FULL PAPER

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Fuzzy Based Image Compression on ROI using Optimized Directional Contourlet Transform

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***Abstract* –To meet the demand for high speed transmission of image in efficient image storage and remote treatment, the efficient image compression is essential. The contourlet transform along with wavelet theory has great potential in medical image compression. The proposed technique aims at reducing the transmission cost while preserving the diagnostic integrity. In this paper we propose a wavelet based contourlet image compression algorithm. Recent reports on natural image compression have shown superior performance of contourlet transform, a new extension to the wavelet transform in two dimensions using Laplacian Pyramid(LP) and directional filter banks. In the diagnosis of medical images, the significant part(ROI) is separated out from the rest of the image using neural network based fuzzy logic technique by comparing the test image with the training patterns and then to the resultant image optimized contourlet transform is applied to enhance the visual quality. 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 which shows better PSNR and high compression ratio. To the resultant image Huffman coding is applied to get the compressed image. The method proposed in this paper has been simulated using the MATLAB software.**

***Keywords*- Contourlet, Directional filter Banks, DWT, EZW, PSNR, Region Of Interest.**

I. INTRODUCTION

As the need for efficient storage and transfer of medical data is dramatically increasing, image compression is essential for medical picture archiving and communication systems (PACS)[1]. Past few years have witnessed abundant techniques in image compression, primarily for its widespread applications in internet, medical imaging etc. A large part of the modern medical data is expressed as images or other types of digital signals, such as MRI, computer Tomography(CT), Ultrasound, Positron Emission Tomography(PET) [2],[3].

Image transformations can be achieved through several transforms like DCT, DFT etc., contourlet based ROI with wavelet transform of digital signals and images have been a topic of interest for better compression. Data compression has relieved the burden of image transmission and storage at the cost of extra computationally extensive processing[4]. 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 data are of interest. These structures typically occupy a small percentage of the data, but their analysis requires contextual information like locations within a specific organ or adjacency to sensitive structures[5]. Therefore, while focusing on a particular region of the data, 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. Neural network based fuzzy logic is used to separate out ROI which compares with test image locally by proper training patterns. 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 compression algorithms like Shapiro's EZW (Embedded Zerotree Wavelet)[6],the SPIHT (Set partitioning in Hierarchical Trees)[7], and the SPECK (Set Partitioning Embedded Block)[8]. These algorithms which rely on embedded coding create an embedded binary flow, a progressive data transmission that allows the image to be reconstructed using various compression ratios. Several compression of EZW algorithm was proposed in literature. In [9], compression is performed by four symbols different from the one used in the original method [6] to code the wavelet coefficients. The authors in [11,12] uses the same coefficients used by [9] and propose a compression scheme adapted for video compression. Huffman coding is then applied to the indices obtained by Modified EZW[10] 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 paper, we propose the modification of the EZW algorithm[9] with improved version of contourlet transform for the significant region and DWT for the insignificant region together with neural network based segmentation technique. This modified algorithm has two specifications: it distributes entropy differently than the original Shapiro EZW algorithm and it optimizes the coding compared to the existing algorithms.

Following this introduction, the remainder of the paper is organized as follows: In section II the contourlet transform is explained with some basics of wavelet transform from which it emerges. Our approach of reduction in computational complexity with increased compression ratio using modified EZW algorithm is explained in section III. Section IV deals with the results and finally conclusions are drawn in section V.

II. DISCRETE CONTOURLET TRANSFORM

Although wavelet transform provides a good representation for one dimensional piece-wise smooth signals, the two dimensional separable wavelet, representing two dimensional signals in two separable one dimensional signals, is not an efficient means in presenting sharp edges and singularities in many nature images. In short, 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[11-13]. Researchers have recently come up with a new family of wavelet methods that can capture the intrinsic geometrical structures such as curvelet transform[14] and contourlet transform[15]. Curvelets are very successful in detecting image activities along curves, while analyzing images at multiple scales, locations and orientations. The contourlet transform exhibit the following important characteristics:

1.Directionality: The image representation should contain basis elements oriented at a variety of directions, much more than the few directions that are offered by separable wavelets.

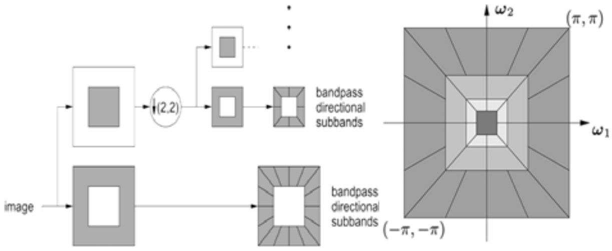
2. Multiresolution: The representation should allow images to be successively approximated, from coarse to fine resolutions

3. Localization: The basis elements in the representation should be localized in both the spatial and the frequency domains.

4. Anisotropy: To capture smooth contours in images, the representation should contain basis elements using a variety of elongated shapes with different aspect ratios.

5. Critical sampling: For some applications like compression, the representation should form a basis, or a frame with small redundancy.

The contourlet transform proposed by Do and Vetterli[15], 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.1(a). 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. Since the DFB was designed to capture the high frequency directionality of the input image and it is poor on handling low frequency content, hence the DFB is combined with the LP, where low frequency of the input image is removed before applying DFB. Fig. 1(b) shows the resulting frequency division, where the whole spectrum is divided both angularly and radially and the number of directions is increased with frequency.



(a) (b)

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

A. Laplacian Pyramid

The multiscale decomposition of Directional Filter Bank(DFB) can be achieved by Laplacian Pyramid(LP) which is introduced by Burt and Adelson [16]. The LP decomposition at each level generates a low pass subband and a high pass subband. The low pass subband is a downsampled coarse version (1/4 size of the original) of the original image and the high pass subband is a detail image containing the difference between the original and the prediction, resulting in a band pass image as in fig 2a. 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.

Fig. 2 (a) and (b) are called analysis and synthesis filters and 'G' is the sampling matrix. The process can be iterated on a coarse version. In Fig. 2(a) the outputs are a coarse approximation 'a' and a difference 'b' between the original signal and prediction. The process can be iterated by decomposing the coarse version repeatedly. The original image is convolved with a Gaussian kernel. The resulting image is a low pass filtered version of the original image. The Laplacian is then computed as the difference between the original image and the low pass filtered image. A set of band pass filtered images is obtained by continuing the above process. By performing these steps several times a sequence of images are obtained.

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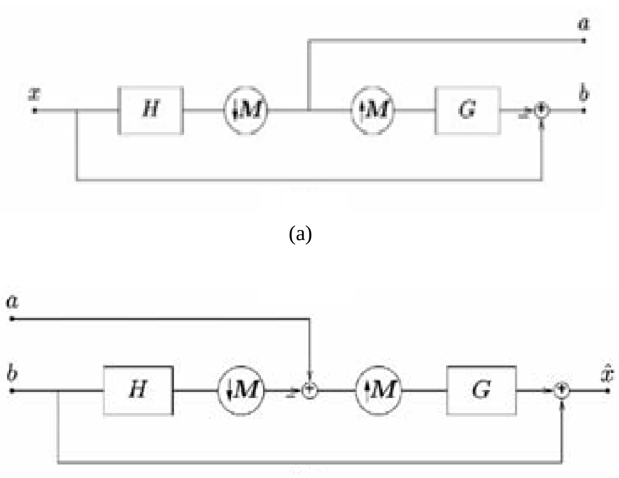

(a)

(b)

Fig. 2. Laplacian pyramid scheme (a) analysis, and (b) Synthesis filters.

B. 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 2^n 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.

III. PROPOSED SCHEME

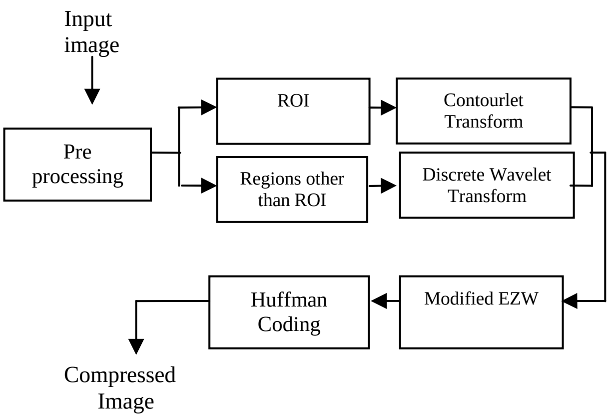

Fig. 3. The Proposed algorithm model

Figure 3. 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. The proposed system starts with the key frame of the video 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.

A. 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. Preprocessing is always a necessity whenever the image to be compressed in noisy, inconsistent or incomplete and it significantly improves the effectiveness of the image compression techniques. Any one of the filtering technique say wiener filtering is used for noise removal.

B. Extraction of ROI

To separate out ROI from the diagnosis image, textural segmentation has to be performed which plays a dominant role in image analysis. The significant visual effects better lies for any kind of image on their textural characteristics. Here, we segment the image into different regions, such that every pixel in these regions is having similar attributes.

Textural characteristics like Energy-Angular second moment, Correlation, Inverse difference moment and entropy can be captured from images using second order distribution gray levels using the following formulas.

Energy-Angular Second Moment

$$f_1 = \sum_i \sum_j p(i, j)^2$$

Correlation

$$f_2 = \frac{\sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (i * j) p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

Inverse Difference Moment

$$f_3 = \sum_i \sum_j \frac{1}{1 + (i, j)} p(i, j)$$

Entropy

$$f_4 = \sum_i \sum_j p(i,j)\log(p(i,j))$$

The suggested approach at first divide the image into subregions according to the distribution of various textural descriptors which belongs to two main categories. First, cooccurence matrices based features and second, coherence analysis based measures are compared at this stage of the proposed methodology. Each subregion is then classified as texturally important or not utilizing fuzzy logic unsupervised techniques.

The textural features for the sliding window size of M=8 for a 256 x 256 images are considered by calculating cooccurrence matrices and statistical metrics like Correlation, entropy, Inverse difference moment, energy-angular moment are calculated and coherence analysis is performed for it. From the measures significant and insignificant regions are determined using fuzzy logic unsupervised techniques.

After determination of cooccurence matrices, second method for deriving textural features is the coherence analysis of the original image. The coherence measures takes on low values in regions of the textures with similar pixels and the variation is higher in those points that are between the regions with different textural structure. Then clustering technique is performed to group pixels of similar textures. Texturally significant and insignificant patterns are grouped into labeling of two logic levels "1" and "0". A black and white image results for the significant and insignificant partitions.

In short, at first texture properties are transformed in to fuzzy set. Appropriate fuzzy membership functions are determined and values corresponding to it are assigned.

C. Proposed ROI based Modified EZW

In Shapiro's EZW algorithm [6], 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.

Quantization and Refinement

A bit corresponding to 2^{j-1} is emitted for all the significant values in the refinement list S in order to increase the precision of those values transmitted. The coefficients are then converted into binary by the coding technique. This process is repeated by dividing the threshold by 2. The process is reiterated until the desired quality of the reconstructed image is reached or until the number of transferable bit required is exceeded.

The modified algorithm works in the following way:

1. Symbols were added to the significance test stage to allow a better redistribution of the entropy.
2. The coding of the dominant elements and the subordinate list quantization bits was optimized.

D. 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 the doing rules of the Shapiro's algorithm, which is the case for the coefficients. 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. Performing the above steps for the two possibilities of coefficient values reduction in code symbol of four results for the both the cases.

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. 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. Surely this will give better result compared with other compression techniques within limited computational complexity.

IV. SIMULATION RESULTS

The method of separate transforms to the two regions proves better results compared to the ordinary way of applying only single transforms to the whole image. The proposed technique of modified EZW for a 8-bit 256 x 256 images were tested. In the 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 Daubechies filter. Fig 4(a) and Fig 4(b) shows the input and reconstructed Images.

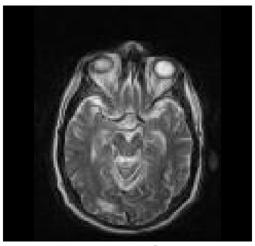

Fig. 4(a). Original Image

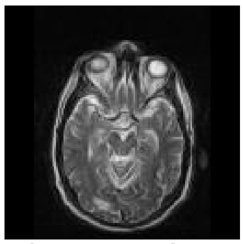

Fig. 4(b).Reconstructed Image

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

Table 4.1 PSNR and CR for EZW, SPIHT and Proposed algorithm.

Type	EZW		SPIHT		MODIFIED EZW	
	PSNR	CR	PSNR	CR	PSNR	CR
CT	35.12	5:1	39.55	8:1	38.3	15:1
MRI	34.16	8:1	36.28	16:1	36.6	20:1

V. CONCLUSION AND FUTURE CONSIDERATIONS

In this paper, we proposed a new image transform which is 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 and is superior to EBCOT, SPIHT, Modified SPIHT. Our new method of compression algorithm can be used to improve the performance of Compression Ratio(CR) and Peak Signal to Noise Ratio(PSNR). 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.

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

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

where Oij is the original image, Cij is the reconstructed image, w is the total number of row elements and h is the total number of column elements, MAX is 255.

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

where n, m is the image size.

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