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Enhanced Lossy Techniques for Compressing Background Region of Medical Images Using ROI-Based Encoding

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Abstract-Image compression is an important task in medical imaging system and consists of mechanisms that reduce storage requirements while maintaining image quality. Medical image compression can be performed in a lossless or lossy fashion and a method that combines both is the Region of Interest (ROI) techniques. ROI techniques separate relevant and irrelevant details of an image and apply lossy technique to irrelevant part and lossless technique to relevant part. This paper proposes an enhanced active contour based ROI algorithm to separate the image as background and foreground. The foreground is compressed using a lossless JPEG algorithm and the background is compressed using an enhanced lossy JPEG algorithm that uses wavelet neural network followed by a post processing algorithm. Experimental results in terms of Compression Rate, Peak Signal to Noise Ratio and speed of compression show that the proposed scheme is an improved version when compared with the traditional algorithm.

Keywords – ROI based Compression, Enhanced Lossy JPEG Compression, Enhanced Active Contour Model.

I. INTRODUCTION

Medical image compression is an area of research which focus on reducing the amount of space required to store images obtained from advanced medical devices like X-ray devices, CT / MRI scanners and electron microscope. The compression task in medical imaging plays a vital role in reducing the cost of hardware and software required during storage and transmission. Medical practitioners demand images of high quality to aid in accurate diagnosis of diseases and therefore the acquired images are normally of high resolution and therefore bigger in size. For example, a 12-bit medical X-ray image of 2048 x 2560 pixel resolution will be 10,485,760 bytes file size. Similarly, a typical 16-bit mammogram image of 4500 x 4500 pixels will produce a file size of 40,500,000 (40 megabytes). According to [15], the storage requirement is increasing steadily and will increase by more than 11 per cent each year. This high storage demand along the increased usage of computer aided medical imaging systems and high volume of digital imagery produced by new filmless radiology departments is necessitating new compression techniques to be implemented. The challenge faced by medical compression techniques is that the imaging devices are constantly changing and many new innovative techniques are being used in producing medical images which require new techniques for compression.

The medical compression techniques work with two primary objectives, namely, reduced file size and high quality of decompressed image. Reduced filed size makes it more suitable for telemedicine and video conferencing applications, while high quality of decompressed images ensures maintenance of relevant information important for diagnosis. Doctors place a high demand of requiring an exact replica of the original image after decompression in a time efficient manner that would help them to provide better healthcare to patients. This demand for fast and efficient coding algorithms in medical field has led to the development of several techniques which have revolutionized the area of image compression ([10], [9]) but still field has a long way to reach maturity.

Out of the several techniques that are proposed to achieve high compression ratios while maintaining high image quality, Region of Interest (ROI) based techniques is more frequently used in recent years [6]. ROI-based compression techniques take advantage of both lossy and lossless techniques to compress images. These techniques use lossless techniques on abnormal regions that are important for diagnosis and therefore require high quality, while using lossy techniques on other all regions. The method used for determining the ROI in medical images is still an active research area. In this research, an active contour based background and foreground segmentation model is proposed for determining the ROI. This study uses MRI brain images, where the ROI is the brain image. The main objective of the ROI technique is to extract the brain image as ROI (foreground) and the rest as background having irrelevant details (background). Development of such ROI-based compression techniques involves three steps. The first step performs ROI and separates the input image into foreground and background. The second step performs a lossless compression on foreground region and the third step performs a lossy compression on background region. The final step combines the results to achieve compression. A reverse process produces the decompressed image. This paper focuses on proposing an improved lossy technique for compressing the background region of the medical image. The traditional lossless JPEG algorithm is used for compressing the foreground of the image. The method is illustrated in Figure 1. The rest of the paper is organized as follows. Section 2 presents a brief discussion on the existing techniques used for compressing medical images. Section 3 presents the proposed methodology, while the experimental results are discussed in Section 4. Section 5 concludes the work along with future research direction.

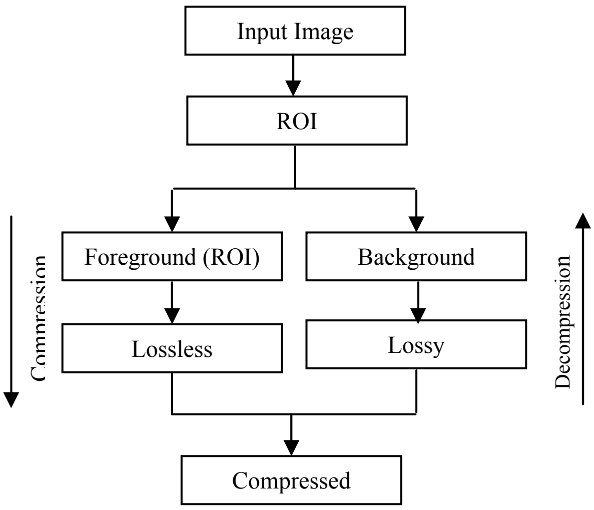

Figure 1 : ROI-Based Compression Model

II.PREVIOUS STUDIES

There have been numerous compression research studies examining the use of compression to medical images. Most have focused on lossless algorithms since the medical community has been reluctant to adopt lossy techniques owing to the legal and regulatory issues that are raised, but this situation may start to change as more lossy research is performed. Popular traditional approaches used for encoding are Huffman encoding, Lempel-Ziv encoding, arithmetic encoding and run-length encoding [14]. Compression of medical images initially started with image preservation techniques like Scan pixel difference [13], followed by intra and inter-frame redundancy reduction [2]. Hu *et al.* [4] investigated linear predictive coding schemes. Several lossless compression techniques like Huffman coding, Lempel-Ziv coding, arithmetic coding have been proposed along with more recent coders like HINT (Hierarchical INTerpolation), DP (Difference Pyramid), Bit-Plane encoding and block truncation coding. All these techniques have concentrated on producing low compress rates. Transformation based coding schemes like Principal Component Analysis, Discrete Cosine Transform, Discrete Wavelet Transform have also been proposed to get better compression rates [16].

Till 2000, JPEG and Wavelet were most popular among medical community. These two compression methods actually gained widespread acceptance as lossy methods. However, each can also be made lossless which is the preferred style in medical imaging. Several studies have been proposed to compress medical images using wavelets and comparison of these techniques has also been studied. Most of the studies have discussed the advantage of using wavelets for image compression. Most of the comparison studies have compared the performance of wavelets with JPEG coder [12]. Rahul *et al.* [8] compared wavelet coder with neural network based compression coder. Comparison between fractal based image compression and wavelets have also been analyzed ([3], [1]). Riazifar and Yazdi [11] analyzed the effectiveness of Contourlet and Wavelet Transform on Medical Image Compression.

III. PROPOSED METHODOLOGY

The Enhanced Region Based Encoding Model compresses medical images in three steps. The first step use active contour model to segment the image into foreground and background region. The second step uses traditional lossless JPEG technique to compress foreground region and while the third step compresses the background region using lossy compression technique. As mentioned previously, this paper focuses on developing efficient method to perform lossy compression on background region of the medical image. The proposed method enhances the traditional lossy JPEG compression technique to use wavelet based neural network and a post processing method to remove the undesired artifacts produced during decompression. This method is referred to as ROI-J in this paper.

A .Proposed ROI Technique based on Modified Active Contour Model

The working of an active contour segmentation model is presented in this section. In this algorithm, the user specifies an initial guess for the contour, which is then moved by image driven forces to the boundaries of the desired objects. The idea behind active contours, or deformable models, for image segmentation is quite simple. Using the user specified initial guess, the contour is moved by image driven forces to the boundaries of the desired objects. In such models, two types of forces are considered - the internal forces, defined within the curve, are designed to keep the model smooth during the deformation process, while the external forces, which are computed from the underlying image data, are defined to move the model toward an object boundary or other desired features within the image.

The main challenge while using active contour models for both segmentation is the initial seed selection. Different initial seed values leads to different segmentation result and often incorrect selection produces inaccurate segmentation. To solve this problem, this paper proposes the use of region growing algorithm first to estimate the initial seeds which are then used by the active contour model. The growing parameter adopted is the average between the maximal and minimal intensities of the input image. A post processing step that performs region merging to merge small regions is included to improve the segmentation result. This method merges several small segments and isolates image background by considering the distance between region's intensity. All groups with similar intensities are grouped together. The algorithm is illustrated in Figure 2.

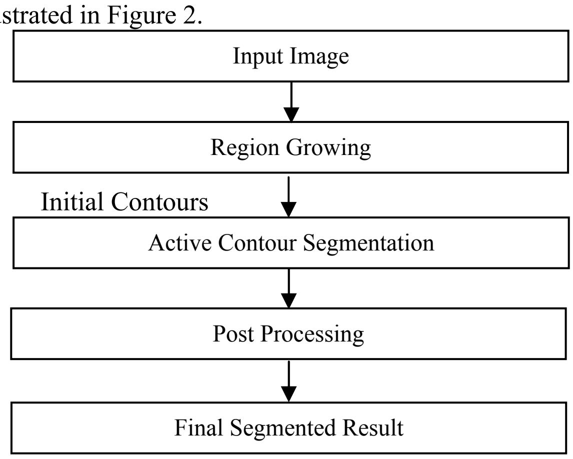

Figure 2 : Segmentation Method

B. Lossless JPEG Compression

Lossless JPEG enables lossless compression using a completely different technique from the lossy JPEG standard. It uses a predictive scheme based on the three nearest neighbors (upper, left, and upper-left) and entropy coding is used on the prediction error. The predictive coding model employed is called Differential Pulse Code Modulation (DPCM). This model predicts sample values by estimating it from the neighboring samples that are already coded in the image. Most predictors take the average of the samples immediately above and to the left of the target sample. DPCM encodes the differences between the predicted samples instead of encoding each sample independently. The differences from one sample to the next are usually close to zero. Detailed information on the working and implementation of this algorithm can be obtained from the publication of Pennebaker and Mitchell [7].

C.PROPOSED LOSSY TECHNIQUES

The aim of the proposed ROI-J model is achieve a nearly lossless quality using lossy technique while compressing the background region of the medical image. The technique enhances the traditional lossy JPEG algorithm. This section first summarizes the working of traditional JPEG lossy technique following by a description of the ROI-J algorithm. The JPEG compression scheme is divided into the following stages and a reverse process produces the original image again.

1. Transform the image into an optimal color space.
2. Down sample chrominance components by averaging groups of pixels together.
3. Apply a Discrete Cosine Transform (DCT) to blocks of pixels, thus removing redundant image data.
4. Quantize each block of DCT coefficients using weighting functions optimized for the human eye.
5. Encode the resulting coefficients (image data) using a Huffman variable word-length algorithm to remove redundancies in the coefficients.

In the above algorithm, the lossiness is produced by the quantization steps (step 4), which when enhanced can improve the compression ratio and quality and of the decompressed image. In this paper, the JPEG encoder is improved by using wavelet neural network to replace the quantization step of traditional JPEG. The compression process that modifies JPEG algorithm with wavelet neural network is explained below.

The image is split into 8 x 8 blocks. Perform Discrete Cosine Transformation (DCT). The coefficients of each block are fed as inputs to the Wavelet Neural Network (WNN). The WNN used combines wavelets with BPNN to extend its ability to approximate complicated patterns. The WNN can be considered as an expanded perceptron where the neurons of the first layer are replaced by wavelet nodes [17]. The wavelet nodes allow the detection of the transient, as well as the extraction and selection of a small number of meaningful features. The WNN employed in this paper is designed as a three-layer structure with an BPNN input layer, a wavelet layer, and an BPNN output layer. The topological structure of the WNN is illustrated in Figure 3. The WNN is used to train each sub-image during compression. In this model the wavelet layers performs the functioning of hidden layers and is designed for the desired compression. The number of neurons in the output layer will be the same as that in the input layer. The input layer and output layer are fully connected to the wavelet layer. The Weights of synapses connecting input neurons and wavelet neurons and weight of synapses connecting wavelet neurons and weight of synapses connecting wavelet neurons and output neurons are initialized to small random values (–1 to +1). The output of the input layer is evaluated using wavelet activation functions of different resolutions and ω_i is the weight connecting the hidden layer and output layer. For an input vector x =[x_1, x_2, …., x_n], the output of the i^{th} wavelet layer neuron is described using Equation (1).

$$\psi_k(x) = \sum_{i=1}^{n} \exp\left(-\left(\frac{x_i - d_k}{t_k}\right)^2\right)\cos\left(5\,\frac{x_i - d_k}{t_k}\right) \qquad (1)$$

where x_i is the i^{th} input vector and k is the number of wavelet nodes, d_k and t_k are translation and dilation parameters respectively. The output of the third layer is the weighted sum of $\psi k(x)$ (Equation 2).

$$y(x) = \sum_{m=1}^{k} \omega_m \psi_m(x) \qquad (2)$$

The Mean Square error of the difference between the network output and the desired output is calculated. This error is back propagated and the weight synapses of output and input neurons are adjusted. With the updated weights error is calculated again. Iterations are carried out till the error is less than the tolerance. At the decompression stage, the values of the coefficients in each block can be recomputed by setting the input of the FFN to the specific spatial coordinates under consideration. Subsequently, the network will produce the equivalent DCT coefficient which will then be transformed to get back the original pixel value.

One undesired effect noticed in ROI-J Lossy Technique was the artifacts introduced after decompression. Two types of artifacts, namely, blocking artifacts and ringing artifacts, are exhibited by ROI-J coder. Blocking artifacts are mainly due to the coarse quantization of low-frequency DCT coefficients and yield an image that look like a mosaic at smooth regions. On the other hand, ringing artifacts occur because of the coarse quantization of high-frequency DCT coefficients and are exhibited as ringing or mosquito noise near the edges of the decompressed image. However, while considering compound images, the ringing artifacts are more prominent on the background region near the edges of a compound image and thus the visual appearance of the image is degraded.

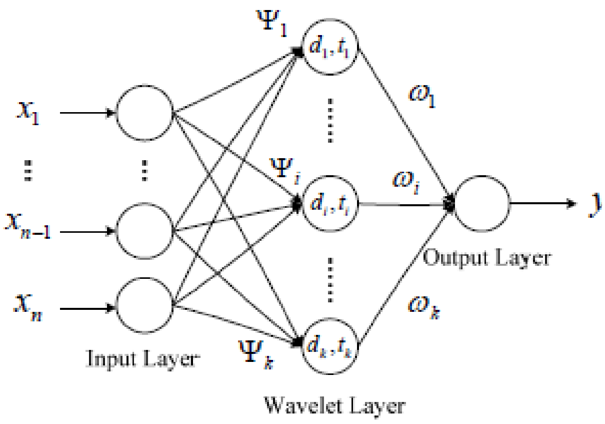

Figure 3 : Wavelet Neural Network Structure

In this research work, a post processing algorithm proposed by [5] is used. Oztan proposed artifacts removal algorithm for gray scale images, which is enhanced to color images in the present research work. The ringing artifact removal algorithm and blocking artifact removal algorithm are shown in Figures 4 and 5. The steps in the proposed ROI-J method are consolidated in Figure 6.

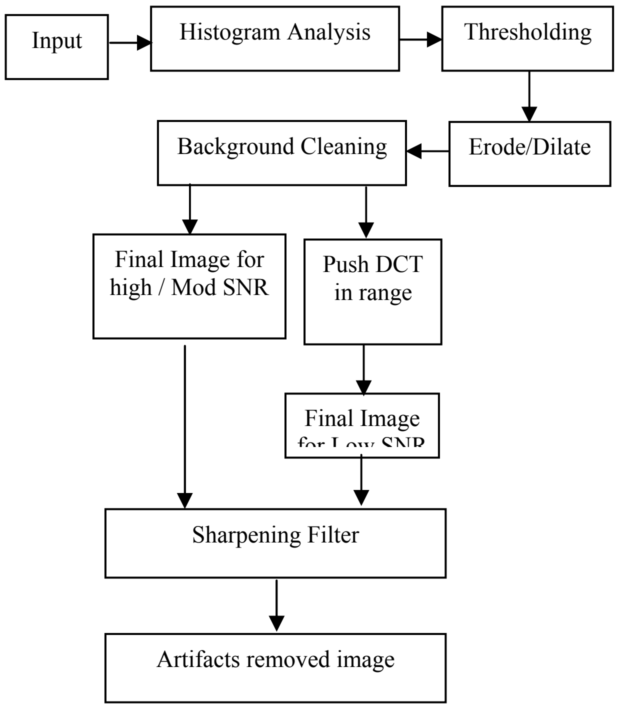

Figure 4 : Ringing Artifact Removal

- Use Canny edge detector to classify pixels as edge and non-edge region.
- Identify pixels that lie on the 8 x 8 tile boundary used in JPEG compression using Maximum A Posteriori (MAP) estimator (Fan and Queiroz, 2003)
- For each non-edge pixel on the tiling boundary, apply a sigma edge preserving filter to smooth out the blocking artifacts. The sigma filter calculates the average over pixels within a small window by considering only those pixels .whose absolute intensity differences with the current pixel is less than a threshold value.
- The result is the blocking artifacts removed image.

Figure 5 : Blocking Artifact Removal

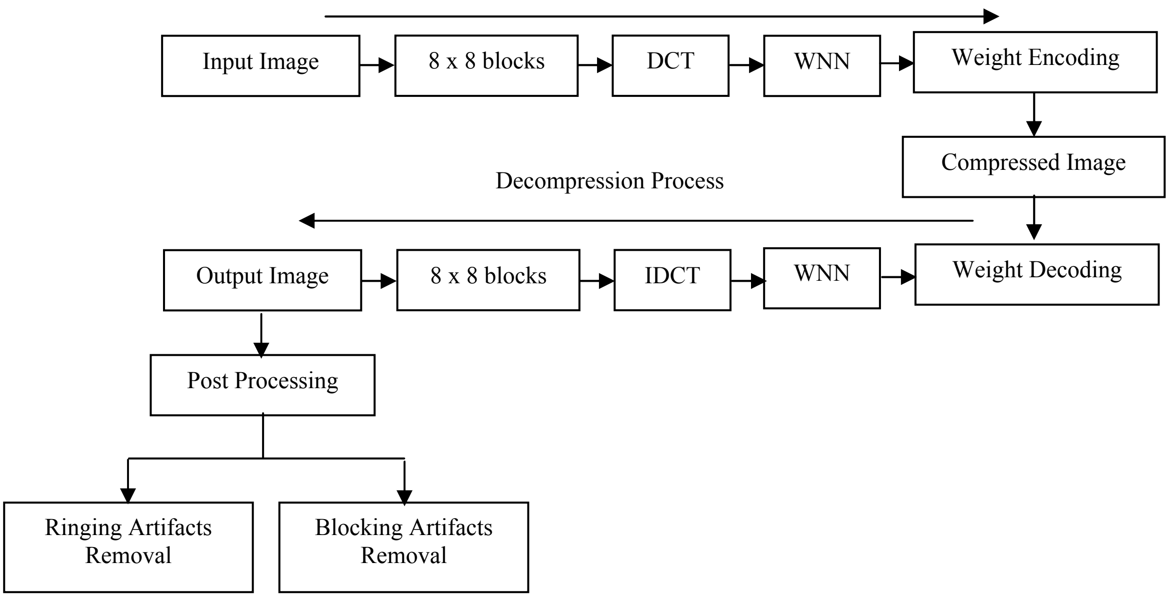

Figure 6 : Proposed ROI-J Lossy Compression Model

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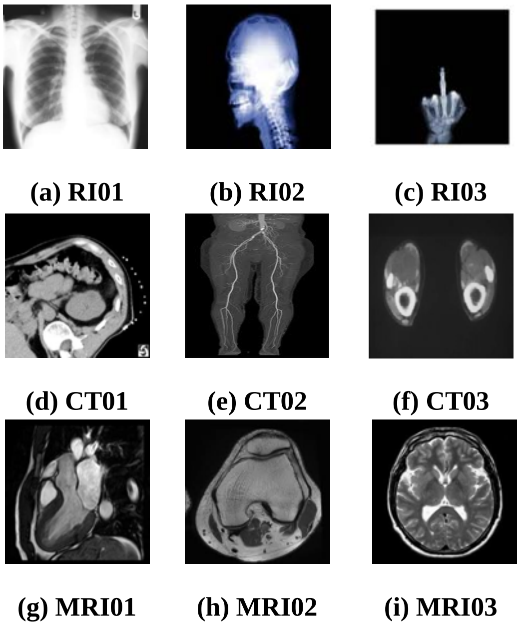

Figure 7 : Image Used in Experiments

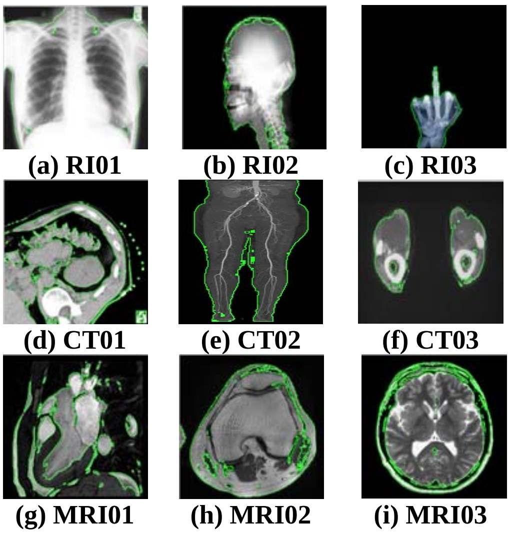

Figure 8 : ROI Segmentation Results

IV. RESULTS

Experimental evaluation was performed using a series of benchmark images (Figure 7). All the images are 512 x 512 8 bit per pixel (bpp) images. The images were selected in such a way that they were a combination of three classes of medical images.

Figures 7a-c are radiographic images, 7d-f are CT images and 7g-i are MRI images. The system is evaluated using three quality metrics, namely, compression efficiency in terms of bits per pixel, Peak Signal to Noise Ratio (PSNR) and compression time and decompression time. The results are compared with the traditional JPEG lossless algorithm. The result after ROI separation is shown in Figure 8.

Image	ROI-J	JPEG
RI01	1.266	1.245
RI 02	1.244	1.218
RI 03	1.301	1.251
CT01	1.955	1.926
CT02	1.919	1.903
CT03	1.932	1.839
MRI01	8.701	8.012
MRI02	8.671	8.246
MRI03	8.532	8.278

Table 1. Compression Efficiency

Image	ROI-J	JPEG
RI01	38.12	35.78
Ri02	37.50	33.28
RI03	38.66	36.01
CT01	29.97	26.34
CT02	29.12	26.56
CT03	28.10	26.98
MRI01	38.82	34.78
MRI02	35.32	32.12
MRI03	37.82	33.75

Table 2. PSNR (dB)

A. Compression Efficiency

Table 1 shows the lossless compression efficiency obtained from the simulations carried out in terms of bit-per-pixel (bpp). From the simulation results, it is shown that the proposed ROI-J coder produces better compression efficiency for all the nine images tested and is found to require the fewest encoding bits. It is also shown that the ROI-J coding has the highest average lossless compression efficiency of 3.96 bpp when compared to JPEG (3.77 bpp). While considering the average efficiency gained, the ROI-J coder showed a 4.51% increase with respect to compression rate. This performance gain plays a critical role during transmission and storage. Table 2 shows the Peak Signal to Noise Ratio obtained for the original and decompressed images.

From Table 2, it is clear that the ROI-J model again outperforms JPEG model in terms of decompressed image quality. On average the proposed model achieved 34.83 dB, while JPEG produced an average PSNR of 31.73 dB, thus the proposed algorithm shows a quality increase of 8.88% over tradition algorithm. All the experiments were conducted using a Pentium IV machine with 512 MB RAM. Table 3 shows the time taken for compression and decompression algorithms to encode and decode images respectively. The compression and decompression time is the execution time taken by the system to perform the compression and decompression processes. The total compression time is calculated as the sum of compression time and decompression time.

Images	ROI-J			JPEG		
	CT	DT	TT	CT	DT	TT
RI01	0.128	0.055	0.183	0.069	0.045	0.114
RI02	0.071	0.057	0.128	0.069	0.043	0.112
RI03	0.138	0.586	0.724	0.071	0.049	0.120
CT01	0.074	0.175	0.249	0.061	0.042	0.103
CT02	0.070	0.171	0.241	0.069	0.040	0.109
CT03	0.139	0.060	0.199	0.072	0.048	0.120
MRI01	0.151	0.065	0.216	0.083	0.052	0.135
MRI02	0.148	0.055	0.203	0.067	0.044	0.111
MRI03	0.13	0.055	0.185	0.088	0.045	0.133

Table 3 : Compression And Decompression Time
CT – Compression Time; DT – Decompression Time; TT – Total Time

From the above data, it is clear that the trend of performance with respect to compression speed has changed and JPEG algorithm is faster by 0.14 seconds. This result is obvious as the proposed algorithm includes a ROI segmentation process. As the speed difference is only less than 0.14, still the proposed algorithm can be considered to be an improvement to the traditional version. From the results obtained it is clear that the proposed lossy compression technique produce good quality compression and are suitable for compressing the background region of medical image compression.

V.CONCLUSION

The fast changing medical field requires compression techniques with maximum image quality produced in a fast manner, while reducing the file size in a significant manner. This will facilitate in improved medical imaging process, reduced file processing, reduced transmission time and minimize storage requirements. To meet this demand this paper introduced an enhanced active contour ROI algorithm, which separates the image into background and foreground. The foreground was compressed in a lossless fashion while the background compressed in a lossy fashion. This paper enhanced the traditional JPEG to compress background region of the medical image. Experimental results prove that both the algorithms were efficient in terms of quality and compression ratio. Moreover, the algorithms have improved the time complexity when compared to its traditional counterparts proving that it is well suited for compressing medical images. In future, research for developing techniques that improve the lossless compression of foreground region is planned.

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