CHAPTER 1

INTRODUCTION

Medical imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), X-ray and Ultrasound (US) produce prohibitive amounts of digitized clinical data that require large storage space. Hence, compression of images becomes essential and is very much desired in medical applications to solve both storage and transmission problems.

1.1 NEED FOR MEDICAL IMAGE COMPRESSION

Digital image is a two-dimensional array of picture elements called pixels which represent the intensity at specific points in an image. Nowadays medical imaging generates images in digital format for easy access, storing for future retrieval and transmission from one location to another location.

Table 1.1 shows the size and storage space requirements of medical images for specified image sizes (Wong et al. 1995, Strintzis 1998, Ansari and Anand 2008 and Ghrare et al.2009). As these imaging techniques produce a large volume of data, compression becomes mandatory for saving storage space and reducing transmission time.

In medical applications, compression method aims to reduce the size of the image without degradation in the diagnostic information. Thus, the development of efficient compression scheme is an ongoing challenge in medical fields, as loss of information may mislead diagnosis.
### Table 1.1 Medical image size and storage requirements

<table>
<thead>
<tr>
<th>Modality</th>
<th>Image size (pixels)</th>
<th>Resolution (bits/pixel)</th>
<th>Average number of images per exam</th>
<th>Average storage requirement (mega bytes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CT</td>
<td>512x512</td>
<td>12</td>
<td>30</td>
<td>15.0</td>
</tr>
<tr>
<td>MRI</td>
<td>256x256</td>
<td>12</td>
<td>50</td>
<td>6.5</td>
</tr>
<tr>
<td>US</td>
<td>512x512</td>
<td>8</td>
<td>30</td>
<td>10.5</td>
</tr>
<tr>
<td>Digital Subtraction Angiography (DSA)</td>
<td>1024x1024</td>
<td>8</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Single Photon Emission Computed Tomography (SPECT)</td>
<td>128x128</td>
<td>8</td>
<td>50</td>
<td>0.8</td>
</tr>
<tr>
<td>Positron Emission Tomography (PET)</td>
<td>128x128</td>
<td>16</td>
<td>62</td>
<td>2.0</td>
</tr>
<tr>
<td>Computer Radiography</td>
<td>2048x2048</td>
<td>12</td>
<td>4</td>
<td>32</td>
</tr>
</tbody>
</table>

### 1.2 IMAGE COMPRESSION

The process of representing the image with less number of bits by removing the redundancies from the image is called compression (Gonzalez and Woods 2002) which is specified in terms of Compression Ratio (CR) or number of bits per pixel (bpp) termed bit rate. CR and bit rate are determined using Equations (1.1) and (1.2) as

\[
CR = \frac{\text{Original image size in bits}}{\text{Compressed image size in bits}} \quad (1.1)
\]
Bit rate (bpp) = \frac{\text{Compressed image size in bits}}{\text{Total number of pixels in the image}} \quad (1.2)

There are three types of redundancies:

- Coding redundancy
- Inter-pixel redundancy
- Psycho-visual redundancy

Compression tries to reduce one or more of these redundancies.

1.2.1 Coding Redundancy

In images, some grey values occur more frequently than others. By assigning less number of symbols (bits) to more probable ones and more number of symbols (bits) to less probable ones, coding redundancies can be reduced. A variable length coding is a commonly used technique which explores coding redundancy to reduce the redundant data from the image (Gonzalez and Woods 2002 and Bhatia 2006). Huffman and Arithmetic coding are variable length coding techniques.

1.2.2 Inter-pixel Redundancy

Inter-pixel redundancy is related to inter-pixel correlations within the image. The neighboring pixels of the image are usually highly correlated and are almost similar. The values of pixels can be predicted or approximated from examining the neighboring pixels. Predictive coding and run length coding techniques will reduce the inter-pixel redundancies efficiently.
1.2.3 **Psycho-visual Redundancy**

The human eye does not respond with equal sensitivity to all visual information. Certain information has less relative importance than other information in normal visual processing. This information is termed as psychovisually redundant information (Banafa 1993). It can be eliminated without changing the visual quality of the image as this kind of information is not essential for normal visual processing (Nystrom 2007). The elimination of psycho-visual redundant data is referred to as quantization, as it results in a loss of quantitative information.

1.3 **IMAGE COMPRESSION MODEL**

The image compression system is shown in Figure 1.1. The source encoder shown in Figure 1.1 (a) reduces redundancies in the input image. The mapper transforms the input image into an array of coefficients to reduce inter-pixel redundancies. This is a reversible process. The quantizer reduces the psycho-visual redundancies of the image and is an irreversible process. The symbol encoder creates a fixed or variable length code to represent the quantizer output.

![Figure 1.1 Block diagram of image compression system](image)

**Figure 1.1 Block diagram of image compression system**
The source decoder shown in Figure 1.1 (b) contains two blocks, namely symbol decoder and inverse mapper. These blocks perform inverse operation of symbol encoder and mapper, respectively. The reconstructed image may or may not be an exact replica of input image (Gonzalez and Woods 2002 and Annadurai and Shanmugalakshmi 2008).

1.4 CLASSIFICATION OF IMAGE COMPRESSION SCHEMES

The image compression schemes can be classified into two categories, namely:

- Lossless image compression
- Lossy image compression

In lossless image compression, the reconstructed image is numerically and visually identical to the original image. The level of image compression achieved can be represented by CR. The CR achieved for lossless techniques are typically around 2:1 to 3:1 (Chen 2007).

In lossy image compression, higher CR can be achieved when compared to lossless compression techniques but the reconstructed image contains degradations relative to the original image. A lossy compression method is called visually lossless when the loss of information caused by compression method is invisible for an observer.

1.5 FIDELITY CRITERIA

In image compression, a decompressed image may not be identical to the original image due to some loss of information. To measure the quality of the reconstructed image, fidelity criteria are used. There are two general classes of fidelity criteria namely objective fidelity criteria and subjective fidelity criteria.
Objective measures are mathematical evaluations. The most common objective measures of image fidelity that are based on pixel differences are Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). The distortion represented by MSE between the original image \(x(i, j)\) and the reconstructed image \(x_R(i, j)\) both of size \(M \times N\) pixels is defined as

\[
MSE = \frac{1}{M \times N} \sum_i \sum_j \left( x(i, j) - x_R(i, j) \right)^2
\]  

(1.3)

where in Equation (1.3), the sum over \(i\) and \(j\) denotes the sum of all pixels in the image. The PSNR relates the MSE to the maximum amplitude of the original image. PSNR is measured in decibels and is defined as

\[
PSNR in dB = 10 \log_{10} \left( \frac{255^2}{MSE} \right)
\]  

(1.4)

where in Equation (1.4), 255 is the maximum possible intensity for 8-bit grey scale images. In image compression, acceptable values of PSNR are in between 30 dB and 50 dB where higher is better (Mastriani 2009 and Kafri and Sulieman 2009).

Image quality index and Mean structural similarity index measure (MSSIM) are the popular correlation-based objective measures. The image quality index is designed by modeling any image distortion in terms of three factors namely loss of correlation, luminance distortion and contrast distortion (Wang and Bovik 2002). Let us assume \(x\) and \(y\) be column vector representations of two image windows say \(8 \times 8\) windows extracted from the same spatial locations from two images \(X\) and \(Y\), respectively. The window moves pixel by pixel horizontally and vertically through all the rows and columns of the image and the image quality index between the original image and reconstructed image is defined as
\[ Q = \frac{\sigma_{xy} + 2 \mu_x \mu_y}{\sigma_x \sigma_y (\mu_x)^2 + (\mu_y)^2 \left( \frac{2 \sigma_x \sigma_y}{\sigma_x^2 + \sigma_y^2} \right)} \]  

(1.5)

where \( x = \{ x_i | i = 1, 2, \ldots, N \} \) and \( y = \{ y_i | i = 1, 2, \ldots, N \} \) and \( N \) is the number of pixels in the selected image block and \( \mu_x, \mu_y, \sigma_x, \sigma_y^2 \) and \( \sigma_{xy} \) represent the mean of \( x \), the mean of \( y \), the variance of \( x \), the variance of \( y \) and the covariance of \( x \) and \( y \), respectively and is calculated as

\[ \mu_x = \frac{1}{N} \sum_{i=1}^{N} x_i \]  

(1.6)

\[ \mu_y = \frac{1}{N} \sum_{i=1}^{N} y_i \]  

(1.7)

\[ \sigma_x^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu_x)^2 \]  

(1.8)

\[ \sigma_y^2 = \frac{1}{N-1} \sum_{i=1}^{N} (y_i - \mu_y)^2 \]  

(1.9)

and

\[ \sigma_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu_x)(y_i - \mu_y) \]  

(1.10)

If \( M \) is the total number of windows, then the overall image quality index is obtained by calculating the average of \( Q \) values over all the windows \( (Q = Q_j | j = 1, 2, \ldots, M) \) and is given as

\[ Q = \frac{1}{M} \sum_{j=1}^{M} Q_j \]  

(1.11)

If original and reconstructed images are identical, \( Q \) is 1.
Wang et al. (2004) developed a measure of structural similarity (SSIM) which compares local patterns of pixel intensities, normalized for luminance and contrast. The structural similarity measure is a Human Visual System (HVS) based measure. The structural similarity between the original image and the reconstructed image is defined as

\[
SSIM = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)}
\]  

(1.12)

In Equation (1.12), SSIM is evaluated by assuming \( c_1 = (k_1L)^2 \) and \( c_2 = (k_2L)^2 \) where \( k_1 = 0.01, \ k_2 = 0.03 \) and \( L = \) dynamic range of pixel values (255 for 8-bit grey scale image) as recommended by Eskicioglu et al. (1995). The SSIM given by Equation (1.12) is computed for local 8 \( \times \) 8 windows of the original and reconstructed images. If there are \( M \) number of windows, the overall image quality is obtained by evaluating mean structural similarity index measure which is given by

\[
MSSIM = \frac{1}{M} \sum_{j=1}^{M} SSIM (x_j, y_j)
\]  

(1.13)

Subjective quality measures may be performed to support the objective evaluations. Subjective evaluations are done by showing the decompressed and original images to experts and averaging their evaluations on absolute rating scale.

1.6 OBJECTIVES OF THE PROPOSED RESEARCH WORK

The objectives of the proposed research work are:

1. To develop appropriate compression algorithms for optimal compression of medical images
2. To achieve low complexity algorithms for compression of medical images

3. To develop compression algorithms which will be oriented towards preserving important components of the medical image that are vital for visual interpretations

4. To assess the efficiency of developed compression algorithms on different medical imaging modalities via objective and subjective evaluations

1.7 ORGANIZATION OF THE THESIS

In this thesis, the following three image compression algorithms are proposed for compressing medical images:

1. Medical image compression with thresholding

2. Threshold-based medical image compression with edge preservation

3. Region of Interest-based medical image compression

Chapter 1 introduces the fundamentals of image compression. Data redundancies are discussed briefly for better understanding of the concept of compression and basic concepts of image compression essential to develop this thesis are outlined. Fidelity criteria to assess the reconstructed image quality with respect to the original image of different image compression algorithms are presented.

Chapter 2 provides a literature review to explore the previous works carried out by various researchers in the area of digital and medical image compression.
Chapter 3 proposes a novel thresholding method for compression of medical images. The selection of threshold is adaptive which is based on the information content of the given image. Based on frequency of occurrence of wavelet coefficient, threshold is evaluated that is used to identify the significant wavelet coefficients of the image. Both subjective and objective performance evaluations are carried out.

Chapter 4 presents threshold-based medical image compression method with edge preservation. Plane fitting parameters are used for preserving edges of the image thereby improving the visibility of diagnostic features.

Chapter 5 presents a Region of Interest (ROI)-based medical image compression. Active contour method is used for extracting ROI. Variational level set with distance regularization term segments ROI and the segmented ROI is processed with lossless scheme whereas the background is with lossy compression scheme.

Chapter 6 presents conclusions and suggestions for future study.

1.8 CONCLUSION

In this chapter, the fundamentals of lossless and lossy image compression are discussed. The distortion measures used for evaluating the performance of digital image compression algorithms are also discussed. The next chapter provides an insight into works carried out by various previous researchers in the area of image compression.