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ROI based Lossless Medical Image Compression using Integer Wavelet Transform and Run-length Coding

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Abstract

Medical images of human body captured from various sources such as Computer Tomography (CT) or Magnetic Resonance Imaging (MRI) are in digital form. These imaging techniques generally produce huge amounts of data, and therefore compression of these images is a need for storage and communication purposes. A lot of progression is already done to compress these medical images which provide significant compression rates but there is a considerable loss of quality of these images. In some cases, it is necessary to maintain the quality of an image in some area of image usually called Region of Interest. In this paper, a method for obtaining compressed image is discussed using hybrid model and lossless compression technique in ROI regions. The proposed algorithm is evaluated on MRI images obtained from experimental database. Different performance metrics such as Mean Square Error, Peak Signal to Noise Ratio and Compression Ratio are used to measure the quality of images. It can be seen that proposed algorithm outperforms over other compression algorithm such as DCT, vector quantization and many more.

Keywords: *Compression, Wavelets, SPIHT, Run-length Coding, Region of Interest.*

1. Introduction

A huge amount of information (called data) is typically obtained from different medical devices such as Computed Tomography (CT) images, Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) images, ultrasound imaging and many more, which are usually stored in picture archiving and communication system or hospital information system [1] [3 -5]. Many imaging diagnostic centers produce an average data of 10 – 15 GB per day [2]. Hence, it is difficult to manage these data for storage purpose. This high ended data therefore requires high ended network capability to transmit the images over a network as in telemedicine applications. This is one of the issues considering the transmission of image in remote areas where there is no network facility. Compression of medical image is one of the important concept which helps in reducing the storage size of image and estimating the bandwidth requirement for transmitting the image. Image Compression can be further classified as lossy compression and lossless compression. In case of medical imaging, although lossy compression techniques provide 10 - 15% compression rates; they are not generally used in practice. It may be because of clinical information loss which can affect the diagnosis procedure [6] [7]. Apart from this, there can also be some legal issues as reported in literature. Storage of medical image is not only difficult but also challenge job as there can be requirement for preserving the best possible image quality. On contrary, Magnetic Resonance Imaging (MRI) image contains various slices which require all information for diagnosis. Therefore, there has to be requirement for additional storage in this case.

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A medical image carries significant characteristics that are considered during compression process. Firstly, it should have high lossless compression ratio. Secondly, it should have better resolution scalability and lastly, it must have a better ability for decoding the image. Digital Imaging Communication in Medicines (DICOM) is one of the most widely used and acquired version of medical imaging communication standard [6] [7]. This file format contains a header section in which most significant information related to the image such as type of image (like CT, MRI, and ultrasound), patient's information and many more. For compressing DICOM file, one must provide special information about the header. Due to degraded image quality in most of the applications for diagnosis procedures, lossy compression algorithms are not used in general. In this regard, for improving the diagnostic information of a medical image using a lossless compression technique, Region of Interest (ROI) coding method is discussed for improving the quality of image in certain areas of interest by applying different lossless compression algorithms keeping the high compression rate in other part of medical image [7] [8] [9].

A. Concept of ROI

Region of Interest are basically extracted samples of images within a given identified dataset for particular application. The concept of ROI is typically used in many applications such as medical imaging, character recognition systems, image retrieval systems and many more. In case of medical images, the tumor boundary defined over an image can be useful for measuring the size of an image. Similarly in case of character recognition, region of interest defines the border of an object under consideration. In most of applications, symbolic or textual labels are added to ROI part for describing the content in more compact way. The first step in obtaining ROI is preprocessing. This usually involves filtering of an image using various image processing tools. Once image is preprocessed, segmentation is done using various techniques for obtaining the ROI and Non – ROI region. Once ROI is extracted from the given medical image, further compression process is carried out. This is usually done to reduce storage and network bandwidth. The proposed approach consists of three steps: 1) Extracting the ROI from given medical image, 2) Applying lossless compression technique, and 3) Decompressing the image for transmission. Region of Interest is one of the intelligent techniques for medical image compression which comprises using both lossless and lossy compression technique. In ROI based image compression technique, the given input medical image is classified into foreground and background regions [7] [8]. The foreground region basically consist diagnostically important region such as tumor of brain of MRI image called ROI part of image and background contains Non – ROI region. The ROI region of medical is compressed using lossless compression algorithm while Non – ROI is compressed using lossy compression technique. In this manner, the quality of image is preserved with high compression rate.

Recognizing ROI region of an image is an automated process which eliminates all kind of manual procedures [7] [9]. Once the ROI region is selected, the foreground region is completely included for processing whereas background pixels are made zero. In such a process, Morphological operators are used for generating the masks which contains '1' in the foreground and '0' in the background. To separate ROI part from image, it is logically ANDed with the mask. Fig. 1 shows the different components of medical image.

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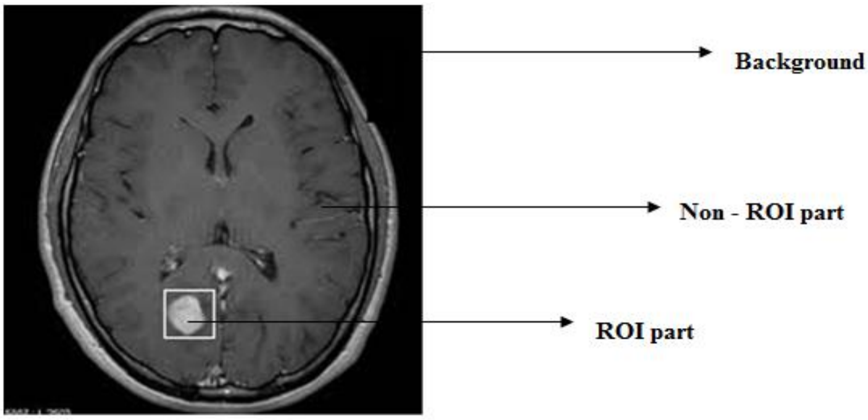

Figure 1. Different components of medical image

B. Detection of ROI

Various methods for detecting the ROI regions from medical images are already discussed in literature. The aim of proposed work is to apply lossless compression algorithm on given medical image for obtaining high quality compressed image for transmission and storage purpose. In present work, MRI images were used for analysis. These images possess soft tissues which contains large amount of contrast levels [9]. The gray-level intensity variation is basis of any algorithm in such case. In case of medical imaging, pixels which possess higher gray-level values needs to be identified. To extract this, Itti–Koch [10] saliency maps are used for construction that uses adaptive thresholding that identifies significant area of an image. The objective of this saliency map is to recognize the varying pixels from background and attract the human intervention for obtaining any diagnostic detail. The following steps are used for detecting the ROI:

Step 1. Read the original medical image and obtain the elements for further processing.

Step 2. Transform the obtained into HSI color space model. HSI color model is more consistent with human color perception system. If input medical image is color image, then it is converted to HSI color space. This image is decomposed into three components: Hue, Saturation and Intensity.

Step 3. Contrast is used as local feature as it stimulates the human visual perception fields. Hence, the contrast between two neighboring pixels a and b is computed.

Step 4. Compute $S(a)$, Salience of pixel a, given by,

$$S(x) = \sum_{v=0}^{m \times n} (\Delta I(a,b) + \Delta H(a,b) + \Delta S(a,b)) \quad (1)$$

Where $m \times n$, represents the total number of pixels in an image.

Saliency Map is generated using Salience $S(a)$ by normalizing in a range [0, 255].

Step 5. Lastly, Segmentation is done using thresholding operation given by following equations,

$$mask(a) = f(a) = \begin{cases} 1, & S(a) \geq Threshold \\ 0, & S(a) < Threshold \end{cases} \quad (2)$$

$$Threshold = 2 \times E(S) \quad (3)$$

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Where saliency of expectation is given by $E(S)$. Mask images are usually formed using these equations where 255 or 1 indicates ROI part and 0 indicates Non-ROI part of a medical image. Extracting the edges of segmented image and adding logically the image outline with original image gives the boundary of ROI region.

2. System Methodology

The following figure shows the block diagram of the proposed system for compressing the given input image.

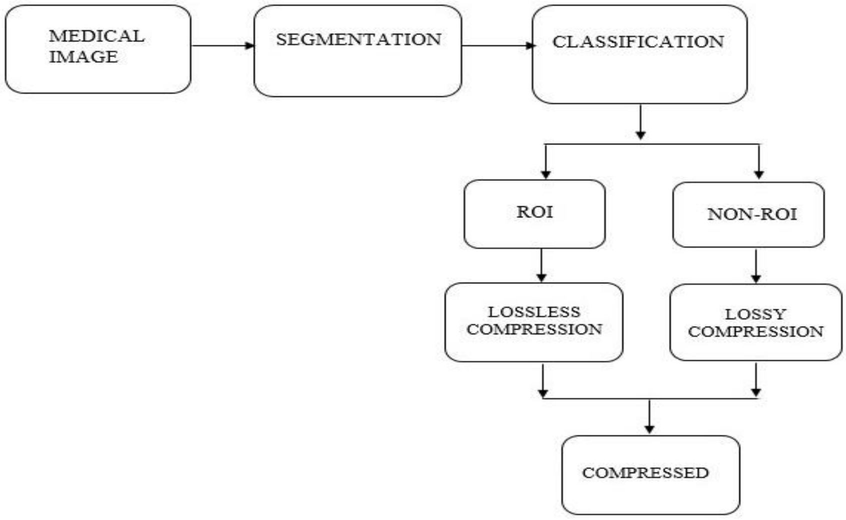

Figure 2. Block Diagram of the Proposed System

Figure 2 shows the block diagram of the proposed system used for medical image compression. Initially, the input medical images which are to be compressed are fed to the system. These input images are the MRI images collected from online databases available and hospitals [17] [18]. All the images are taken in DICOM format for compression. The size of input images and its dimensions are taken into consideration for further processing. Further, the images are partitioned into multiple segments for better analysis. This step is actually incorporated for locating the objects (in this ROI part) and the boundary of the image to classify the ROI and Non-ROI regions for further compression process. After segmenting the image, ROI and Non-ROI regions are extracted and given for further processing. The background pixels of a medical image are discarded or made zero. The ROI region is compressed using lossless compression technique whereas Non-ROI part is compressed using lossy compression technique. In present work, Run-length coding technique was used for encoding and decoding process.

A. Lossless Compression using Wavelet Transform

Wavelet Transform is one of the most popular techniques in image compression application because it possesses two important properties: i) multiresolution and ii) high energy computation. Variety of wavelet transform based coding techniques is reported in literature. Firstly, the wavelet transform is used for de-correlating the image data. Then transform coefficients are quantized and coded. This is called lossy coding. Several research works are published on performance of different wavelet filters. In lossless medical image compression, the image can be reconstructed as the original image. Predictive coding, Entropy based coding such as Huffman, Arithmetic Coding, Run-length Coding, LZW Coding can be used for lossless compression. The multiresolution nature of wavelet transform is suitable for

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progressive transmission of medical images. These techniques yield compression rates of order 2:1, 5:1 depending on image data. Wavelet transform in lossy compression is considered to be lossless as the mathematical transformation is reversible. In present research work, Integer Wavelet Transform (IWT) [9] is applied on medical images for compression. To use wavelets in specific application, it should possess certain properties such as orthogonality, linear phase, compactness and perfect reconstruction. No wavelet can reflect all such properties and therefore, the choice is to be done considering the application. Haar-, Daubechies- and Bi-orthogonal are some renowned choices for selection of wavelets. These wavelets carry relevant properties for various ranges of applications. The Integer Wavelet Transform (IWT) has some advantages such as: i) Computation is faster as compared to DWT, ii) No temporary memory required, iii) Computational complexity is low as it generates only integers and iv) It is completely reversible [10] [11].

As in [12], it is highlighted that SPIHT outperforms well for compression of medical images. For lossy and lossless image compression, IWT and SPIHT techniques are combined. SPIHT algorithm also supports embedding coding standards. This is usually required for telemedicine applications. Computational as well as algorithmic complexities are important factors which needs to be considered for ROI based medical image compression.

B. System Execution

In present work, MRI images in DICOM format were used with size 256×256 and resolution of 8 – bits. The system consists of two processes i) Encoding and ii) Decoding. The Non-ROI part is compressed using combination of IWT and SPIHT technique whereas ROI part is compressed using Run-length coding. The output image is generated at the decoder section once the reconstruction process ends. Before reconstruction of output image, it is decoded using Run-length coding. The encoder output consists of bit stream of numbers of ROI section. The algorithm is executed on 100 images and various performance parameters are computed as discussed in next section. The medical images were collected from private hospitals from city and some were used from online databases. It can be seen that SPIHT algorithm gives better results compared to other techniques discussed in literature. Although, Bioorthogonal wavelets gives better results, in current research work, Daubechies wavelet was used for decomposition. But, it is observed that applying SPIHT algorithm to the whole image, ROI information gets lost as that part also gets affected by lossy compression algorithm. Therefore, ROI part is kept as separate part and therefore during reconstruction processes it remains intact. But non-ROI information may get lost to some extent during the process. In present developed algorithm, compression ratios are obtained using SPIHT at 0.5 bits per pixel and arithmetic coder.

3. Results & Discussions

In literature, several different ROI based techniques are discussed for medical image compression. It can be seen that MAXSHIFT algorithm, EZW coding and Vector Quantization (VQ) requires additional coefficients for decoding process. This can be considered as drawback of the algorithm which can increase computational complexity in general. Other such algorithm like region growing can be used for ROI extraction but again its complexity is more. Therefore, in present research work, saliency maps and contrast based ROI extraction techniques are explored. This makes developed system “semi-automated”. The developed algorithm also tries to preserve the ROI region without introducing any artefacts like pixel blending as discussed in [13]. Any arbitrary ROI shape can be supported by the developed algorithm for compression. The use of IWT and SPIHT reduces the

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algorithmic complexity to greater extent as compared to other techniques discussed in literature. In present work, different performance parameters such as Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) and Compression ratio (CR) are used for validating the results obtained in the study. Table.1 summarizes the results obtained in the research work for sample images. Let us discuss this performance measures in detail.

1) Mean-Square-Error (MSE): This performance parameter is used for measuring the image compression quality. MSE measures the cumulative squared error between compressed image and original image. Lower the value of MSE, lower is the error. Mathematically it is computed as,

$$MSE = \frac{\sum_{M,N}[I_1(x,y) - I_2(x,y)]^2}{M \times N} \quad (4)$$

In above equation, M and N are number of rows and columns of an image.

2) Peak Signal to Noise Ratio (PSNR): This ratio is basically used as a quality measurement between the original and a compressed image. Higher the value of PSNR, better the quality of compressed or reconstructed image. Mathematically it is computed as,

$$PSNR = 10 \log_{10}\left(\frac{R^2}{MSE}\right) \quad (5)$$

In above equation, R represents maximum fluctuation in input image data type. If input image consist of double-precision floating point data type, then R equals to 1. If it is 8-bit unsigned integer data-type, then R equals to 255.

3) Compression Ratio: It is the ratio of size of original image to size of compressed image. Mathematically it can be written as,

$$Compression\ Ratio\ (CR) = \frac{Size\ of\ original\ image}{Size\ of\ compressed\ image} \quad (6)$$

The first image shows the original image which needs to be compressed. This image needs to be enhanced in order to get the results which are more suitable for further analysis as well as processing. It is necessary for one to remove unwanted noise and high frequency components from an image. Morphological filtering, Wiener filtering, contrast stretching or histogram equalization can be used for enhancing the quality of image.

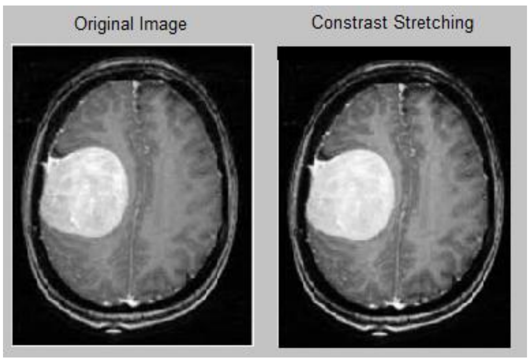

Figure 3. Results obtained after image enhancement.

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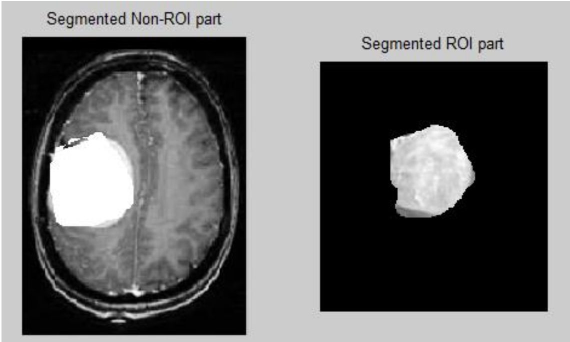

Figure 4. Segmentation of ROI and Non-ROI regions

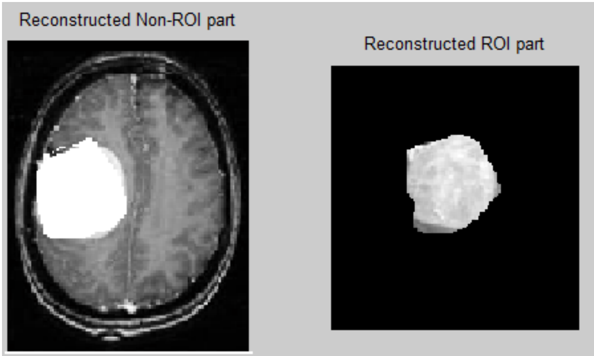

Figure 5. ROI and Non-ROI image after reconstruction process

After this, segmentation is carried for obtaining the ROI and Non-ROI part of an image. Then, IWT is applied to these images along with encoding and decoding process using Run-length coding. After decoding the image at the output side, different parameters such as Mean Square Error, Peak Signal to Noise Ratio and Compression Ratio are computed as indicated in Table. 1.

Table. 1 Obtained values for different performance parameters

Dataset Images	MSE	PSNR (in dB)	CR
Image 1	75.241	31.56	0.341
Image 2	17.70	40.12	0.4021
Image 3	13.25	34.23	0.541
Image 4	98.91	30.03	0.771
Image 5	89.54	32.19	0.791

5. Conclusion and Future Scope

In this paper, a method for medical image compression is presented using lossless compression technique considering the ROI and non-ROI region. Use of Integer Wavelet Transform (IWT) is recommended since DWT produces error and increases algorithmic complexity. IWT has certain advantages like it has perfect reconstruction property and less complexity. In present research, non-ROI region is also considered for encoding purpose as it gives correct position of ROI region. For examining the quality of reconstructed image, different performances measures such as Compression Ratio (CR), Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) are computed and compared since only the conventional quality measures may not be reliable in all the cases. From obtained results, it can be concluded that better results are obtained in terms of compression ratios, MSE and PSNR using ROI technique for lossless medical image compression comparing with

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other techniques discussed in literature [13][14][15]. Run-length coding was used for encoding and decoding processing along with SPIHT algorithm. The developed has less algorithmic complexity and takes less time for encoding and decoding process. Therefore, this method can be recommended for telemedicine applications in remote areas where network bandwidth is limited. In future, a method for lossless medical image compression will be considering the texture and symmetry of an image.

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