Asian Journal of Information Technology 15 (23): 4875-4883, 2016
ISSN: 1682-3915

Investigations and Analysis of a Fast and Efficient Coding Technique for Medical Images Using Contourlet Transform

[1]M. Tamilarasi and [2]V. Palanisamy
[1]Department of Electronics and Communication Engineering, Karur College of Engineering, Tamil Nadu India
[2]Institute of Engineering, Tamil Nadu, India

Abstract: The proposed algorithm presents a new coding technique based on image compression using contourlet transform used in different modalities of medical imaging. Recent reports on natural image compression have shown superior performance of contourlet transform, a new extension to the wavelet transform in two dimensions using nonseparable and directional filter banks. As far as medical images are concerned the diagnosis part (ROI) is of much important compared to other regions. Therefore, those portions are segmented from the whole image using Fuzzy C-Means (FCM) clustering technique. Contourlet transform is then applied to ROI portion which performs Laplacian Pyramid (LP) and directional filter banks. The region of less significance are compressed using discrete wavelet Transform and finally modified embedded zerotree wavelet algorithm is applied which uses six symbols instead of four symbols used in Shapiro's EZW to the resultant image which shows better PSNR and high compression ratio. Finally Huffman coding is applied to get the compressed image.

Key words: Contourlet, directional filter Banks, DWT, EZW, PSNR, region of interest, performance measure

INTRODUCTION

Compression of images in all fields is very essential nowadays for efficient and effective transmission. Past few years have witnessed abundant techniques in image compression, primarily for its widespread usage in internet technologies, medical applications etc. Wavelet based compression of digital signals and images have been a topic of interest for quiet sometimes now. Video and image applications require intensive data acquisition storage and processing in order to transmit high quality images through limited bandwidth. Data/Image compression has relieved the burden of image transmission and storage at the cost of extra computationally extensive processing (Olyaei and Genov, 2005). Innovative visualization techniques are therefore needed to assist the radiologist: in approaching the growing amounts of information available to interpret and to perform diagnosis. A large part of the modern medical data is expressed as images or other types of digital signals, such as MRI, CT, PET. Image transformations can be achieved through several transforms like DCT, DFT, wavelet etc. Contourlet based ROI with wavelet transform of digital signals and images have been a topic of interest for better compression. Video and image applications require the acquisition of huge amount of such sophisticated image data that give rise to the development of automatic processing and analysis of medical images in order to transmit high quality images through limited bandwidth. Data compression has relieved the burden of image transmission and storage at the cost of extra computationally extensive processing. Innovative visualization techniques are therefore needed to assist the radiologist: in approaching the growing amounts of information available to interpret and to perform diagnosis.

Medical diagnosis becomes effective if it identifies the defective areas in limited processing. In medical images, some structures in the image are of interest. These structures typically occupy a small percentage of the whole image, but their analysis requires contextual information like locations within a specific organ or adjacency to sensitive structures. Therefore while focusing on a particular region of the image, designated as a Region of Interest (ROI), contextual information surrounding that region is important. However, the same amount of detail is not required for the context and the ROI. Fuzzy C- means logic is used to separate out ROI by

Corresponding Author: M. Tamilarasi, Department of Electronics and Communication Engineering, Karur College of Engineering, Tamil Nadu, India

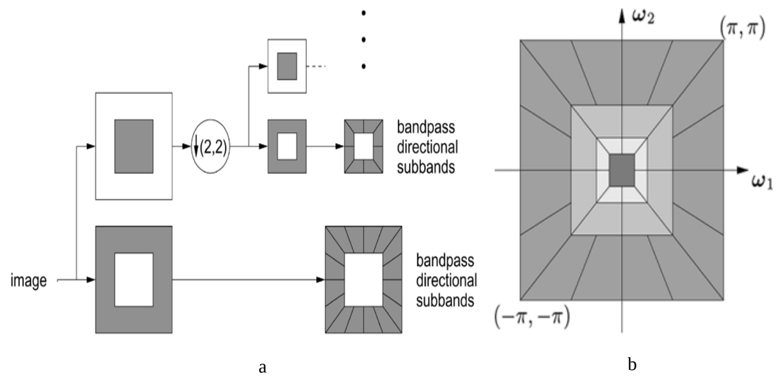


Fig. 1: The contourlet transform: a) Block diagram and b) Resulting frequency division

extracting image features. After performing segmentation contourlet transform is applied to significant region and wavelet transform is applied to rest of the image for better compression ratio.

Several algorithms like Shapiro's EZW (Embedded Zerotree Wavelet), (Shapiro, 1993) the SPIHT (Set partitioning in Hierarchical Trees) (Said and Pearlman, 1996) and the SPECK (Set Partitioning Embedded Block) (Islam and Pearlman, 1999) exists for image compression. Several compression of EZW algorithm was proposed in literature. In compression is performed by four symbols different from the one used in the original method to code the wavelet coefficients. The previous works uses four coefficients namely P, N, IZ and ZT but our proposed coding technique additionally uses two more symbols Pt and Nt. Huffman coding is then applied to the indices obtained by modified EZW to get the encoded image. Contourlets have the property of preserving edges and fine details in the image, the encoding complexity in the proposed scheme is less when compared to tree structured quantization.

In this study, we propose the modification of the EZW algorithm with improved version of contourlet transform for the significant region and DWT for the insignificant region together with fuzzy C-means based segmentation technique.

Discrete contourlet transform: Wavelet transform is a powerful transform to represent images that contains smooth areas separated with edges, it lacks in its performance when the edges are smooth curves. Contours are the boundaries of regions in an image. Contourlets are a sparse efficient expansion for two dimensional signals that are piecewise smooth away from smooth contours (Po and Do, 2003). Researchers have recently come up with a new family of wavelet methods that can capture the intrinsic geometrical structures such as curvelet transform and contourlet transform (Selvathi and Anitha, 2009). Curvelets are very successful in detecting image activities along curves while analyzing images at multiple scales, locations and orientations. The contourlet transform proposed by Do and Vetterli (2005) uses a structure similar to that of curvelets, except at discrete domain and has good approximation property for smooth 2D functions and is therefore computationally efficient. It is a multiresolution and directional decomposition of a signal using a combination of Laplacian Pyramid (LP) and a Directional Filter Bank (DFB) (Fig. 1a). The Pyramidal Directional Filter Bank (PDFB) overcomes the block-based approach of curvelet transform. The LP decomposes images into subbands and DFB analyzes each detail image. Figure 1b shows the resulting frequency division where the whole spectrum is divided both angularly and radially and the number of directions is increased with frequency. It was shown that the discrete contourlet transform achieves perfect reconstruction and has a redundancy ratio that is <4/3 (Po and Do, 2006). Contourlets have elongated supports at various scales, directions and aspect ratios. This allows contourlets to efficiently approximate smooth contours at multiple resolutions.

Laplacian pyramid: The multiscale decomposition of Directional Filter Bank (DFB) can be achieved by Laplacian Pyramid (LP) which was introduced by Burt and Adelson (1983). The LP decomposition at each level generates a low pass subband and a high pass subband. The low pass subband is a down sampled coarse version (1/4 size of the original) of the original image and the high pass subband is a detail image (same size of the original) containing the difference between the original and the prediction, resulting in a band pass image (Esakkirajan *et al.*, 2006). The process can be iterated by decomposing the coarse subband repeatedly. If this process is performed continuously, bandpass filtered images corresponding to different bands of frequencies can be obtained, each sampled at successively different densities.

Directional Filter Bank (DFB): The directional filter bank partitions the frequency plane into set of wedge shaped bandpass regions. An important property of the DFB is its ability to extract 2D directional information of an image which is important in image analysis. The DFB is efficiently implemented n-level tree structured decomposition that leads to 2n subbands. To obtain the desired frequency partition, an involved tree expanding rule has to be followed. The DFB is designed to capture the high frequency that represents directionality of images and is maximally decimated. This means that the total number of subband coefficients is the same as that of the original image and they can be used to reconstruct the original image without any error. More specifically, low frequency components are handled poorly by the DFB.

MATERIALS AND METHODS

Proposed scheme: Figure 2 shows the overall system flow diagram. It accepts input image and produces segmented image as output. It consists of various modules namely preprocessing, fuzzy segmentation (Nguyen and Oraintara, 2004). The proposed system starts with the key frame of the medical image, preprocessing of the image is done for removing the noise for a better segmentation. After preprocessing, segmentation and tracking are performed. A model fitting technique is to be proposed after tracking the borders. The tracked borders are to be decomposed into meaningful regional parameters. The original image can be reconstructed from the compressed image using inverse transforms to the above proposed algorithm model.

Noise removal: In order to make the image noise free, preprocessing should be performed as the first step. Preprocessing phase of the images is necessary to improve the quality of the images and make the images more reliable for further processing. In the development of medical image compression usually the tumor region depends on the region of interest which are usually of low contrast and noisy nature. Hence an image denoising and enhancement may be required to preserve the image quality, highlighting image features and suppressing the noise. In the proposed algorithm, median filter is selected as it removes impulse noise without blurring sharp edges.

The median filter was once the most popular nonlinear filter for removing impulse noise because of its good denoising power and computational efficiency.

The idea of median filtering is simply to replace each pixel value in an image with the median value of its neighbors including itself. Often a 3×3 square kernel is used, although larger kernels (e.g., 5×5 squares) can be used for more severe smoothing. Figure 3a and b are the input image and preprocessed images, respectively.

Extraction of ROI: The purpose of feature extraction is to reduce the original data set by measuring certain properties or features, that distinguish one input pattern from another pattern (Haralick, 1979). The extracted feature should provide the characteristics of the input type to the classifier by considering the description of the relavant properties of the image into a feature space. Two textural features namely contrast, correlation based on the Gray Level Cooccurence Matrices (GLCM) have been used in this research.

Spatial gray level co-occurrence estimates image properties relates second order statistics. Haralick (Chen *et al*., 1998) suggested the use of Gray Level Co-occurrence Matrices (GLCM) which have become one of the well known and widely used texture features. GLCM $\{P_{(d,\theta)}(i,j)\}$ represents the probability of the occurrence of a pair of gray levels (i,j) separated by a distance d at angle θ. The commonly used unit pixel distances and the angles are 0°, 45°, 90° and 135°. A detailed algorithm of calculation of GLCM $\{P_{(d,\theta)}(i,j)\}$ has been given in Chen *et al* (1998). Textural characteristics like Contrast and Correlation can be captured from images using second order distribution gray levels using the following equations. Contrast B:

$$S_c = \sum_i \sum_j (i-j)^2 P(i,j) \tag{1}$$

Correlation B:

$$S_o = \frac{\sum_i \sum_j (ij)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{2}$$

Where; μ_x, μ_y σ_x σ_y are the means and standard deviations of p_x and p_y.

Modified fuzzy c means technique: To separate out ROI from the diagnosis image, textural based fuzzy C-means segmentation has performed which plays a dominant role in image analysis. The significant visual effects better lies for any kind of image on their textural characteristics (Julesz, 1986). Textural characteristics like correlation, contrast are calculated from the denoised image and fuzzy

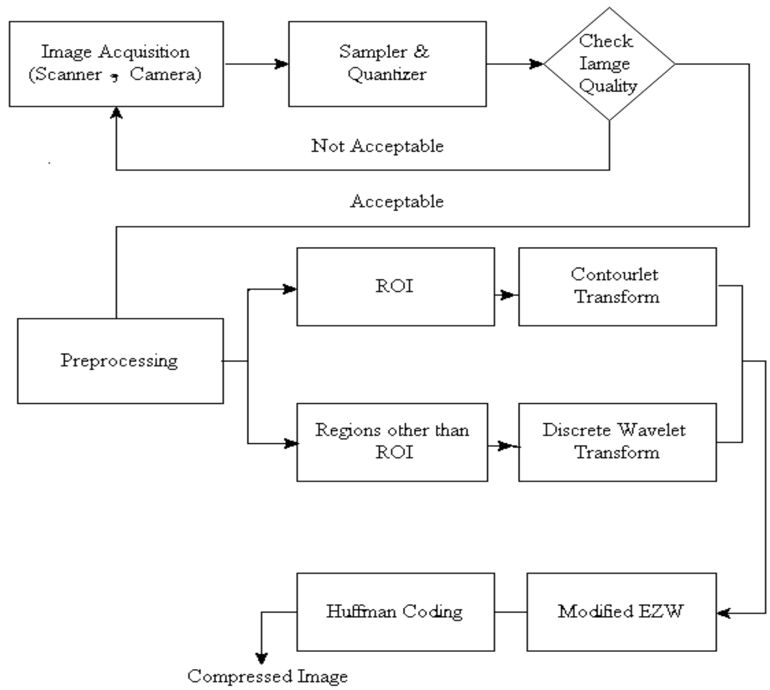
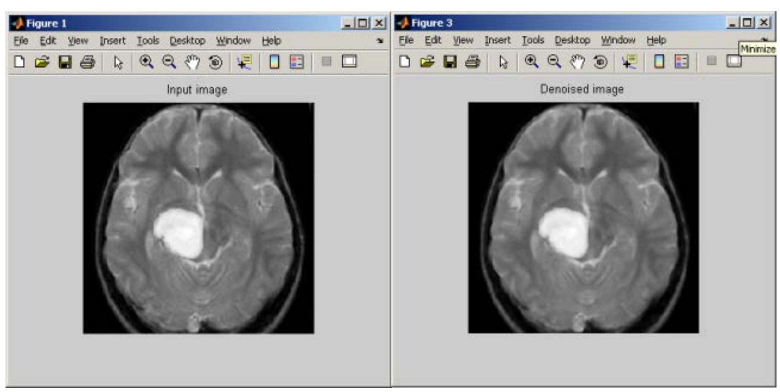


Fig. 2: The proposed algorithm model



(a) (b)

Fig. 3: Output of the preprocessed image: a) Input image; b) Denosend image

c-means clustering algorithm is applied to the resultant image. It has a prime contribution in pattern recognition.

Clustering is a group of data with similar characteristics. To divide the data into several groups the similarity of objects are used. The distance functions are used to find the similarity of two objects in the image set. Here, priori information about classes is not required. Clustering can also be thought of as a form of image compression where a large number of samples are converted into a small number of representative prototypes or clusters (Riazifar and Yazdi, 2009).

Fuzzy C-Means (FCM) is a method of clustering which allows one pixel to belong to two or more clusters. The FCM algorithm attempts to partition a finite collection of pixels into a collection of “C” fuzzy clusters with respect to some given criterion. Depending on the image and the application, different types of similarity measures may be used to identify classes. Some examples of values that can be used as similarity measures include distance, connectivity and intensity. In this research, the images are segmented into four clusters based on the feature values shown in Fig. 4. Fuzzy c-means algorithm is based on minimization of the following objective function:

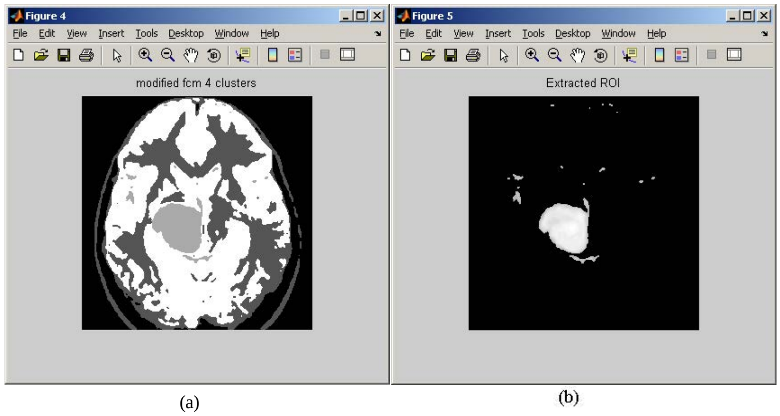


Fig. 4: Segmented output: a) Fuzzy C-means (FCM) output; b) ROI output using FCM

$$J(U, c_1, c_2, \ldots, c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{\ m} d_{ij}^{\ 2} \tag{3}$$

Where:

u_{ij} = That is between 0 and 1
c_i = The centroid of cluster i
d_{ij} = The euclidian distance between ith centroid (c_i) and j^{th} image point
$m \in [1, \infty]$ = The a weighting exponent

The modified FCM algorithm is based on the concept of image compression where the dimensionality of the input is highly reduced. The image compression includes two steps: quantization and aggregation. The quantization of the feature space is performed by masking the lower 'm' bits of the feature value. The quantized output will result in the common intensity values for more than one feature vector. In the process of aggregation, feature vectors which share common intensity values are grouped together. A representative feature vector is chosen from each group and they are given as input to modified FCM. Once the clustering is complete, the representative feature vector membership values are distributed identically to all the members of the quantization level. Since, this technique uses a reduced image set, the convergence rate is highly improved.

Algorithm:

The entire algorithm can be summarized as follows:
Step 1: Initialize the membership matrix, $U=[u_{ij}]$.
Step 2: At k^{th} number of iteration:
Calculate the entire vectors c_i with u_{ij}

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^{\ m} y_j}{\sum_{j=1}^{n} u_{ij}^{\ m}} \tag{4}$$

Where y = reduced data set.
Step 3: Update the membership matrix U for the k^{th} step and $(k+1)^{th}$ step.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \tag{5}$$

Where $d_{ij} = y_j - c_i$
Step 4:
If $\|U(k+1)-U(k)\| < \epsilon$ then stop; otherwise return to step 2.
FCM output with 4 clusters is shown in following Fig. 4.

The ROI segmented output through fuzzy c-means algorithm are subjected to contourlet transform and the region of less significance are performed with discrete wavelet transform. For wavelet comparison we chose 'Haar' wavelets of the first order. The contourlet transform and Haar DWT outputs for the test image are shown in Fig 5.

ROI based modified EZW: In Shapiro's EZW algorithm, a "zerotree" consist of a parent and its offsprings are insignificant , then the ancestor is coded as zerotree. If the value of the coefficient is lower than the threshold and has one or more significant descendants with respect to 'j'th level , then they are coded as "isolated zero".

The insignificant coefficients of the last sub-bands which do not accept descendants and are not themselves descendants of a zerotree are also considered to be zerotree. The significance symbols of the image coefficients are then placed in the dominant list. The amplitudes of the significant coefficients are placed in the subordinate list. Their values in the transformed image are set to zero in order not to undergo the next step. Finally, to the above coefficients, Huffman coding is applied.

Modified compression technique: If a coefficient is tested and found to be significant, its offsprings are also tested. If at least one coefficient is significant, then the descendants are coded according to doing rules of the Shapiro's algorithm which is the case for the coefficients.

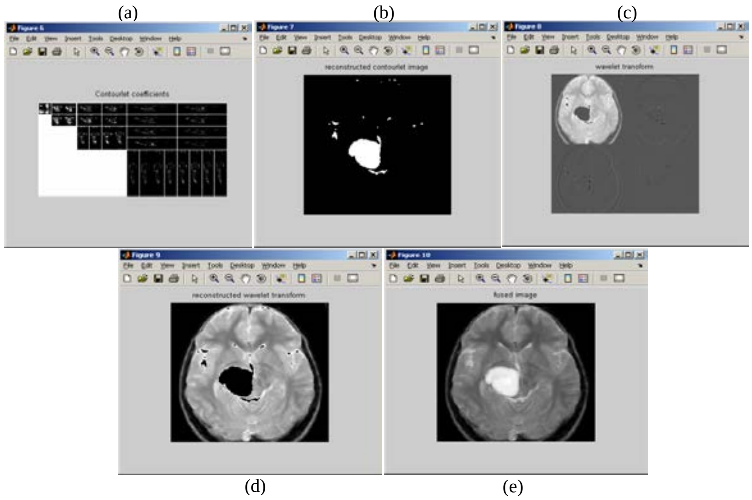


Fig. 5: Segmented ROI: a) Contourlet coefficients applied to ROI; b) Contourlet transform output for ROI; c) Wavelet transform output; d) Reconstructed DWT and e) Fused image combining controlet and DWT outputs

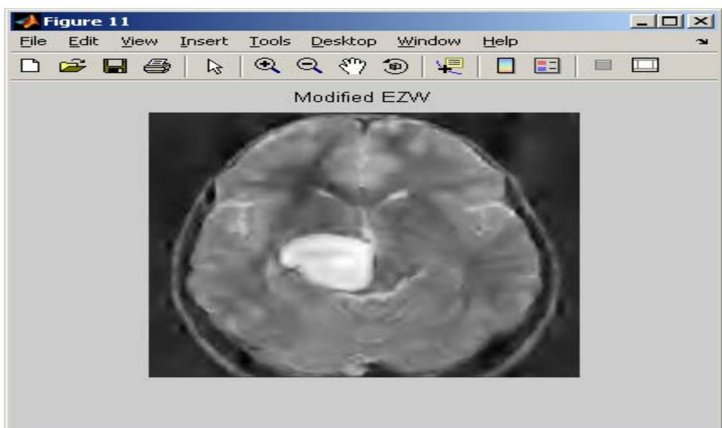


Fig. 6: Modified EZW output

If a coefficient is tested and found to be significant, its offsprings are also tested.

If all the coefficients are significant, then the descendants are coded with symbols Pt, for positive coefficient and with symbol Nt for negative coefficients. Performing the above steps for the two possibilities of coefficient values reduction in code symbol of four results for the both the cases. Figure 6 shows the output of the modified EZW.

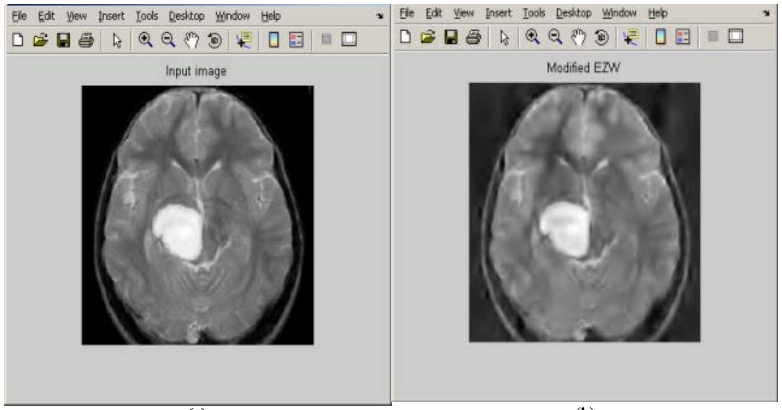
In Shapiro's EZW algorithm, the dominant list D is composed of four symbols (P,N, Z and T) each one coded into binary on two bits; these symbols are coded huffman coded before transmission. Therefore in this method increased symbol results in reduced image set.

Huffman encoding: Huffman coding assigns less codes for coefficients whose probabilities of occurrence is high and vice versa for coefficients whose probabilities of occurrence is low. The significant size is obtained by binary regrouping of several symbols.

Further all the possibilities regarding the coefficient are to be worked with and has to performed for the different iteration levels. Further the proposed method proves to yield better result with limited computational complexity. This error can be overcome by huffman coding in the proposed coding which yields better results with computationally efficient technique.

RESULTS AND DISCUSSION

The proposed method of separate transforms to the two regions proves better results compared to the



(a) (b)

Fig. 7: a) Input image and b) Reconstructed image

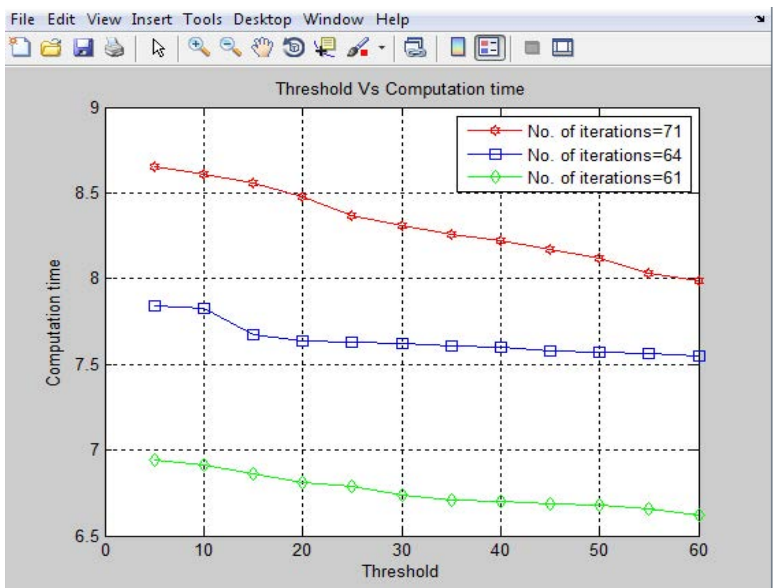


Fig. 8: Threshold vs. computation time

Table 1: PSNR and CR for EZW, SPIHT and proposed algorithm

Type	EZW		SPIHT		Modified	
EZW	PSNR	CR	PSNR	CR	PSNR	CR
Test MRI image 1	34.16	8:1	36.28	16:1	32.08	17:1
Test MRI image 2	32.04	20:1	33.16	30:1	33.74	31:1
Test MRI image 3	31.50	20:1	33.07	31:1	34.39	32:1

ordinary way of applying only single transform to the whole image. Proposed technique of modified EZW for a 8-bit 256×256 images were tested. In proposed method of compression, to take the whole value as array of bytes, the medical image values having attributes are coded and taken as a sequence of bits. The Region of Interest region is coded using the contourlet transform and the remaining portions are coded using haar wavelet filter. Figure 7a and b shows the input and reconstructed images.

The compression ratio for contourlet based modified EZW increases than the normal EZW algorithm. The PSNR and CR for the proposed algorithm is shown in Table 1.

The performance comparison of fuzzy segmentation for various parameter change of the algorithm are shown in Fig. 8 and 9.

The graphical plots shown in Fig. 8 and 9 reveals that as threshold and kernel gets increased the computation time required for the completion of the proposed work gets reduced thereby computational complexity becomes effective. Identifying a local minima the entire cluster can be obtained taking minimum number of iterations.

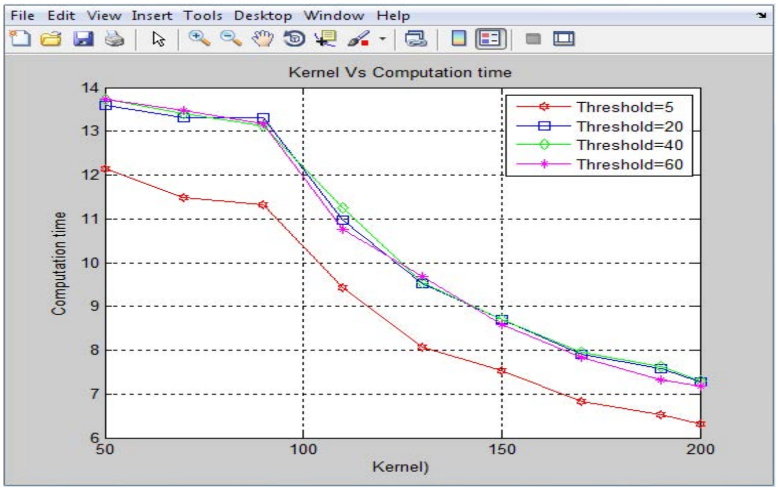


Fig. 9: Kernel vs. computation time

CONCLUSION

In this study, we proposed a new image transform called MEZW to compress medical image based on the combination of the wavelet transform and the nonsampled directional filter banks. The proposed algorithm is simple and computationally less complex which is based on embedded block coding with coefficient truncation. Further addition of two new symbols results in efficient compression with reduced computational time. The compression of the proposed algorithm is superior to EZW, SPIHT etc. Our new method of compression algorithm can be used to improve the performance of Compression Ratio (CR) and Peak Signal to Noise Ratio (PSNR).

RECOMMENDATIONS

In future this work can be extended to real time applications for video compression in medical images. The result shown above reveal the superior performance of contourlet against wavelet transform at higher compression ratios. However at lower compression ratios wavelet transform proves a suitable approach.

Performance measures formulas: The bit per pixel (bpp) and PSNR for the arbitrary shaped region is evaluated by the following. The PSNR is the measure of quality of reconstruction of lossy compression codecs:

$$\text{PSNR} = 10\log\frac{\text{MAX}^2}{\frac{1}{w\times h}\sum_{i=1}^{w}\sum_{j=1}^{h}\left(o(i,j)-c(i,j)\right)^2}$$

Where:

Oij = The original image
Cij = The reconstructed image
w = The total number of row elements
h = The total number of column elements
MAX = The 255

$$\text{CR(bpp)} = \frac{\text{number of coded bits}}{n\times m}$$

Where: n, m is the image size.

REFERENCES

Burt, P.J. and E.H. Adelson, 1983. The laplacian pyramid as a compact image code. IEEE Trans. Commun., 31: 532-540.

Chen, H, L.F. Pau and P.S.P. Wang, 1998. The Handbook of Pattern Recognition and Computer Vision. 2nd Edn., World Scientific Publishing Company, Singapore,.

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

Esakkirajan, S., T. Veerakumar, V.S. Murugan and R. Sudhakar, 2006. Image compression using contourlet transform and multistage vector quantization. ICGST-GVIP J., 6: 19-28.

Haralick, R.M., 1979. Statistical and structural approaches to texture. Proc. IEEE, 67: 786-804.

Islam, A. and W.A. Pearlman, 1998. Embedded and efficient low-complexity hierarchical image coder. Proccedings of the Conference on Visual Communications and Image Processing, December 28, 1998, USA., pp: 294-305.

Jain, A.K., 1989. Fundamentals of Digital Image Processing. Prentice Hall, Englewood Cliffs, NJ., ISBN-10: 0133361659, Pages: 569.

Julesz, B., 1986. Texton gradients: The texton theory revisited. Biol. Cybern., 54: 245-251.

Nguyen, T.T. and S. Oraintara, 2004. Texture classification using non-uniform directional filter bank. Proceedings of the 2004 IEEE 11th Conference on Digital Signal Processing Workshop; 2004 IEEE 3rd Signal Conference on Processing Education Workshop, August 1-4, 2004, IEEE, New York, USA., ISBN: 0-7803-8434-2, pp: 147-150.

Olyaei, A. and R. Genov, 2005. Mixed-signal CMOS wavelet compression imager architecture. Proceedings of the 48th Midwest Symposium on Circuits and Systems, August 7-10, 2005, IEEE, New York, USA., ISBN: 0-7803-9197-7, pp: 1267-1270.

Po, D.D. and M.N. Do, 2003. Directional multiscale statistical modeling of images. Proceedings of the of SPIE Conference on Wavelet Applications in Signal and Image Processing X, November 14, 2003, SPIE, San Diego, USA., pp: 69-79.

Po, D.D.Y. and M.N. Do, 2006. Directional multiscale modeling of images using the contourlet transform. IEEE Trans. Image Proces., 15: 1610-1620.

Riazifar, N. and M. Yazdi, 2009. Effectiveness of contourlet vs wavelet transform on medical image compression: A comparative study. World Acad. Sci. Eng. Technol., 49: 837-842.

Said, A. and W.A. Pearlman, 1993. Image compression using the spatial-orientation tree. Proceedings of the IEEE International Symposium on Circuits and Systems, May 3-6, 1993, Chicago, IL., pp: 279-282.

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.

Selvathi, D. and J. Anitha, 2009. Effective fuzzy clustering algorithm for abnormal MR brain image segmentation. Proceedings of the 2009 IEEE International Conference on Advance Computing Conference IACC 2009, March 6-7, 2009, IEEE, New York, USA., ISBN: 978-1-4244-2927-1, pp: 609-614.

Shapiro, J.M., 1993. Embedded image coding using zerotrees of wavelet coefficients. IEEE Trans. Signal Process., 41: 3445-3462.