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Vinayak Bairagi
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Automated region-based hybrid compression for digital imaging and communications in medicine magnetic resonance imaging images for telemedicine applications

V.K. Bairagi[1] *A.M. Sapkal*[2]

[1]*Department of Electronics and Telecom Engineering, Sinhgad Academy of Engineering, Pune, India*
[2]*Department of Electronics and Telecom Engineering, College of Engineering, Pune, India*
E-mail: vbairagi@yahoo.co.in

Abstract: Many classes of images contains spatial regions which are more important than other regions. Compression methods which are capable of delivering higher reconstruction quality are attractive in this situation for the important parts. For the medical images, only a small portion of the image might be diagnostically useful, but the cost of a wrong interpretation is high. Hence, Region Based Coding (RBC) technique is significant for medical image compression and transmission. Lossless compression in these 'regions' and lossy compression for rest of image can helps to achieve high efficiency and performance in telemedicine applications. This paper proposes an automated, efficient and low complexity, lossless, scalable RBC for Digital Imaging and Communications in Medicine (DICOM) images. The advantages of RBC are exploited in this paper, segmenting the region into various regions of importance and subjecting varying bit-rates for optimal performance. Moreover, the combined effects of Integer Wavelet Transform (IWT) and bit-rate limiting compression technique for lesser important regions helps reconstruct the image, reversibly, up to a desired quality. The overall compression thus reaches a satisfactory level to be able to safely transmit the image in limited bandwidth over a telemedicine network and reconstruct diagnostic details for treatment, most faithfully.

1 Introduction

A large amount of image data is produced in the field of medical imaging, in the form of computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET) and ultrasound images, which can be stored in picture archiving and communication system (PACS) or hospital information system (HIS) [1]. A medium scale hospital with the above facilities produces on an average 5–15 GB of data per day [2, 3]. So, it is very difficult for hospitals to manage the storing facilities for the same. Moreover, such high data demands a high-end network, especially for transmitting the images over the network such as in telemedicine. This is a very significant issue owing to the limitations of the transmission media in information and communication technology (ICT), especially for rural areas. Image compression is useful in reducing the storage and transmission bandwidth requirements of medical images [3]. If the image is compressed by 8:1 compression without any perceptual distortion, the capacity of storage increases eight times [4]. Compression methods are classified into lossless and lossy methods. In the medical imaging scenario, lossy compression schemes, even though it gives up to 10% compression ratio, are not generally used. This is due to the possible loss of useful clinical information that may influence diagnosis. In addition to these reasons, there can be legal issues. Storage of medical images is generally problematic because of the requirement to preserve the best possible image quality which is usually interpreted as a need for lossless compression [5]. Three-dimensional magnetic resonance imaging (MRI) contains multiple slices representing a part of a body, requires all information of that part. The storage size for such 3D images is huge.

Some of the most desirable properties of any compression method for medical images include: (i) high lossless compression ratios, (ii) resolution scalability, which refers to the ability to decode the compressed image data at various resolutions and (iii) quality scalability, which refers to the ability to decode the compressed image at various qualities or signal-to-noise ratios (SNR) up to lossless reconstruction [5]. Digital imaging and communications in medicine (DICOM) is the most comprehensive and accepted version of an imaging communications standard. DICOM format has a header which contains information about the image, imaging modality and information about patient [6]. To compress such a DICOM file, special attention should be given to header information.

Distortion-limited wavelet image codec performs better in case of medical images of large sizes [6]; lossy compression is implemented by multiplexing a small number of wavelet coefficients, resulting in statistically higher compression results concerning the file size. However, lossy medical image compression is considered to be unacceptable for performing diagnosis in most of the medical imaging applications, owing to quality degradation. Therefore in order to improve the diagnostic value of lossy compressed images, the region of interest (ROI) coding concept is introduced in the proposed application to improve the quality in specific regions of interest only by applying lossless compression in these regions, maintaining the high compression in non-ROI of the image.

1.1 Region of interest

Basic concept of ROI is introduced owing to limitations of lossy and lossless compression techniques. Fig. 1 shows the spectrum of image compression system. For well-known lossless compression techniques, the compression ratio is near to 80% of original size, whereas for lossy encoders the compression ratio is much higher (up to 5–30%) [1, 3] but there may be significant loss in data. This loss may hamper effective treatment, losing diagnostically important parts of the medical image. Hence, there is a need for some hybrid technique which will preserve diagnostically important part (ROI) as well as provide high compression ratio [1, 6]. The functionality of ROI is important in medical applications where certain parts of the image are of higher diagnostic importance than others. For most medical images, the diagnostically significant information is localised over relatively small regions, near about 5–10% of the total area as shown in Fig. 2. In such cases, these regions need to be encoded at a higher quality than the background, lesser important regions. During image transmission for telemedicine purposes, these regions are required to be transmitted first or at a higher priority.

In [7], the state-of-art comparison of different ROI-based coding techniques is summarised. The JPEG 2000 imaging standard has been tested in previously published works on medical images. A major drawback, however, of the JPEG2000 standard is the fact that it does not support lossy-to-lossless ROI compression. An overview of ROI coding scalable techniques applied on medical images is summarised in [6, 7], which further proposes an ROI-based coding technique based on discrete wavelet transform (DWT). The observed drawback of this method is that every time, in each sub-band the information about the ROI shape has to be maintained. This may increase computational complexity. Here in this proposed work, an attempt has been made to reduce this complexity.

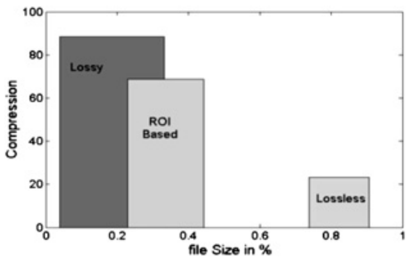

Fig. 1 *Spectrum of compression*

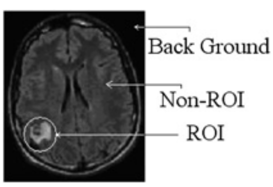

Fig. 2 *Different parts of the medical image*

2 Proposed method

For a CT or MRI image, it contains three parts: ROI (the diagnostically important part), non-ROI image part, and background (part other than image contents) as shown in Fig. 2 and its cross-section in Fig. 3. Its corresponding 3D pixel intensity map is shown in Fig. 4. Now these background regions even though black in colour (ideally grey level value is zero) did not have zero value.

Initially, this background is made zero

$$\begin{aligned} &\text{img}[i, j] \le x\_\text{th} \\ &\text{then} \\ &\text{img}[i, j] = 0 \end{aligned} \tag{1}$$

where x_th is the threshold value of the background of an image (img). For all pixel values that correspond to this threshold value or lower, are forcibly made 0. Here also, complete lossless compression is achieved. This ready-to-process image is then subjected to segmentation as shown in Fig. 5.

The ROI is detected by an automated process, eliminating all forms of manual intervention. Depending on the selected part, an ROI-mask is generated in such a way that the foreground part is totally included and the pixel values in the background part are made zero. Morphological operations can be effectively used to generate image masks, which contain a value of ‘1’ in the foreground and a value of ‘0’ in the background. Then the mask is logically AND-ed with the image to separate out the ROI part (IMG_ROI) and non-ROI image part as shown in

$$\text{ROI\_mask}\&\&\text{img} = \text{IMG\_ROI} \tag{2}$$

where ROI_mask is a binary image which when AND-ed with the original img gives the ROI part of the image. The

Fig. 3 *Cross-sectional view of medical image (diagrammatic representation)*

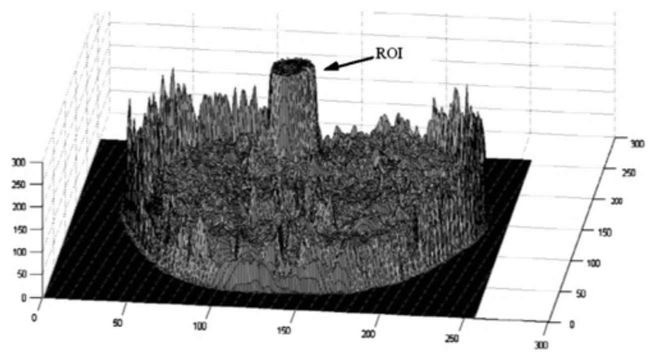

Fig. 4 *Three-dimensional view of image with ROI*

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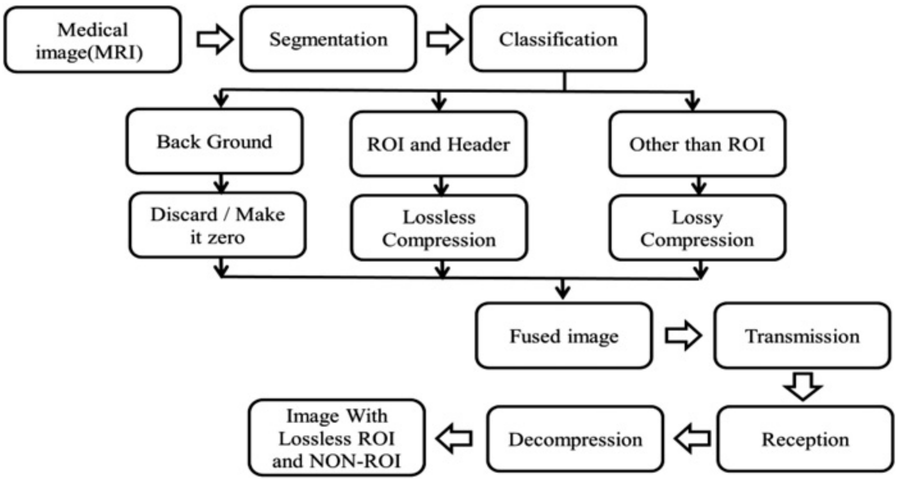

Fig. 5 *Block diagram of the proposed method*

two separated parts can be processed separately as per the requirement, that is, ROI part can be processed by lossless technique, whereas the non-ROI part can be compressed with accepted lossy compression methods.

2.1 ROI detection

MRI images possess high amount of contrast for soft tissues such as tumours [8]. The basis of the algorithm is on the grey-level intensity variation of the image. The pixels in the medical image, which possess a higher grey-level, must first be identified and distinguished against the other part of the image. Also, in some other cases especially for pathological images, the ROI is blacker than the surrounding part. For this purpose, Itti–Koch saliency map [9] is used for construction which uses adaptive thresholding to pop out the important regions.

The main intention of using saliency map on a medical image is to have an effect of blurring on the image, so that the most prominent regions containing most of the diagnostically important information can be recognised. The principle used here is based on human visual perception. Since the application is that of medical diagnosis, human perception is of utmost importance. The main objective of salience map is to highlight any pixels that vary from the rest of the background and catch the human attention towards any diagnostic detail [8].

Steps to find ROI:

Step 1. Read image and get its dimensions. Accept the original medical image as input to the system and read its dimensions for further processing.
Step 2. Transformation: Hue, Saturation, Intensity (HSI) space consistent with human colour perception system. Image is transformed to HSI space model. If the input image is a colour MRI image, an HSI transformation is performed. The HSI model is more consistent with human visual perception than the RGB colour space model. The image is decomposed into three components: hue, saturation and intensity.
Step 3. Contrast is the most commonly used local feature for attention detection because the contrast operator simulates the human visual receptive fields. The regions in medical images with high contrast have rich information and are most likely to attract human attentions. So the contrast between the two neighbouring pixels x and y is calculated.
Step 4. Calculate salience $S(x)$ of pixel x

$$S(x) = \sum_{y=0}^{m*n} (\Delta I(x, y) + \Delta H(x, y) + \Delta S(x, y)) \tag{3}$$

where m^*n represents the total number of pixels in the image; (see (4))

By normalising to [0, 255], all saliency $S(x)$ form a saliency map.
Step 5. Segmenting using a threshold.

$$\text{mask}(x) = \begin{cases} 0, & S(x) < \text{threshold} \\ 1, & S(x) \geq \text{threshold} \end{cases}$$
$$\text{threshold} = 2 \times E(S) \tag{5}$$

where $E(S)$ is expectation of saliency map.

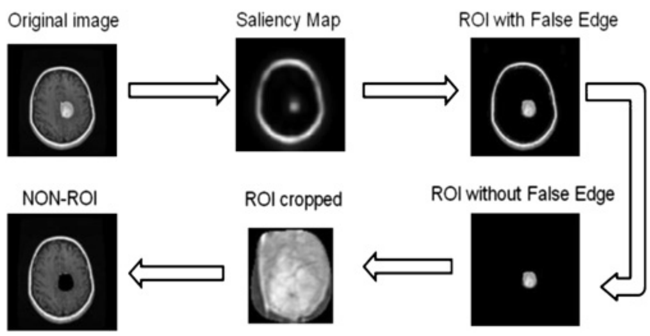

Fig. 6 *ROI extraction process*

$$\begin{aligned} &\Delta I(x, y) \text{ is the intensity contrast between the two pixels } x \text{ and } y; && \Delta I(x, y) = |I(x) - I(y)| \\ &\Delta H(x, y) \text{ is the hue contrast between the two pixels } x \text{ and } y; && \Delta H(x, y) = |H(x) - H(y)| \\ &\Delta S(x, y) \text{ is the saturation contrast between the two pixels } x \text{ and } y; && \Delta S(x, y) = |S(x) - S(y)| \end{aligned} \tag{4}$$

These equations help in forming a mask image where 1, or grey level-255, represents the ROI, whereas 0 represents the non-ROI part. The outline of the regions of interest is obtained by extracting edges of the segmented image and then logically adding the outline of the image to the original image. The ROI extraction process is shown in Fig. 6. Skull is the outer part of the brain surrounding it, that is, skull removal is the removal of the non-cerebral tissues. In the ROI detection process, this skull may be wrongly taken as ROI as its intensity is prominent and may be falsely detected as ROI, given its high contrast in the saliency map. The main problem in skull stripping is the segmentation of the non-cerebral and the intracranial tissues owing to their homogeneity intensities. Finding the skull in MR images is difficult because the skull appears as a set of high contrast voxels in T1 and T2 weighted MR (differently in both types of MR images) and typically has a width of only three or four voxels. The problem gets more difficult if the ROI region touches the skull part. Morphological operators can be used to address this issue. Such an operator mainly deals with the contour and structure of the object. Morphological operators use a binary image and a structuring element as input. Dilation and erosion by larger structuring elements is performed by applying the corresponding structuring elements multiple times.

Lossless compression, progressive transmission and RBC are important functionalities for a compression scheme useful in telemedicine applications [4]. ROI is compressed with the lossless version of compression techniques such as arithmetic coding, whereas non-ROI is compressed using set partitioning in hierarchical trees (SPIHT) algorithm, used after wavelet transform. ROI can be of any arbitrary shape, and our algorithm can be used to detect them.

2.2 Integer wavelet transform

New integer wavelet transform (IWT) is said to aid lossless processing of images. The wavelet transform (WT), in general, produces floating point coefficients. Although these coefficients can be used to reconstruct an original image perfectly in theory, the use of finite precision arithmetic and quantisation results in a lossy scheme. Recently, reversible integer WT has been introduced. Lifting provides an efficient way to implement the DWT and the computational complexity of the lifting implementation can be up to 30% less than the traditional direct convolution-based implementation [10]. Spline (5,3) (vanishing moments of analysis and synthesis high-pass filters respectively) transform can be used effectively. Lifting allows simple inverse transform of the same complexity as the forward one. Reversible IWT, being composed of the elementary operations of the forward one, is simply carried out in the reverse order [11]. The advantages of IWT are:

1. Faster calculation with respect to traditional DWT (~30% fast).
2. Allows a fully in-place calculation of the wavelet transform, no need of temporary memory.
3. Generates only integer numbers, low computational complexity as compared to DWT, which generates floating point numbers.
4. Completely reversible.

For telemedicine purposes, a fast responding (processing time in milliseconds) and low-complexity system is required. Hence, it is recommended to use IWT.

2.3 Coding algorithm

The SPIHT coding algorithm is best in terms of compression performance [12]. Previously, the SPIHT was designed for lossy data compression. By combining the IWT with the SPIHT, both the lossy and lossless compression modes can be supported. The major advantage of using SPIHT coding technique is that, it supports embedded coding along with progressive transmission, which is recommended for telemedicine. The optional user interface is given for selection of compression level, which is helpful in the case of displaying images on low-processing units such as personal digital assistants.

A new coding algorithm is presented here:

1. Read image from database and get dimensions. Extract the header information from it.
2. Apply thresholding to remove background.
3. Use saliency to detect ROI.
4. Separate out ROI and non-ROI.
5. Accept compression levels from user (optional).
6. Apply wavelet for non-ROI to execute two-dimensional heap.
7. Do operation of distortion as per level selected by user for non-ROI, and lossless arithmetic coder technique for ROI [13].
8. Append header and non-ROI to ROI to form a string.

SPIHT is proved to be the best [12], but for ROI-based compression, computational complexity is also one of the important issues to be considered, while addressing real-time applications [14, 15]. A new and simple algorithm as explained above is used to encode the image. Fig. 7 shows the block diagram of developed system with different stages of development. The decoding part is symmetric and exactly reverses the process of encoding.

3 Experimental result

Original MRI image formatted in DICOM format of size 256×256 with 8 bit resolution is input to software. In Fig. 7, the 'output image' is the image that is generated at the decoder side after reconstruction process. The output of encoder is a bit stream of numbers arranged in a manner so as to support the progressive transmission, with initial part as an ROI compressed bit stream, with arithmetic encoding. This bit stream is ready to be transmitted over the telemedicine network using GSM mobile device. The algorithm is implemented on more than 500 MRI DICOM

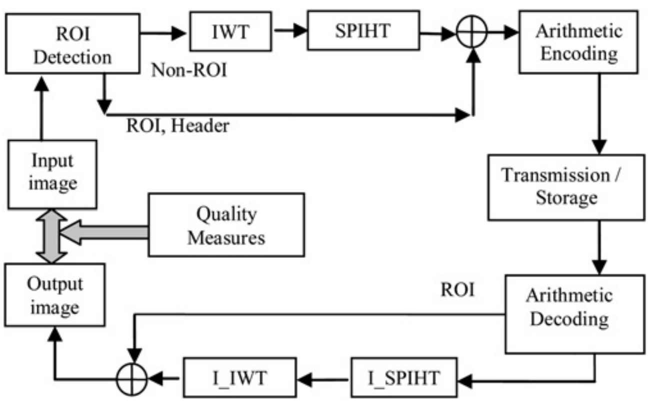

Fig. 7 *Block diagram of developed system*

Table 1 Comparison of SPIHT with EZW algorithm

Image	bpp	Levels	PSNR (EZW)	PSNR (SPIHT)
No. 1 (normal image)	0.1	6	25.4951	26.7486
	0.1	7	25.5621	26.8071
	0.2	6	27.2294	28.6099
No. 2 (normal image)	0.1	6	19.3344	21.4152
	0.1	7	19.4682	21.5842
	0.2	6	21.9878	24.3716
	0.2	7	22.0476	24.5071
No. 3 (with ROI)	0.1	6	19.2852	21.2608
	0.1	7	19.3493	21.370
	0.2	6	22.0409	23.9018
	0.2	7	22.0433	23.9645
No. 4 (with ROI)	0.1	6	21.5216	24.8781
	0.1	7	21.7062	25.0606
	0.2	6	24.3417	28.7866
	0.2	7	24.4504	28.8585
No. 5 (with ROI)	0.1	6	32.9834	36.4061
	0.1	7	33.0402	36.6092
	0.2	6	36.1725	39.9628
	0.2	7	36.2567	40.0478

images (available from private domain database as well as from public domain images) [16–18], out of which performance analysis of one is shown in Table 1. Original file size was 257 kB.

Table 1 clearly points out important issues, which prompts to adopt SPIHT as the lossy compression scheme. SPIHT shows superior performance compared to embedded zero-tree wavelet (EZW) in all cases [19]. The performance of SPIHT with respect to time and compression is shown in Table 2, also shown in graphical format in Fig. 8. Bi-orthogonal 4.4 wavelet is used in decomposition [20]. Time required to encode and decode the data is increasing with respect to bits per pixel (bpp). Also, the compression ratio achieved in the process is directly proportional to bpp. The reconstructed image using ROI-based technique is shown in Fig. 9. Same numbers of average bits are used in both the cases. The observation is made for various types of images with different tumours location. In all the cases the algorithm is working without fail, giving satisfactory performance.

From Fig. 9, which were obtained after reconstruction, it can be seen that when SPIHT is applied to the entire image, the ROI information is lost, since that area also is affected by the lossy nature of algorithm. However, if ROI is considered as a separate entity in itself, then it can be seen that, in reconstruction, the ROI part is intact, although the non-ROI information may be partially lost in the process. The current JPEG2000 image coding standard defines two kinds of region of interest (ROI) coding methods: the general scaling-based method and the maximum shift

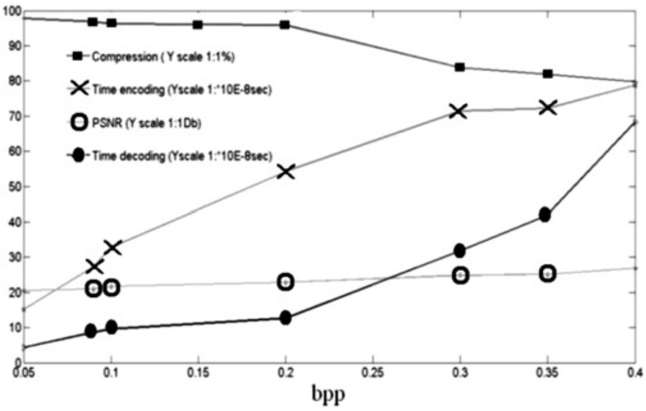

Fig. 8 *Graphical representation of Table 2*

(MAXSHIFT) method. The former requires shape coding of the ROIs, which leads to increased complexity of codec implementations and limits the choice of ROI shapes (currently, only rectangle and elliptical shapes are defined). The latter allows for arbitrarily shaped ROI coding, without explicitly transmitting any shape information to the decoder, but does not have the flexibility to select an arbitrary scaling value to define the relative importance of the ROI and the background wavelet coefficients. The proposed method is suitable and verified for multiple ROIs in the same image.

Table 3 indicates the performance of proposed algorithm with respect to image quality measures (IQM). Overall compression ratio obtained for proposed algorithm with SPIHT at 0.6 bpp + arithmetic coder. It can be seen that even though the bit rate is 0.6, the correlation is maximum. The compression ratio [21] results are superior to lossless compression algorithms (which gives compression ratio about 0.6–0.8).

4 Comparison with other reported technique and discussion

Several ROI-based techniques are reported and compared in [7], the general scaling, the MAXSHIFT, the EZW-based and the ROI–VQ methods require additional coefficients to decode the object. This may be the bottleneck of the system, which may increase its complexity [6, 22]. Consider region growing algorithm as an alternate algorithm for ROI detection and extraction. Although our algorithm, based on saliency map and thresholding concentrates on a contrast-based logic, region growing algorithm exploits the similarities in a set of pixels, connected to each other. The homogeneity is checked among the pixels, which may be intensity/texture based. However, one major drawback of such an algorithm is that it requires an initial seed point,

Table 2 Performance of SPIHT

bpp	SPIHT encoding time, ns	SPIHT decoding time, ns	Output final size, kB	Compression, kB	PSNR
0.05	1.520746	0.43007	6.53	97.79	20.60
0.09	2.720	0.867	7.53	96.82	20.93
0.1	3.277	0.958	8.15	96.21	21.75
0.2	5.428	1.264	8.55	95.83	22.83
0.3	7.145	3.182	16.75	83.74	24.85
0.35	7.215	4.204	18.75	81.80	25.18
0.4	7.875	6.827	20.85	79.76	26.86

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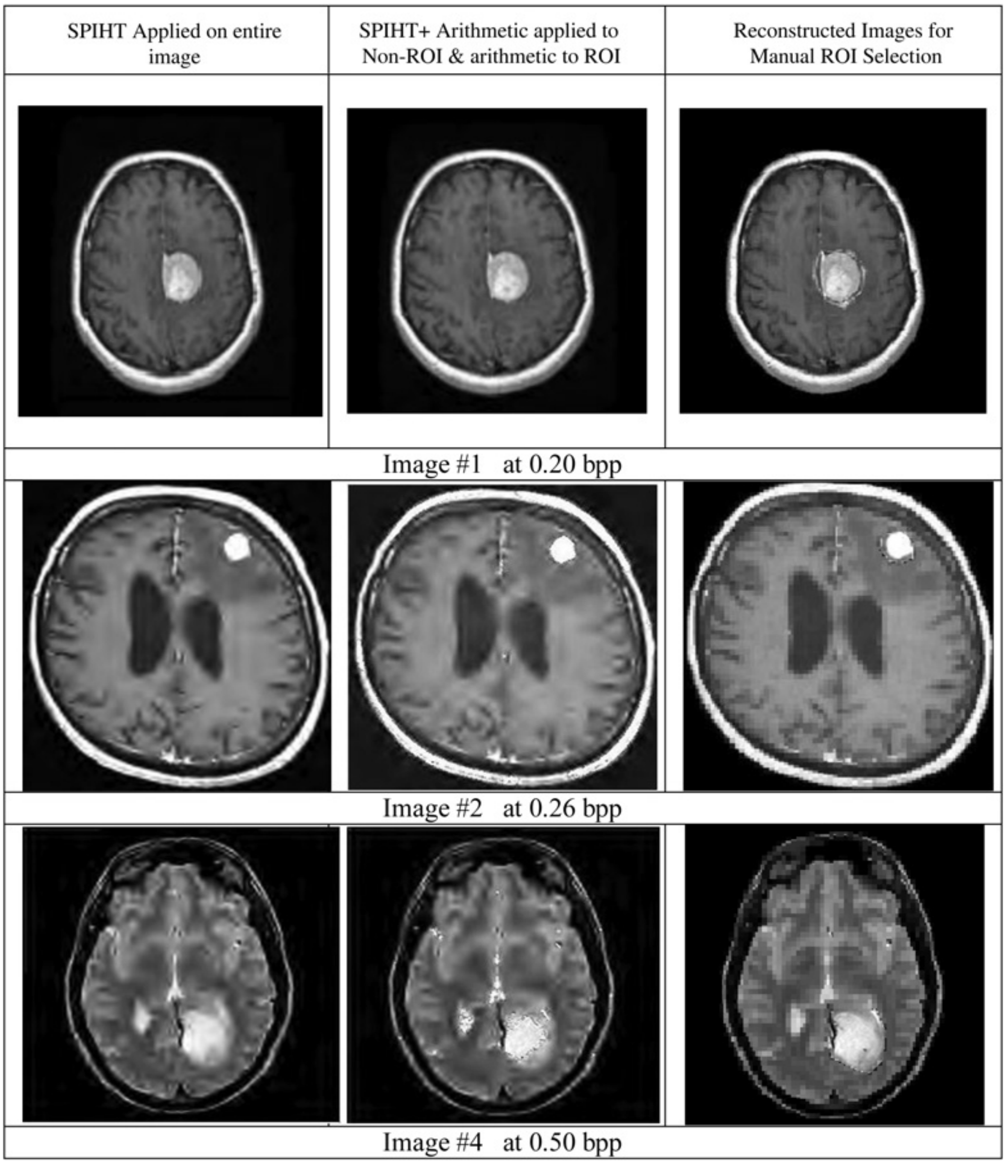

Fig. 9 *Reconstructed images at various qualities*

Table 3 Performance of proposed method

Image no.	Size, kB	PSNR, dB	Cross-correlation	Average difference	Normalise absolute error	Compression ratio
1	65.7	33.9439	0.9977	3.7135	0.0346	0.0966
2	41.3	32.3241	0.9950	3.7515	0.0720	0.1380
3	52.2	37.0393	1.0005	2.6553	0.0287	0.1396
4	22.4	38.4282	0.9990	1.7150	0.0319	0.2285

which in most of the cases is a manually provided one. This makes the approach a 'semi-automated' one [23]. Another drawback in context to this approach maybe that it may fail to detect multiple ROIs, as it would require some connectivity between the initial seed point and the ROIs. Since our algorithm focuses on intensity levels, this task may be possible. One can also use a texture-based approach to detect ROI but it would be a very tedious and time consuming process as texture-based ROI finding uses filters.

The feasibility of exact decoding refers to the ability of the method to preserve the entire ROI without pixel-blending artefacts. One of the features of ROI-based coding technique, is to support any arbitrary shape of ROI [7]. The proposed technique does not require any additional bits for encoding as required by MAXSHIFT method. Hence the algorithmic complexity is less, and such low complexity systems are recommended for telemedicine. Use of IWT in coding itself has reduced the complexity as compared in [6]. Also, our proposed technique supports arbitrary and automated coding of ROI, as well as progressive transmission of data with priority to ROI. Further, the ROI is also compressed by lossless compression method allowing more compression. For the proposed method the computational execution time is calculated using Big-oh notation [22] which equals to $26^{*}1 + 32^{*}N + 20^{*}N^{2} + 12N^{3}$. Therefore the computational complexity is $O(N^{3})$.

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5 Conclusion

This paper discusses an automated ROI-based, medical image compression. The floating point representation of DWT produces error in the system thus IWT is recommended for critical medical applications because of its perfect reconstruction property along with less complexity. Different techniques can be used for non-ROI compression for the medical image, depending on the desired image quality and compression performance. If the ROI is the only important part, then why encode and transmit the non-ROI part? Non-ROI part must be encoded, because it gives the accurate position of the ROI in the medical image. Also, when ROI-based coding is used along with lossy compression for non-ROI, a new class of objective quality measures are needed, to reflect an accurate measure of algorithmic performance. The conventional objective quality measures used in lossy compression schemes may not be truly reliable.

ROI-based compression provides better compression as compared to other lossless methods, along with preservation of diagnostically important information. The proposed technique is less complex as it need not take care of the ROI part in wavelet decomposition. It allows multiple ROI detection and progressive bit stream transmission enabling it to be transferred on a heterogeneous network. This method is recommended for telemedicine systems especially in rural areas, where network resources are limited. Advanced version of our proposed method may include the compression based on the information content as well as on ROI, using textural properties.

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7 References

1 Miaou, S.-G., Ke, F.-S., Chen, S.-C.: 'A lossless compression method for medical image sequences using JPEG-LS and interframe coding', *IEEE Trans. Inf. Technol. Biomed.*, 2009, **13**, (5), pp. 818–821
2 Placidi, G.: 'Adaptive compression algorithm from projections: application on medical grayscale images', *J. Comput. Biol. Med.*, 2009, **39**, pp. 993–999
3 Baeza, I., Verdoy, A.: 'ROI-based procedures for progressive transmission of digital images: a comparison', *J. Math. Comput. Model.*, 2009, **50**, pp. 849–859
4 Javid Ali, T., Akhtar, P.: 'Significance of region of interest applied on MRI and CT images in teleradiology-telemedicine' (Springer-Verlag, Berlin, Heidelberg, 2008), pp. 151–159
5 Sanchez, V., Abugharbieh, R., Nasiopoulos, P.: 'Symmetry-based scalable lossless compression of 3D medical image data', *IEEE Trans. Med. Imaging*, 2009, **28**, (7), pp. 1062–1071
6 Maglogiannis, I., Kormentzas, G.: 'Wavelet-based compression with ROI coding support for mobile access to DICOM images over heterogeneous radio networks', *Trans. Inf. Technol. Biomed.*, 2009, **13**, (4), pp. 458–466
7 Doukas, C., Maglogiannis, I.: 'Region of interest coding techniques for medical image compression', *IEEE Eng. Med. Biol. Mag.*, 2007, **26**, (5), pp. 29–35
8 Zhang, Q., Xiaio, X.: 'Extracting regions of interest in biomedical images'. Int. Seminar on Future BioMedical Information Engineering, 2008, pp. 3–6
9 Yu, Y., Wang, B.: 'Saliency based compressive sampling for image signals', *IEEE Signal Process. Lett.*, 2010, **17**, (11), pp. 973–976
10 Calderbank, A.R., Daubechies, I., Sweldens, W., Yeo, B.L.: 'Wavelet transforms that map integers to integers', *Appl. Comput. Harmon. Anal.*, 1998, **5**, pp. 332–369
11 Reichel, J., Menegaz, G., Nadenau, M.J., Kunt, M.: 'Integer wavelet transform for embedded lossy to lossless image compression', *IEEE Trans. Image Process.*, 2001, **10**, (3), pp. 383–392
12 Said, A., Pearlman, W.A.: 'A new, fast and efficient image codec based on set partitioning in hierarchical trees', *IEEE Trans. Circuits Syst. Video Technol.*, 1996, **6**, pp. 243–250
13 Lehtinen, J.: 'Limiting distortion of a wavelet image codec', *J. Acta Cybern.*, 1999, **14**, pp. 341–356
14 Bhaskaranarayana, A., Satyamurthy, L.S.: 'Bridging health divide between rural and urban areas – satellite based telemedicine networks in India', in Olla, P. (Ed): Space technologies for the benefit of human society and Earth, (Springer, 2009), pp. 160–178
15 Park, K.-h., Park, H.W.: 'Region-of-interest coding based on set partitioning in hierarchical trees', *IEEE Trans. Circuits Syst. Video Technol.*, 2002, **12**, (2), pp. 106–113
16 The Whole Brain – Atlas [Online]. Available at http://www.med.harvard.edu/AANLIB/home.htm, accessed December 2011
17 Computer vision group [Online]. Available at http://decsai.ugr.es/cvg/index2.php, accessed August 2011
18 The National Library of Medicine (NLM) [Online]. Available at http://www.nlm.nih.gov, accessed July 2011
19 Sayood, K.: '*Introduction to data compression*' (Elsevier Publication, 2010, 3rd edn.), pp. 473–512
20 Bairagi, V.K., Sapkal, A.M.: 'Selection of wavelets for medical image compression'. IEEE Int. Conf. ACT 2009, IEEE Digital Library, Trivandrum, India, December 2009, DOI 10.1109/ACT.2009.172, pp. 678–680
21 Solomon, D., Motta, G.: 'Handbook of data compression' (Springer, 2010, 5th edn.), pp. 1–51
22 Black, P.E.: 'Big-O notation', in Black, P.E. (Ed.): 'Dictionary of algorithms and data structures [online]' (U.S. National Institute of Standards and Technology, 2008), Available from: http://www.itl.nist.gov/div897/sqg/dads/HTML/bigOnotation.html, accessed July 2008
23 Mancas, M., Gossellin, B., Macq, B.: 'Segmentation using a region growing thresholding'. Proc. SPIE 5672SPIE, Image Processing: Algorithms and Systems, USA, 2006, pp. 388–398