $\mathrm{M}(x)$ can be expressed as equation (1) of section 2.3 of chapter 2. $\mathrm{SMQT}_{\mathrm{L}}$ is represented as a binary tree where all the nodes of the tree denotes mean quantization units (MQUs). Each of the MQU is divided into three steps: A mean calculation, a quantization and a split of the input set.

2.5.1. Mean Calculation

In this algorithm instead of the mean value of a node, the threshold value from OTSU's algorithm acts as the mean value of the root node of the binary tree[9].

1. First the OTSU algorithm is executed in order to find the OTSU's threshold value which is described in section 2.4 of chapter 2. After executing the algorithm, the best threshold value is taken for the entire image pixels. Then the founded threshold value is considered as the mean value for the root node of the binary tree which is used in SMQT.
2. The mean value $\bar{V}$ of the pixels of the rest of the nodes which are the child of the root node are denoted by the equation (2) in section 2.3.1 of chapter 2.

2.5.2 Quantization

In the quantization step, by using the mean of the pixel values are quantized into $\{0, 1\}$ shown is equation (3) of section 2.3.2 of chapter 2. After following the step we find $\bar{V}$ and $V(x)$ is concatenated using the equation (4) of section 2.3.2 of chapter 2. When the equation is executed we find $u(x)$ which can be regarded as the mean quantized pixel set which is the main output of MQUs.

2.5.3 Split of the Input Set

We split the input into two parts using equation (5) and (6) of section 2.3.3 of chapter 2. After execution two values are found $D_0(x)$ and $D_1(x)$ where $D_0(x)$ denotes the left branch and $D_1(x)$ and denotes the binary tree, which is shown in figure 8.

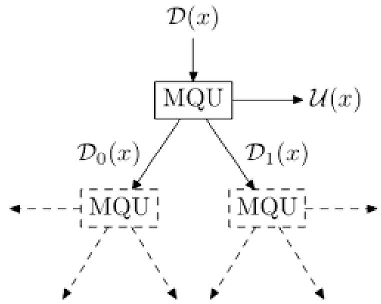


Figure 8: The operation of one Mean Quantization Unit (MQU) based on OTSU Threshold

The output set $u(x)$ from MQU can be considered as the structure of $D(x)$. In SMQT the main calculation area is MQU. The first level transform $SMQT_1$ is based on the output from separate MQU, where the output set of the root node is u. Let $u_{(l,n)}$ is defined as an output from MQU in the binary tree, in which the present level l= 1, 2 , …. , L and the output number from the MQU at level l is n=1,2, …., $2^{(l-1)}$ in figure 9.

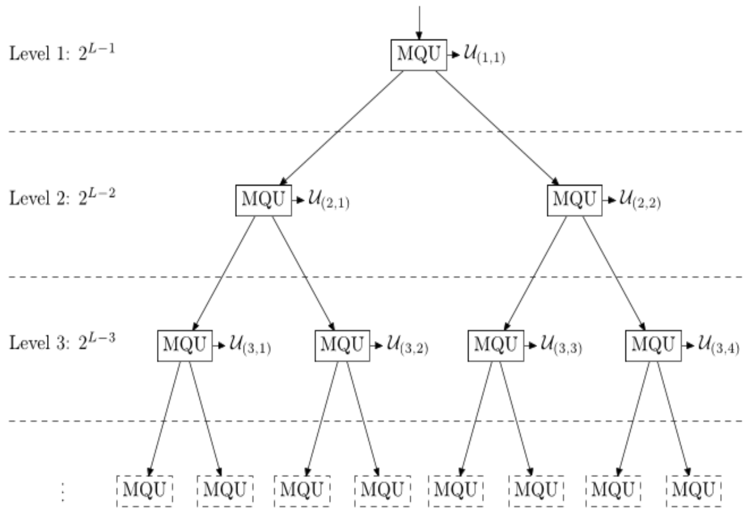


Figure 9: The Successive Mean Quantization Transform (SMQT) as a binary tree of Mean Quantization Units (MQUs) based on OTSU Threshold

In the algorithm the only variable that can be change is L. The digital image pixel value gray range from 0 to 255 with 8 bit binary representation. That is why a parameter L=8 is taken for the image pre-processing of the 8 bit image, which provides a great control to the degree of enhancement. Finally the result of the $SMQT_L$ is expressed in an equation which is shown in equation (7) of section 2.3 of chapter 2.

2.5.4. Algorithm

1. Find the threshold value from the OTSU's thresholding algorithm.
2. Consider the value for the root node of the binary tree.
3. Calculate the $\bar{V}$ using the mean equation for each remaining nodes in the binary tree.
4. Calculate the quantized pixel set $u(x)$
5. Split one node into two child node and find the value of D_0 and the D_1 depending on the $\bar{V}$.
6. Continue from 2- 5 step until level L=8
7. Find the out of the MQU which is $u_{(l,n)}$
8. Finally calculate the $SMQT_L$ result $M(x)$

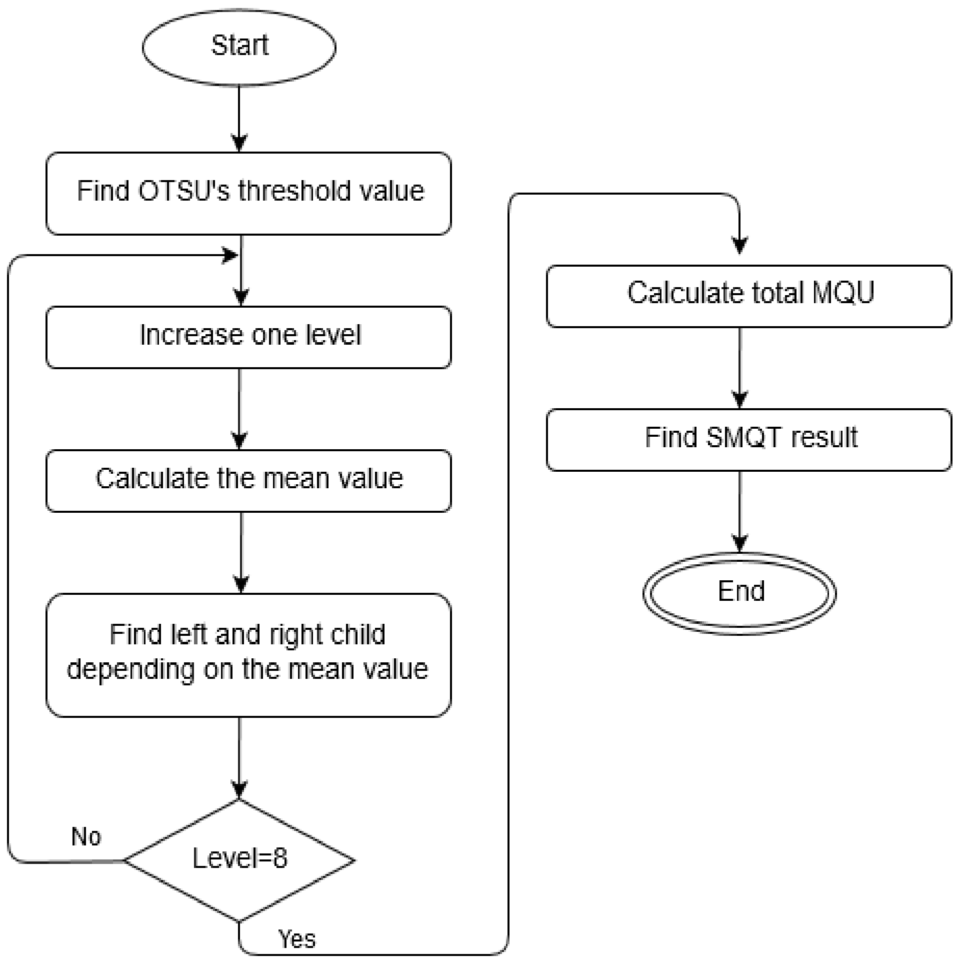


Figure 10. Flowchart SMQT based on OTSU

CHAPTER 03: Proposed Model and Methodology

3.1 System Design and Algorithm

First Step: A grayscale medical image is taken as the host image

Second Step: The image is enhanced using SMQT enhancement based on OTSU

Third Step: The image is segmented using OTSU thresholding method

Fourth Step: The medical host image is watermarked using DWT

Fifth Step: The image with embedded water is going through different attacks

Sixth Step: The watermark image is extracted by IDWT method

Seventh Step: Finally we get the host medical image and watermark image

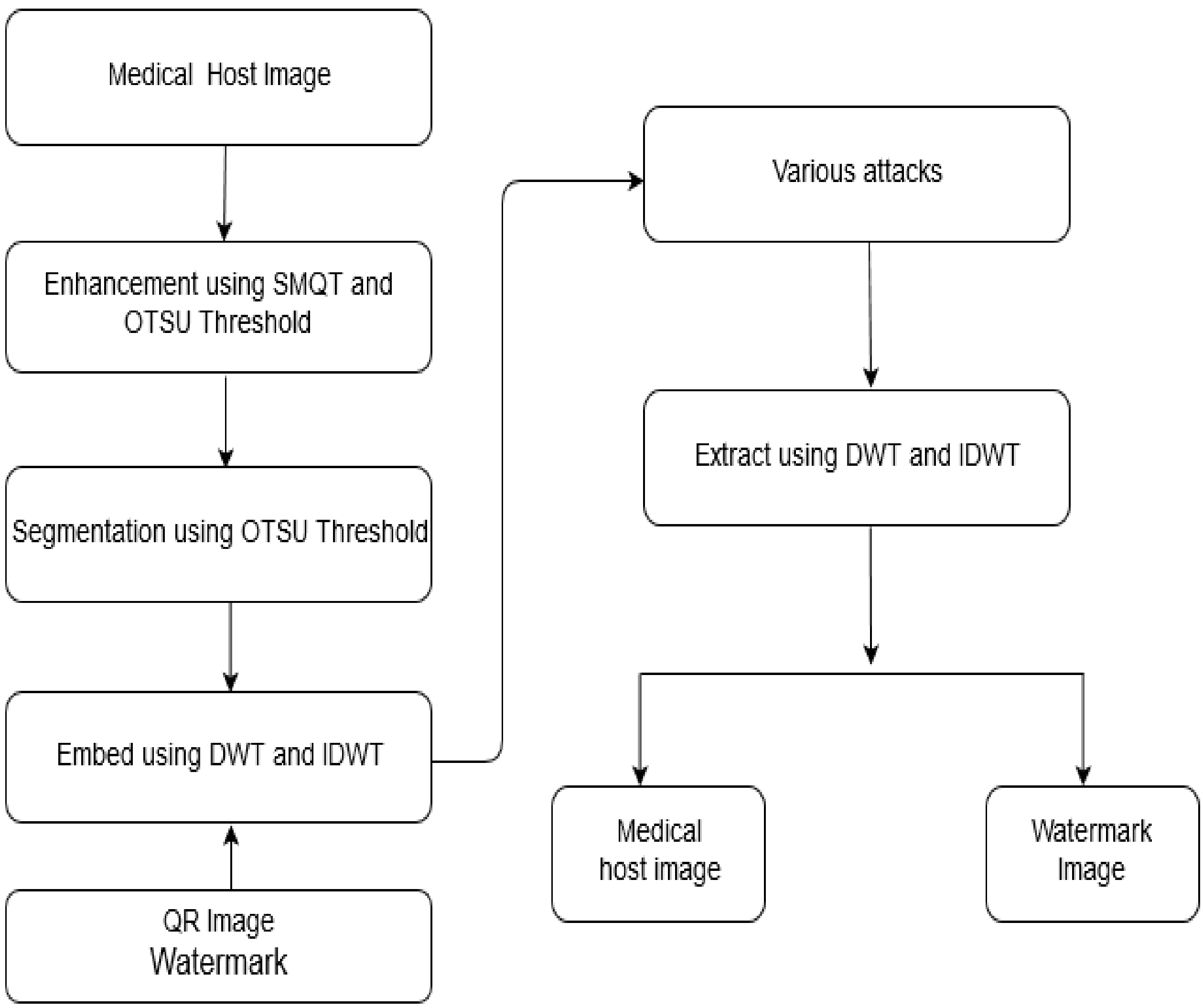


Figure 11. Block diagram of proposed model

In this proposed model, we have used SMQT algorithm based on OTSU threshold value, as the mean of root node of SMQT, to pre-process the medical image. It is used the point of view of set theory to analyze the function and performance of the transformed image enhancement. The enhanced image can maintain the basic shape of the original histogram by performing a nonlinear stretch. So, it can reveal the underlying structure in data, and decompose the details of information in the image. After the enhancement of the image we have used OTSU thresholding is used to segment the image. Otsu algorithm is considered to be the optimum algorithm of the image segmentation, which is basically not affected by image brightness and contrast.

In order to embed watermark, two-level DWT is applied using Algorithm 1. We have used Low frequency sub-bands so that it becomes more robust since it contains most of the image energy. In this model, we have took a MR image, which is a image produced by MRI medical imaging technique used in radiology to form pictures of the anatomy and the physiological processes of the body in both health and disease. We used QR image as watermark so that in real life patients information can be embedded as watermark. Then we have used common image attacks which a medical image may face before, during and after transmission. After the attack we have extracted the watermark from the host image using Inverse Discrete Wavelet Transform (IDWT) function which simply reverses the process of DWT to acquire the watermark bits re-composing the watermark image so that we can check the performance of the proposed model. Then we evaluated our model using performance measuring parameters like PSNR, MSE and CC. The chapter five shows that our proposed model gives better performance than other existing models.

3.2 Flowchart

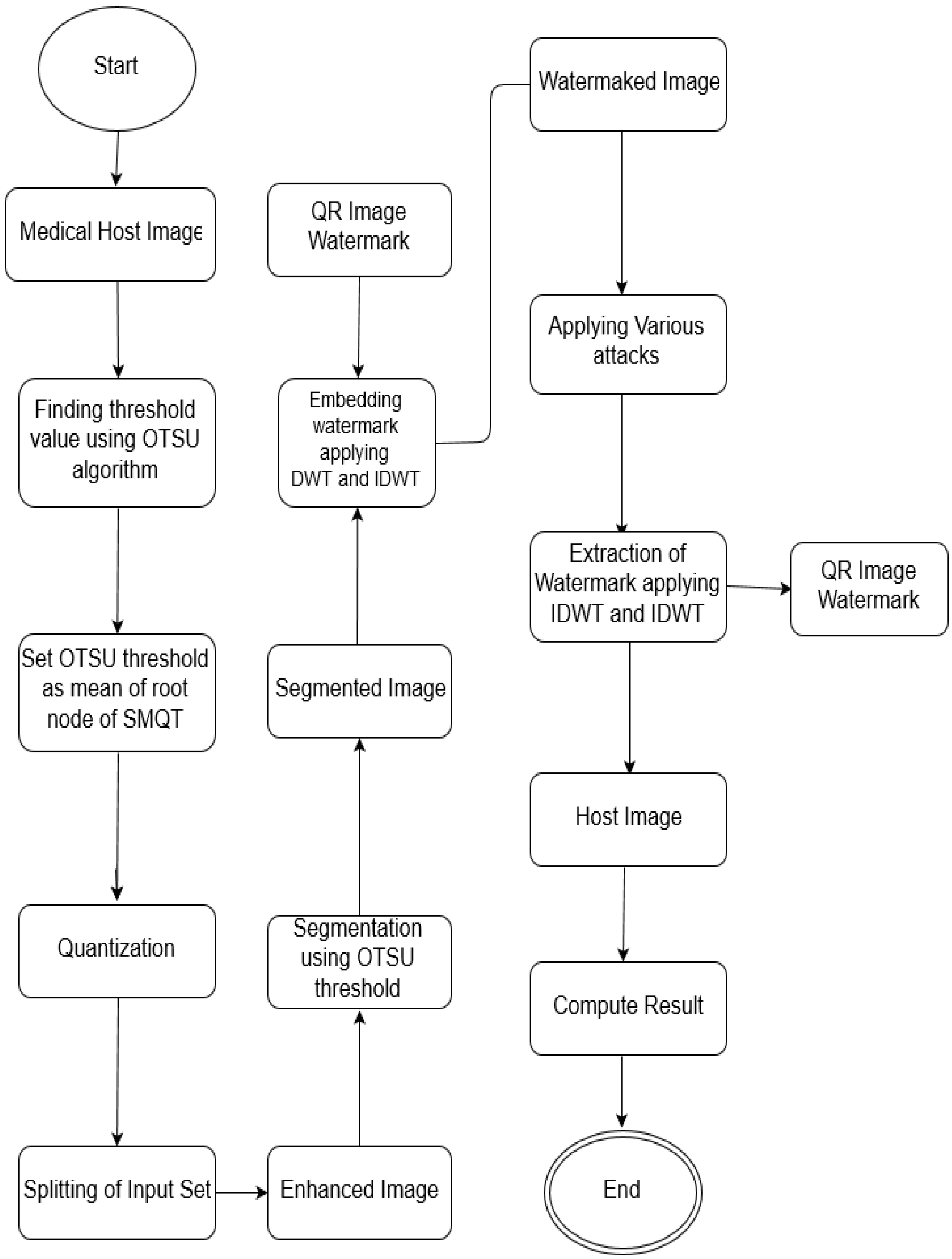


Figure 12. Detailed flowchart of proposed model

CHAPTER 04: Experimental Results

The experiment of this algorithm in this thesis is performed in the AMD FX(tm)-8300 Eight-Core Processor, ~3.3GHz, 16384MB RAM environment using MATLAB software R2016a(9.0.0.341360). In order to verify the validity of the model, in the experiment, various number of images are used. And then the result of our experiment is compared with other watermarking schemes in quality evaluation like PSNR, MSE, and CC etc.

Table 1: Performance analysis of Proposed Model

Evaluation Parameter	Watermarked Values after extraction			
	SMQT-DWT model	OTSU based SMQT-DWT model	OTSU based SMQT-K MEANS- DWT model	Proposed model
PSNR	43.2341	44.2218	43.7801	49.0942
MSE	0.0141	0.0127	0.0143	0.0083

We have taken gray image from renowned database like CVG UGR in order to access our proposed watermarking scheme. We used the images of dimension 256x256 for host image and 375x375 QR image as watermark and then converted to 2048x2048. In this case have used QR image as watermark so that patients information can be encoded in the QR and then QR encoded into the image.

Digital Watermarking on the medical image was done using 4 different models. The image was then the extracted medical were matched without different and performance were recorded using PSNR, MSE. And it is represented in table 1. From the table 1 it is found that our model gives the better results comparing with other watermarking methods. (Image mr038.pgm)

PSNR and MSE

The amount of invisibility of a watermarked image in comparison to non-watermarked image is called imperceptibility and can be measured by statistical standard metrics such as PSNR. The PSNR function implements the following equation to calculate the Peak Signal-to-Noise Ratio (PSNR):

$$PSNR = 10 \log_{10}(peakval^2/MSE) \tag{26}$$

Where *peakval* is either specified by the user or taken from the range of the image data type (e.g. for uint8 image it is 255). *MSE* is the mean square error, i.e. *MSE* between A and ref.[14]. The equation of MSE is as follows:

$$MSE = \sum_{a=0}^{C-1} \sum_{b=0}^{D-1} \frac{[D(a,b) - D'(a,b)]^2}{C \times D} \tag{27}$$

Where D = host image, D' = watermarked image with size C x D [14]

Table 2: PSNR and MSE values after Salt and Pepper Attack

Evaluation Parameter	After salt and pepper attack					
	DWT model	SMQT-DWT model	OTSU-DWT model	OTSU based SMQT - DWT	OTSU based SMQT -K MEANS- DWT model	Proposed model
PSNR	43.1465	42.8094	47.8034	43.6736	43.5711	47.818
MSE	0.015	0.0147	0.0096	0.0134	0.0146	0.0094

Watermarking on the medical image was done using six different models. The image gone through Salt and Pepper Attack, then the extracted medical image were matched without different and performance were recorded using PSNR, MSE which is represented in table 2. From the table 2 it is found that our model gives the better results comparing with other watermarking methods. (Image mr038.pgm)

Correlation Coefficient

The correlation coefficient of two random variables is a measure of their linear dependence. If each variable has *N* scalar observations, then the Pearson correlation coefficient is defined as

$$\rho(A,B) = \frac{1}{N-1} \sum_{i=1}^{N} \left(\frac{\overline{A_i - \mu_A}}{\sigma_A}\right)\left(\frac{B_i - \mu_B}{\sigma_B}\right), \tag{28}$$

Where μA and σA are the mean and standard deviation of A, respectively, and μB and σB are the mean and standard deviation of B. Alternatively, you can define the correlation coefficient in terms of the covariance of A and B:

$$\rho(A, B) = \frac{\operatorname{cov}(A, B)}{\sigma_A \sigma_B}. \tag{29}$$

The correlation coefficient *matrix* of two random variables is the matrix of correlation coefficients for each pairwise variable combination,

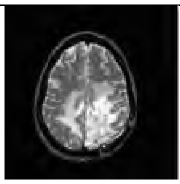
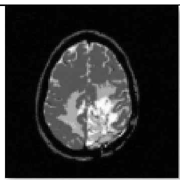
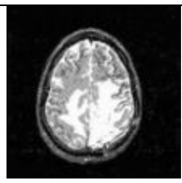
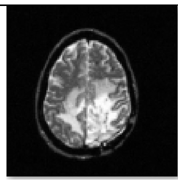
$$R = \begin{pmatrix} \rho(A, A) & \rho(A, B) \\ \rho(B, A) & \rho(B, B) \end{pmatrix} \tag{30}$$

Since A and B are always directly correlated to themselves, the diagonal entries are just 1, that is,

$$R = \begin{pmatrix} 1 & \rho(A, B) \\ \rho(B, A) & 1 \end{pmatrix} \tag{31}$$

The image gone through Salt and Pepper Attack, then the extracted medical image were matched without different and performance were recorded using CC which is represented in table 3. From the table 3 it is found that our model gives the better results comparing with other watermarking methods. Images after different attack are also shown in this table.

Table 3: CC values after Salt and Pepper Attack

Evaluation Parameter	DWT model	k-means - DWT model	OTSU based SMQT - K MEANS- DWT model	Proposed model
salt and pepper attack				
CC	0.9593	0.9836	0.9874	0.9923

After Salt and Pepper Attack for more evaluation, we have used Mean Attack and then we measured the performance with the help of MSE of three different models and presented in the table 4.

Table 4: MSE values after Mean Attack

Evaluation Parameter	DWT model	K means - DWT model	Proposed model
Mean attack			
MSE	0.9243	0.9484	0.9239

Digital Watermarking on the medical image was done using five different models and Median Attack was performed. The medical image was then extracted and matched and performance were recorded using PSNR, MSE and represented in the table 5. From the table 4 and table 5, it is found that our proposed model gives the better results comparing with other watermarking methods in terms of MSE in table 4 and in terms of PSNR and MSE in the table 5. The condition of the images after Mean Attack is also shown in table 4.

Table 5: PSNR and MSE values after Median Attack

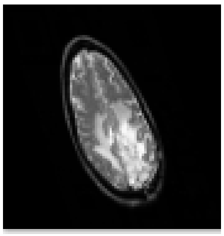
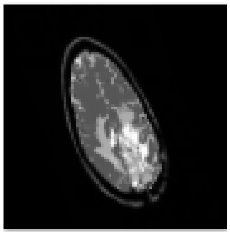
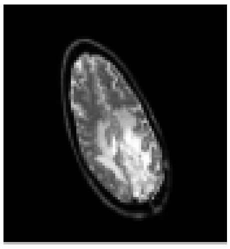
Evaluation Parameter	AFTER MEDIAN ATTACK				
	DWT model	SMQT-DWT model	OTSU based SMQT DWT	OTSU based SMQT -K MEANS- DWT model	Proposed model
PSNR	43.7958	43.2399	44.2245	43.7813	49.0957
MSE	0.0141	0.014	0.0127	0.0143	0.0083

Table 6: PSNR and MSE values after Rotation Attack

Evaluation Parameter	Watermarked Values after extraction			
	OTSU based SMQT - K MEANS-DWT model	SMQT- DWT model	OTSU based SMQT- DWT model	Proposed model
PSNR	27.2742	27.2421	28.1327	30.1618
MSE	0.0745	0.0696	0.0635	0.0548

Digital Watermarking on the medical image was done using four different models and Rotation Attack was performed. The medical image was then extracted and then was matched and performance were recorded using PSNR, MSE and represented in the table 6. After Shear Attack on three different models including our proposed model, the condition of the MRI image and the value of CC is presented in table 7.

Table 7: CC values after Shear Attack

	DWT model	K MEANS- DWT model	Proposed model
AFTER SHEAR ATTACK			
CC	0.7203	0.7111	0.7214

From the table 6 And 7 it is found that proposed model gives the better results comparing with other watermarking methods.

Finally, Shear Attack was performed on OTSU based SMQT-K MEANS- DWT model, SMQT- DWT model, OTSU based SMQT- DWT model and proposed model and Crop Attack was performed on OTSU based SMQT-K MEANS- DWT model, SMQT- DWT model, OTSU based SMQT- DWT, OTSU-DWT model and proposed model. Then the extracted medical image were matched and performance were recorded using PSNR, MSE.

Table 8: MSE and PSNR values after Shear Attack

Evaluation Parameter	Watermarked Values after SHEAR ATTACK			
	OTSU based SMQT-K MEANS- DWT model	SMQT- DWT model	OTSU based SMQT- DWT model	Proposed model
PSNR	27.8696	27.355	28.4476	32.6352
MSE	0.0702	0.0688.	0.0615	0.0428

Table 9: MSE and PSNR values after Crop Attack

Evaluation Parameter	Watermarked Values after CROP ATTACK				
	OTSU based SMQT-K MEANS- DWT model	SMQT- DWT model	OTSU based SMQT- DWT model	OTSU- DWT model	Proposed model
PSNR	18.9413	18.703	19.6977	25.0937	25.0939
MSE	0.1715	0.1634	0.1476	0.091	0.091

Both the table 8 and 9 shows that the proposed model is better than the existing models shown in the table.

CHAPTER 05: Conclusion and Future Work

5.1 Conclusion

In this paper, our proposed model of digital watermarking on medical images using Successive Mean Quantization Transform (SMQT) algorithm based on Otsu algorithm, Otsu thresholding. This can be used for the security and privacy of patients and diagnosis while transporting medical images. Firstly, the host image is preprocessed using SMQT based on Otsu then it is segmented using Otsu thresholding. The contribution of this paper is that our proposed model provides better imperceptibility and robustness against common image processing attacks. It is evaluated that quality degradation of the host image is minimal.

5.2 Future Work

In this model, we worked on the watermarking on the whole host medical image. We look forward to implement the watermarking on the region of non-interest of medical image, where watermarking will be embedded only on the region of non-interest.

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