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Coding of Clinical ROI Using S-FCM and WBCT

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Abstract: Medical imaging plays a vital role in the field of diagnosis and surgical planning. Compression of medical images differs from standard image coding as it needs to preserve the clinically critical information with reduction in storage space required. Recent research has demonstrated the merit of encoding the Clinical ROI separately and encoding the insignificant part of the image using standard SPIHT technique. One unaddressed combination is the segmentation of CROI using soft computing approaches such as spatial FCM. This study proposes a technique for extracting the clinical ROI using spatial FCM and encoding the segmented portion using a suitable transform with directionality and multi resolution capability. The goal of the proposed technique is to preserve the clinical useful information with smooth contours to obtain a better compression ratio. In the proposed study, modified set partitioning in hierarchical tree (modified SPIHT) is used to code the wavelet based contourlet transformed coefficients of the Clinical Region of Interest (CROI) and remaining portion is encoded using DWT and SPIHT. The proposed study produces a better compression ratio for the MRI brain images with increased PSNR. Also it provides efficient representation of smooth edges in Digital Imaging and Communications in Medicine (DICOM) images.

Key words: Medical image segmentation, clinical region of interest, directional analysis of wavelet subbands, WBCT, modified SPIHT, medical image compression

INTRODUCTION

Medical image compression plays a vital role in the field of telemedicine. Telemedicine technology supports the transfer of imaging reports of patients taken from different advanced imaging modalities such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Ultrasounds (US), X-rays. To decrease the data rate for high speed transmission of medical images, an efficient image compression algorithm is required. Medical image diagnosis and analysis are effective only when the compression techniques preserve the relevant and important information efficiently. Therefore, the challenging goal of medical image compression is to reduce the bit rate as much as possible to enhance the compression ratio with an acceptable diagnostic image quality.

The Clinical Region of Interest (CROI) is the region where certain anatomical parts are of higher diagnostic importance than others and those image-regions are needed to be transmitted with higher priority. The objective of medical image segmentation is to partition the image into different anatomical regions thereby separating the regions of interest such as blood vessels and tumors, from their back ground. Computerized medical image segmentation is a challenging problem, due to poor resolution and weak contrast. Moreover, the task becomes more difficult due to the presence of noise, due to the limitations of instruments and due to movement of subjects. There is no universal automated segmentation algorithm for medical image segmentation. The success rate of the segmentation algorithm often changes according to the problem under investigation. Segmentation is used to identify the significant region in the medical images. In general, pixel classification and tracking variation boundary (Zhao *et al.*, 2009) are the two techniques developed in image segmentation. In pixel classification technique it is assumed that the pixel in each sub cluster will have nearly uniform intensities which is true for the different anatomical regions with similar physiological properties. Such algorithms can detect multiple componentsbut the method is unsuitable in the presence of environmental noise and image in-homogeneity. On the other hand, tracking "Variation boundary method" makes use of both intensity and spatial information. Therefore, a sub cluster has to be homogeneous and it must be enclosed in a specific variational boundary. But the above techniques fail to produce the successful segmentation in the case of medical images due to intrinsic noise and artifacts (Pham *et al.*, 2000; Martin *et al.*, 2004, Suri, 2001). Level

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set methods are established on Dynamic Implicit Interfaces and Partial Differential Equations (PDEs). Level set techniques have been effective for medical image segmentation (Li *et al*., 2009). There have been many hybrid intelligent systems using fuzzy clustering to facilitate automatic level set segmentation (Chuang *et al*., 2006; Li *et al*., 2009; Cai *et al*., 2007). Mostly, medical image segmentation algorithms use fuzzy clustering, based on image intensity, for initial segmentation and employ level set methods by tracking boundary variation for object refinement. In this proposed algorithm, a fuzzy clustering algorithm is used for medical image segmentation. The fuzzy clustering algorithm incorporates spatial information during an adaptive optimization which eliminates the need for intermediate morphological operations.

Different segmentation techniques are available such as thresholding methods, clustering methods, transform methods and texture methods. In order to identify the clinical region of interest, clustering approach is widely used in biomedical application. Fuzzy C Means (FCM) clustering technique is the widely used unsupervised method for medical image segmentation. Clustering of medical data pose challenges especially in terms of spatial and temporal components of the data (Chuang *et al*., 2006; Li *et al*., 2009; Cai *et al*., 2007).

Zhao *et al.* (2009) proposed a lossless compression method based on combining an integer wavelet transform with DPCM for medical images. Reversible Integer Wavelet Transform was executed on predicted DPCM values and their results were found to yield better compression ratio. Chen and Tseng (2007) proposed an adaptive prediction coding method based on wavelet transform where the correlation between wavelet coefficients are analyzed and the predicted variables are evaluated to determine the relative coefficients should be included in the prediction model. Hwang *et al.* (2003) have proposed a Layered SPIHT technique for implementing scalable medical data transmission systems. Their results have found to be better than JPEG2000 and SPIHT.

Recently wavelet based methods have been abundantly used for the compression of medical images. To overcome the missing directional details of wavelet transforms, Multi resolution Geometric Analysis of wavelet subbands has been introduced. Among the directional transforms, the analysis using Ridgelet (Do and Vetterli, 2003), Curvelet (Saudagar and Syed, 2013), Contourlet (Do, 2001; Do and Vetterli, 2005) are considered to be the best tools.

Sparse representation of both smooth and edges was possible with ridgelet transform and curvelet transforms (Saudagar and Syed, 2013). Ridgelet transform was proposed by Candes and Donoho (1999) to solve the problem of sparse approximation to smooth objects with straight edges, because ridgelets had global length and variable widths. But in medical images, edges are typically curved rather than straight. So, ridgelets could not yield efficient representations in the case of medical images.

Wavelets are not optimal in capturing the singularities in images. The images which have textures and patterns of oscillatory nature are not effectively represented by wavelets. The smooth contours are also not represented effectively by the wavelet transform. Contourlet transform proposed by Do and Vetterli (2005), is incorporated with multi resolution directional analysis to capture edges in natural image efficiently.

Contourlet is one of the geometrical transforms which can efficiently extract the directional features with multi-resolution capability from images which have textures with smooth contours (Do, 2001; Do and Vetterli, 2005). Contourlet transform uses a structure similar to that of curvelets. The scheme consists of double filter bank structure, by combining the Laplacian pyramidal decomposition with a directional filter bank (Do and Vetterli, 2005). The contourlet transform outperforms the conventional wavelet transforms in terms of capturing the singularities found in the images. But due to redundancy nature of Laplacian pyramidal representation of images, the use of contourlet transform has not become popular for image compression algorithms (Sudhakar *et al*., 2006; Said and Pearlman, 1996; Ikonomopoulos and Kunt, 1985). To overcome this, many geometrical transforms have been used in the literature. Since the natural images consist of ridges, the multi-scale with multi-resolution transforms such as Wavelet Based Contourlet transform could be used to compress the natural images by preserving the directional properties.

In order to develop a non redundant contourlet transform, the octave band directional filter banks (Hong and Smith, 2002), the Critically Sampled Contourlet (CRISP) Transform (Lu and Do, 2003) and the wavelet-based Contourlet Transform (Eslami and Radha, 2004, 2007) are developed. Hong and Smith (2002), proposed the octave band directional filter banks which are capable of performing the decomposition of image data into angular directional and octave band radial details. Da Cunha *et al*. (2006), proposed a single stage implementation of a non-separable filter bank based critically sampled contourlet transform to provide a non-redundant directional decomposition.

In our proposed method, spatial FCM clustering is used to separate the clinical region of interest by extracting image features. Wavelet based Contourlet transform is applied to the significant region and biorthogonal wavelet based DWT is applied to the rest of the image. The WBCT is implemented by directional filter bank analysis of wavelet subbands. The parent-children relationship between coefficients in different sub bands in WBDT domain is different from that of wavelet domain. In order to use the encoding algorithms of wavelet domain, a repositioning algorithm (Eslami and Radha, 2004, 2007) for WBCT coefficients is implemented. Repositioning algorithm is useful in generating spatial orientation trees similar to the wavelet tree structure. The rearranged detail sub band coefficients are encoded using SPIHT encoder.

REVIEW OF RELATED THEORY

The proposed scheme uses sFCM clustering to extract the clinical region of interest. Once the image is segmented, WBCT is applied to the clinical region and the coefficients are repositioned to resemble the subband structure of DWT subbands and encoded using Set Partitioning in Hierarchical Trees (modified SPIHT). The insignificant portion of the background information is encoded using the conventional DWT and SPIHT algorithm. The proposed scheme is illustrated in Fig. 1.

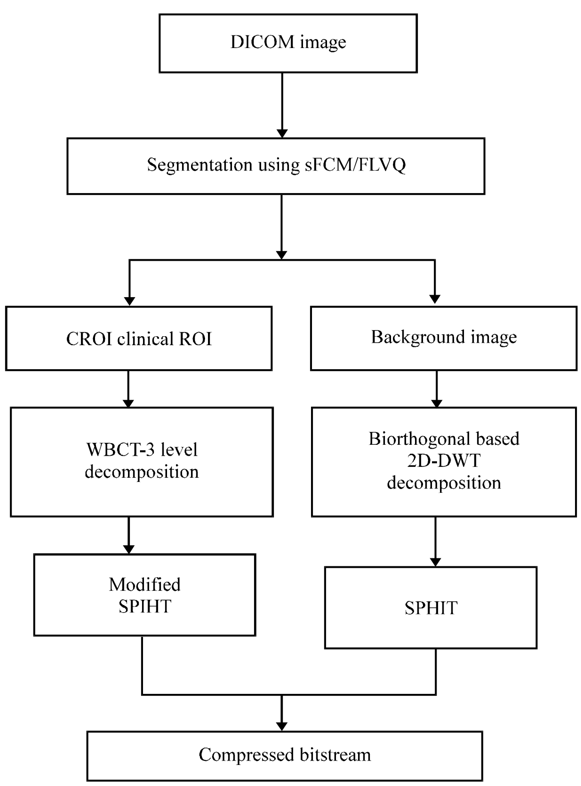

Fig. 1: Flow diagram of the proposed compression method

Segmentation using spatial FCM: The input MRI brain images which are in DICOM file formats-T2 flair axial of size 320×280×16, MRI brain image-T2W axial of size 448×364×16, MRI brain image-T2_corflair axial of size 320×280×16 are first segmented using sFCM (Chuang *et al.*, 2006) to extract the Clinical Region of Interest (CROI). The spatial relationship of neighboring pixel is an important characteristic in image segmentation. The sFCM incorporates spatial information and the membership weighting of each cluster is altered after the cluster distribution in the neighborhood. The sFCM modifies the partition on the basis of spatial distribution and cause deterioration of the compactness in the feature domain. The sFCM is powerful method for both single and multiple feature data like medical images with spatial information playing an vital role.

In fuzzy clustering, the centroid and the members of each sub cluster are estimated adaptively in order to minimize a pre-defined Hamilton-Jaccobian cost function (Chuang *et al.*, 2006). Fuzzy Clustering is a kind of adaptive thresholding technique. Fuzzy C-Means (FCM) is one of the most popular algorithms in clustering based on soft computing techniques. The FCM has been widely applied to medical image segmentation problems (Chuang *et al.*, 2006; Li *et al.*, 2009; Cai *et al.*, 2007).

The conventional algorithm for FCM based clustering is derived from the k-means algorithm. The k-means algorithm assigns N-members to k-clusters based on their attributes, where k<N. For medical image segmentation, the total number of members N is estimated from the number of image pixels $N_x \times N_y$. The results of clustering process include the centroid of each cluster and the affiliations of N members. Standard k-means clustering attends to minimize the cost function given in Eq. 1:

$$J = \sum_{m=1}^{K}\sum_{n=1}^{N}\left\| i_n - v_m \right\|^2 \quad (1)$$

where, i_n is the specific image pixel, v_m is the centroid of the m^{th} cluster and $\|\,\|$ denotes the L_2-norm. After the specified number of iterations, the results of the k-means algorithm are expected to maximize the inter-cluster variations but minimize the intra-cluster variations.

In k-means clustering, each pixel can be a member of one and only one of the k-clusters. On the other hand, the clustering based on FCM uses a membership function μ_{mn} to indicate the degree of membership of the n^{th} pixel to the m^{th} cluster. The principle of FCM suits for the medical image segmentation because the physiological tissues are not homogenous. The cost function of FCM is similar to cost function of k-means as given in the Eq. 2:

$$J = \sum_{n=1}^{N}\sum_{m=1}^{C}\mu^{l}_{mn}\left\| i_n - v_m \right\|^2 \quad (2)$$

where, l is a parameter controlling the fuzziness of the resultant segmentation due to FCM. The membership are subject to the following constraints given in Eq. 3:

$$\sum_{m=1}^{C}\mu_{mn} = 1;\ 0 \le \mu_{mn} \le 1;\ \sum_{n=1}^{N}\mu_{mn} > 0 \tag{3}$$

The membership function μ_{mn} and the cluster centers v_m are updated iteratively as specified in the following Eq. 4 and 5, respectively.

$$\mu_{mn} = \frac{\left\| i_n - v_m \right\|^{-2/(l-1)}}{\sum_{k=1}^{C}\left\| i_n - v_k \right\|^{-2/(l-1)}} \tag{4}$$

$$v_i = \frac{\sum_{n=1}^{N}\mu_{mn}^{l} i_n}{\sum_{n=1}^{N}\mu^{l}{}_{mn}} \tag{5}$$

The conventional FCM algorithm optimized, when pixel to their cluster center are assigned high membership values, whereas low vales are assigned to those are away. One of the problems of standard FCM algorithms in image segmentation is the lack of spatial and structural information (Chuang *et al*., 2006). Since the noise impairments affect the performance of the FCM Clustering based segmentation it becomes necessary to incorporate spatial information into an FCM clustering. Cai *et al.* (2007) proposed a generalized FCM algorithm that includes a factor to incorporate local intensity and spatial information. Chuang *et al*. (2006), proposed another method of incorporating the spatial information is done by morphological operations. Chuang *et al.* (2006) proposed another spatial FCM clustering in which spatial information can be included into fuzzy membership functions directly using Eq. 6:

$$\mu_{mn} = \frac{\mu_{mn}^{p} h_{mn}^{q}}{\sum_{k=1}^{C}\mu_{kn}^{p} h_{kn}^{q}} \tag{6}$$

where, p and q are the values to control the respective contribution of the membership and spatial parameter and h_{mn} includes spatial information (Eq. 7):

$$h_{mn} = \sum_{k \in N_v} \mu_{nk} \tag{7}$$

where, N_v indicates a local window positioned around the pixel to be classified, n. The weighted μ_{mn} and the cluster center v_m are updated as per the Eq. 4 and 5.

WAVELET BASED DIRECTIONAL TRANSFORM

Similar to the Contourlet transform, the WBCT consists of two filter bank stages. The first stage provides sub band decomposition which in the case of WBDT, is a wavelet transform. The Mallat's Pyramidal decomposition is used in contrast to the Laplacian pyramid used in contourlets. The second stage of the WBDT is the Directional Filter Bank (DFB) analysis which provides angular decomposition (Ikonomopoulos and Kunt, 1985; Bamberger and Smith, 1992). For the DFB stage, the iterated tree structure filter banks using fan filters are employed. The DFB with equal number of directional decompositions to each high pass band at that level of sub band decomposition are applied. At nth level decomposition in the wavelet transform, the LH, HL and HH detail sub bands are produced. Angular analysis of wavelet sub bands is carried out using DFB with the same number of directions to each sub band at the specified level. Direction analysis with maximum number of directions is performed on the wavelet sub bands of the finest level. The number of directions for the next consecutive level sub band is decreased so as to satisfy anisotropy scaling law. Even though it is mentioned in the literature that LH and HL sub bands have the vertical and horizontal details, wavelet filters do not the split the frequency space with sharp boundaries in the frequency domain. So, the directional analysis is preferred and the directions specified in the angular sub band analysis will completely cover all the directions in a particular subband.

Bamberger and Smith (1992) presented a minimally decimated initially sampled 2-D DFB along with a proposal for perfect reconstruction. The DFB proposed by Bamberger and Smith (1992) is a single level tree structured Filter Bank which is used to decompose the images into number of directions. The DFB construction explained in the thesis of Do (2001) uses diamond-shaped and fan-beam filters in the Quincnux Filter Bank (QFB) (Do and Vetterli, 2005). The filters in the DFB are designed to capture the directional high frequency features of the image. The DFB alone cannot provide a sparse representation of the image. It is always combined with multi-resolution analysis system. The high pass subbands generated by the Mallat's wavelet decomposition scheme are analyzed using directional filter bank at different scales.

Rearrangement of coefficients and encoding: The WBCT coefficients are rearranged based on the relationship between coefficients at directional subbands, so that coefficients at multi resolution and multi scale directional details can be scanned in the same manner as specified in the Set Partitioning in Hierarchical Tree algorithm for encoding for wavelet based decomposition.

Spatial orientation tree relationship between WBCT coefficients at different scales can be developed as in the case of wavelet coefficients along different wavelet scales. Normally in WBCT construction, the scale in which the children lie has twice as many directional subbands as the scale in which the parent lies and then the four children will be situated in twice adjacent directional subbands (Eslami and Radha, 2004, 2007).

The children coefficients are positioned in the adjacent directional subbands but at the same location in those subbands. Although the parent coefficient is found in one subband in the previous scale, the children are split and positioned in two adjacent subbands (Eslami and Radha, 2004, 2007). Adjacent directional subbands are combined such that the columns of adjacent horizontal subbands are placed alternatively. Similarly the rows of vertical subbands are also arranged to develop the same spatial orientation tree relationship between the wavelet coefficients at different scales.

Modified SPIHT algorithm: An effective adaptive subband coding technique for images with straight singularities, along with curves and edges, are proposed in this study. The proposed coding algorithm scans and codes the significant WBCT coefficients as much as possible to satisfy the demand of embedded coding algorithm. Depending on the subband significance the adaptive subband coding algorithm is initialized. Subband significance is determined by the number of significant coefficients in the subband.

PROPOSED COMPRESSION SCHEME

The overall system flow diagram of the proposed compression method is illustrated in Fig. 1. The proposed technique consists of various modules, the input DICOM images MRI brain image-T2 flair axial of size 320×280×16, MRI brain image-T2W axial of size 448×364×16, MRI brain image-T2_corflair axial of size 320×280×16 are first segmented using spatial FCM clustering to extract the Clinical Region of Interest (CROI). The spatial relationship of neighboring pixel is an important characteristic in image segmentation.

Performance evaluation: The performance of the proposed method are evaluated on a set of DICOM images MRI brain image-T2 flair axial of size 320×280×16, MRI brain image-T2W axial of size 448×364×16, MRI brain image-T2_corflair axial of size 320×280×16 and the quality of the compressed images has been assessed in terms of PSNR (dB), bit rate (bpp) and compression ratio. The segmentation using spatial FCM followed by WBCT decomposition and encoding the repositioned coefficients using SPIHT (Said and Pearlman, 1996) and compression of the background information using the Conventional DWT and SPIHT were implemented with MATLAB®. The first experiment was to evaluate the performance of spatial fuzzy clustering. The dicom images in Fig. 2 shows the difficult case in which the white matter and gray matter overlapped in a MRI slice of cerebral tissue. It is evident that the white matter and gray matter overlaps in terms of characteristics with each other and are dispersed over the entire slice. This makes manual initialization nearly impractical. The FCM based clustering is found to be advantageous.

The next experiment is to transform the segmented image into WBCT using 3-level DWT decomposition using bi-orthogonal wavelet. For images with smooth contours, Bi-orthogonal wavelet yields good subband representation. At each decomposition level, four subbands are produced. They are approximation sub band (LL) and detail subbands (LH, HL and HH). Each subband will be half of the size of the input. Detail subbands at various resolutions are further analyzed using dfbdec function which is available in the controulet toolbox. The filters chosen for the directional decomposition are PKVA filters which are proposed by Phoong *et al*. (1995). They are of quincunx/fan filter type. Three levels decomposition are performed using wavelet analysis filters. The subbands of the finer level decomposition are analyzed to produce 8 directional decompositions and the second level are further decomposed with 4 directional decompositions and the subbands of coarser level are not decomposed further. The resultant coefficients are repositioned such that the arrangements of coefficients are identical to the arrangement of DWT of an image. The detail subbands at a particular wavelet scale are all further analyzed with equal number of directional decompositions using DFB. The maximum number of directional analysis is carried out on the wavelet subbands of the finest scale. The number of directional decompositions on the next consecutive scale is decreased in order to satisfy the anisotropy scaling law. The WBCT coefficients are repositioned based on the relationship between coefficients at directional subbands at a specific wavelet scale, so that coefficients can be scanned in the same way as specified in the Set Partitioning in Hierarchical Tree algorithm for encoding for wavelet subbands. In WBCT representation, the scale in which the children-coefficients located will have twice the directional subbands as the scale in which the parent-coarser wavelet scale. Thus the four children of a parent coefficient are located in two adjacent directional subbands (Eslami and Radha, 2004, 2007; Sudhakar *et al*., 2006).

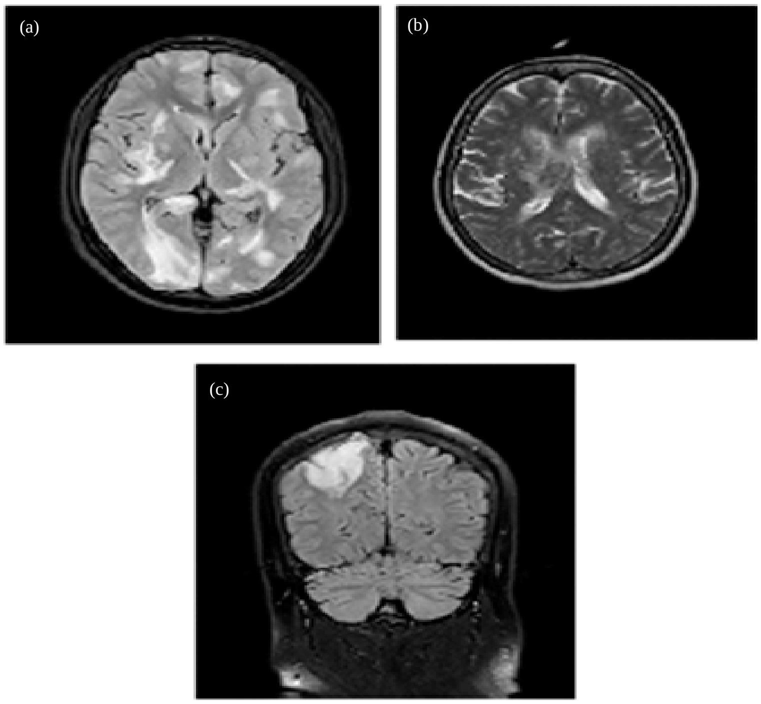

Fig. 2(a-c): Set of medical images used for evaluation, (a) MRI brain image-T2 flair axial, (b) T2W axial and (c) T2_corflair axial

Hence, the adjacent directional subbands are combined such that the columns of adjacent horizontal sub bands are placed alternatively. Similarly the rows of vertical sub bands are also arranged to develop the same spatial orientation tree relationship between the wavelet coefficients at different scales.

By applying the WBCT recursively, the dimension of the input can be reduced by a factor of 2j to produce an approximation subband, where j is the number of wavelet decomposition levels. The efficiency of the proposed method is evaluated based on the comparison with JPEG, Wavelet (Haar-SPIHT, Biorthogonal-SPIHT) methods. The following are the experimental investigations of the overall behavior of the proposed method. The output for spatial FCM clustering based segmentation with 4 clusters is shown in Fig. 3.

Evaluation of image quality based on PSNR: Objective of compression method is to obtain the best visual quality with minimum bit allocation. PSNR is one of the most adequate parameter to analyze the quality of compression. PSNR is defined as:

$$\text{PSNR} = 10\log 10 \frac{\max|X(i,\ j)|^2}{\text{MSE}} \tag{8}$$

$$\text{MSE} = \sum_{j=1}^{M}\sum_{k=1}^{N}[X(j,\ k) - \hat{X}(j,\ k)]^2 / MN \tag{9}$$

where, X(j, k) is the original image, $\hat{x}$ (j, k) is the reconstructed image M×N-size of the image.

The term bitrate refers to the number of bits that are conveyed or processed per pixel:

$$\text{bpp} = \frac{\text{Total No. of bits}}{\text{Total No. of pixels}} \tag{10}$$

Evaluation of Compression Ratio (CR): Compression Ratio (CR) is used to evaluate the efficiency of a compression method:

$$\text{CR} = \frac{\text{Size of the compressed stream}}{\text{No. of bits in the input image}} \tag{11}$$

The proposed method outperforms wavelet based methods, biorthogonal-SPIHT and Haar_SPIHT by 2.16 and 2.16% for T2 flair axial of size 320×280×16, 3 and 1.840% for T2W axial of size 448×364×16 and 3.14 and 5.4% for T2_corflair axial of size 320×280×16 (Table 1 and Fig. 4).

Table 1: PSNR, Bitrate, Compression ratio (CR) for JPEG, Biorthogonal-SPIHT, Haar-SPIHT and proposed algorithm

				Wavelet methods								
	JPEG			Biorthogonal-SPIHT			Haar-SPIHT			Proposed method		
DICOM images	bpp	CR	PSNR (dB)	bpp	CR	PSNR (dB)	bpp	CR	PSNR (dB)	bpp	CR	PSNR (dB)
T2 flair axial	0.4558	0.2099	27.76	2.3486	29.324	26.282	2.3462	29.327	29.95	1.5962	9.2216	29.952
T2W axial	0.3391	0.2668	24.63	2.8467	60.585	31.846	2.7832	34.79	31.74	1.678	11.356	32.126
T2_corflair axial	0.7249	0.2307	26.14	2.3354	29.193	29.219	2.7676	59.595	36.85	1.782	7.0862	34.081

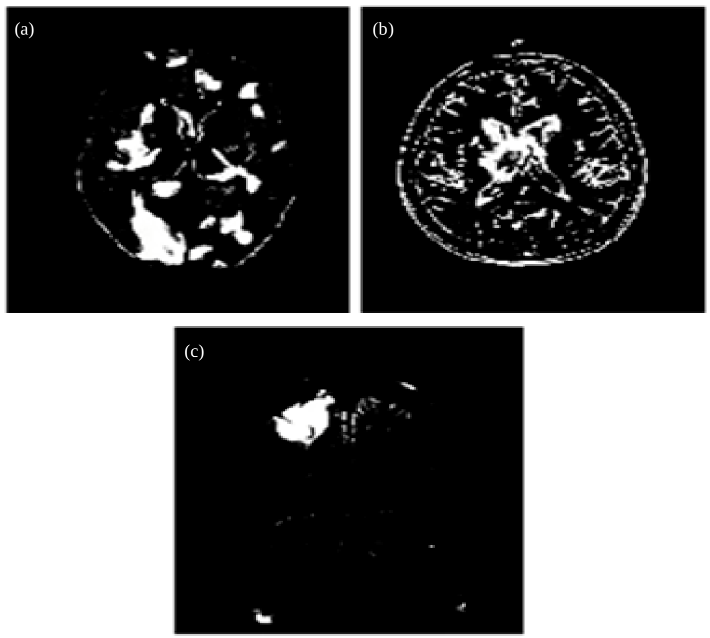

Fig. 3(a-c): Extracted CROI using sFCM segmentation with 4 clusters, (a) MRI brain image-T2 flair axial, (b) T2W axial and (c) T2_corflair axial

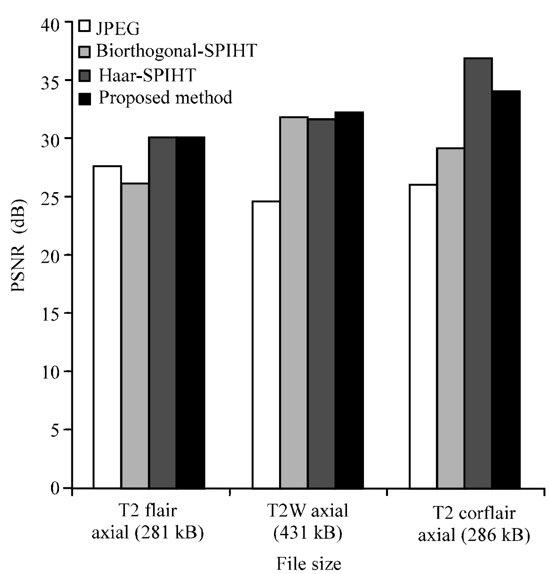

Fig. 4: Peak Signal-to Noise Ratio (PSNR) (dB) obtained for test images using different compression methods. Evaluation of image quality based on Bitrate (bpp)

CONCLUSION

The proposed medical image compression algorithm is evaluated for different MRI brain images. The main focus of the proposed work is that it uses WBCT with anisotropy capability to represent singularities along arbitrarily shaped curves. Experimental results demonstrate that the proposed method provides high PSNR and directionality with improved compression ratio against wavelet transform. In future this work can be extended for the compression medical images other than MRI. It is decided to use directional lifting schemes to produce the quality of reconstruction equal to that of lossless medical image compression schemes.

REFERENCES

Bamberger, R.H. and M.J.T. Smith, 1992. A filter bank for the directional decomposition of images: Theory and design. IEEE Trans. Signal Process., 40: 882-893.

Cai, W., S. Chen and D. Zhang, 2007. Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation. J. Pattern Recognit., 40: 825-838.

Candes, E.J. and D.L. Donoho, 1999. Ridgelets: A key to higher-dimensional intermittency. Phil. Trans. R. Soc. Lond. A, 357: 2495-2509.

Chen, Y.T. and D.C. Tseng, 2007. Wavelet-based medical image compression with adaptive prediction. Comput. Med. Imaging Graph., 31: 1-8.

Chuang, K.S., H.L. Tzeng, S. Chen, J. Wu and T.J. Chen, 2006. Fuzzy c-means clustering with spatial information for image segmentation. Comput. Med. Imaging Graph., 30: 9-15.

Da Cunha, A.L., J. Zhou and M.N. Do, 2006. The nonsubsampled contourlet transform: Theory, design and applications. IEEE Trans. Image Process., 15: 3089-3101.

Do, M.N., 2001. Directional multiresolution image representations. Ph.D. Thesis, Department of Communication Systems, Swiss Federal Institute of Technology Lausanne.

Do, M.N. and M. Vetterli, 2003. The finite ridgelet transform for image representation. IEEE Trans. Image Process., 12: 16-28.

Do, M.N. and M. Vetterli, 2005. The contourlet transform: An efficient directional multiresolution image representation. IEEE Trans. Image Process., 14: 2091-2106.

Eslami, R. and H. Radha, 2004. Wavelet-based contourlet transform and its application to image coding. IEEE Int. Conf. Image Process., 5: 3189-3192.

Eslami, R. and H. Radha, 2007. A new family of nonredundant transforms using hybrid wavelets and directional filter banks. IEEE Trans. Image Process., 16: 1152-1167.

Hong, P.S. and M.J.T. Smith, 2002. An octave-band family of nonredundant directional filter banks. Proceedings of the IEEE International Conference on Acoustics Speech and Signal Processing Volume 2, May 13-17, 2002, Orlando, FL, USA., pp: 1165-1168.

Hwang, W.J., C.F. Chine and K.J. Li, 2003. Scalable medical data compression and transmission using wavelet transform for telemedicine applications. IEEE Trans. Inform. Technol. Biomed., 7: 54-63.

Ikonomopoulos, A. and M. Kunt, 1985. High compression image coding via directional filtering. Signal Process., 8: 179-203.

Li, B.N., C.K. Chui, S.H. Ong and S. Chang, 2009. Integrating FCM and level sets for liver tumor segmentation. Proceedings of the 13th International Conference on Biomedical Engineering Volume 23, December 3-6, 2008, Singapore, pp: 202-205.

Lu, Y. and M.N. Do, 2003. CRISP-contourlets: A critically sampled directional multiresolution image representation. Proceedings of SPIE Conference on Wavelet Applications in Signal and Image Processing X, August 2003, San Diego, USA., pp: 655-665.

Martin, P., P. Refregier, F. Goudail and F. Guerault, 2004. Influence the noise model on the level set active contour segmentation. IEEE Trans. Pattern Anal. Mach. Intell., 26: 799-803.

Pham, D.L., C. Xu and J.L. Prince, 2000. Current methods in medical image segmentation. Ann. Rev. Biomed. Eng., 2: 315-337.

Phoong, S.M., C.W. Kim, P.P. Vaidyanathan and R. Ansari, 1995. A new class of two-channel biorthogonal filter banks and wavelet bases. IEEE Trans. Signal Process., 43: 649-665.

Said, A. and W.A. Pearlman, 1996. A new fast and efficient image codec based on set partitioning in hierarchical trees. IEEE Trans. Circ. Syst. Video Technol., 6: 243-250.

Saudagar, A.K.J. and A.S. Syed, 2013. Image compression approach with ridgelet transformation using modified neuro modeling for biomedical images. Neural Comput. Applic., 24: 1725-1734.

Sudhakar, R., R. Karthiga and S. Jayaraman, 2006. Fingerprint compression using contourlet transform with modified SPIHT algorithm. Iran. J. Electr. Comput. Eng., 5: 3-10.

Suri, J.S., 2001. Two dimensional fast magnetic resonance brain segmentation. IEEE Eng. Med. Biol. Magaz., 20: 84-95.

Zhao, L., Y. Tian, Y. Sha and J. Li, 2009. Medical image lossless compression based on combining an integer wavelet transform with DPCM. Front. Electr. Electron. Eng. China, 4: 1-4.