Compression and Texture representation of Ultrasound thyroid images by Contourlet transform

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Abstract—**I n this paper we present a contourlet based lossy image compression method and texture representation for medical ultrasound thyroid images. Texture representation of ultrasound (US) images is currently considered a major issue in medical image analysis. In this algorithm we use contourlet transform for image decomposition. Then, we apply a thresholding process on the coefficients before quantization. We select the threshold due to coefficients occurrence in the contourlet domain. This algorithm has the ability of simultaneous speckle reduction using another thresholding. Due to this time saving ability, the algorithm can be used in online image transmission systems. We implement our method on ultrasound images. Results proved that our proposed method has acceptable performance and good performance over common compression methods such as wavelet based SPIHT in the case of PSNR. Texture representation of ultrasound (US) images is currently considered a major issue in medical image analysis. This paper also investigates the texture representation of thyroid tissue via features based on the Contourlet Transform (CT) using different types of filter banks. A variety of statistical texture features based on CT coefficients, have been considered through a selection schema. The Sequential Float Feature Selection (SFFS) algorithm with a *k*-NN classifier has been applied in order to investigate the most representative set of CT features. For the experimental evaluation a set of normal and nodular ultrasound thyroid textures have been utilized. The maximum classification accuracy was 93%, showing that CT based texture features can be successfully applied for the representation of different types of texture in US thyroid images.**

Index Terms— **contourlet transform, ultrasound images, feature extraction, thyroid, feature selection.** ***(Key words)***

I. INTRODUCTION

Ultrasound imaging is the most popular medical imaging modality due to its non-invasive and low cost nature. Despite advantages of digital image technology, these images are large in size and need large number of bits for storage. The other limitation of these large images is bandwidth that is needed for transmission. So, compression of images as a solution to overcome these limitations is introduced. Image compression is a part of data compression which its aim is to reduce the data required to represent the image information. Data is different from information as data are means by which information is transformed. So various amount of data can be used to represent the same amount of information [1].

Data compression is typically characterized into two groups of algorithms: lossless compression and lossy compression. In lossless compression the original image can be reconstructed exactly without any loss hence it is a reversible process. Run-Length Encoding (RLE) is example of lossless compression. Lossless methods suffer from low compression ratios. In lossy techniques there is some information loss. Lossy compression algorithms have high compression ratios and some errors.

Different image compression methods are presented in literature. Transform based image compression algorithms are very popular in medical community. Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) are used broadly in this field. DCT based JPEG standard, divides the input image into blocks, DCT is performed on each block then the resulting coefficients are quantized and coded. The main problem of this compression method is blocking artifact [2]. After the introduction of wavelet transform, it has gained broad popularity according to its unique de-correlation property. The most important advantage of DWT based image compression techniques is lack of blocking artifact [3]. After the introduction of DWT, many compression algorithms were proposed to code wavelet coefficient. Among these algorithms, Embedded Zero trees Wavelet (EZW) [4], Set Partitioning in Hierarchical Trees (SPIHT) [5], Embedded Block Coding with Optimized Truncation (EBCOT) [6] are the most popular methods. Fractal compression algorithm is another compression technique which involves pixel to pixel comparison between the image blocks [7].

A new image representation tool was introduced in 2005 by Minh N. Do. It was contourlet transform with unique property of representing images with soft contours [8]. Due to the advantages of contourlet over other transforms, it is widely used in image processing tasks such as image denoising and compression [9], [10]. In this paper we present a contourlet based lossy image compression method.

Texture representation is a fundamental issue in image analysis and computer vision. It has been extensively investigated in the literature for more than three decades. Numerous approaches have been proposed dealing with textural features extraction which can be divided into four main categories [1] statistical, signal processing, model-based and geometrical. Signal processing approaches have drawn much attention, resulting in the proposal of a variety of texture representation methods, including the power spectral methods using the Fourier spectrum, the Discrete Cosine Transform (DCT), the Discrete Hartley Transform (DHT) [2], and more recently, the Gabor filters [3], the Haar [4] basis functions, the Discrete Wavelet Transform (DWT) and the Contourlet Transform (CT) [5] [6].

The aim of this study is to investigate the performance of the Contourlet Transform (CT) for the representation of medical ultrasound (US) textures of the thyroid gland. A set of statistical features calculated from the CT coefficients are evaluated through a supervised classification schema on real thyroid US images. Additionally, a feature selection phase has been applied through the Sequential Float Feature Selection (SFFS) algorithm, for the extraction of the most representative set of CT features.

II. LOSSY COMPRESSION

In lossy image compression methods, image is decomposed using different kinds of transforms. Wavelet and Discrete Cosine Transform are used for transform images. The goal of transformation is to represent the original image in a more effective way. The second process is quantization which is the key issue for lossy methods and it is the difference between lossless and lossy methods. Quantization reduces the symbols used to represent the image. Two types of quantization are used in lossy compression methods: scalar quantization and vector quantization. In scalar quantization each symbol quantized separately but in vector quantization some number of successive symbols form a vector and that vector is quantized. Last part of lossy compression process is entropy encoding. Quantized symbols are encoded using different entropy coding algorithms, like Huffman encoding. Huffman coding is an entropy encoding algorithm used for lossless data compression. In this coding a variable-length code table is used for encoding a source symbol where the variable-length code table has been derived in a particular way based on the estimated probability of occurrence for each possible value of the source symbol. The output of this process is a compressed image bit stream [1]. Fig.1 shows lossy image compression process.

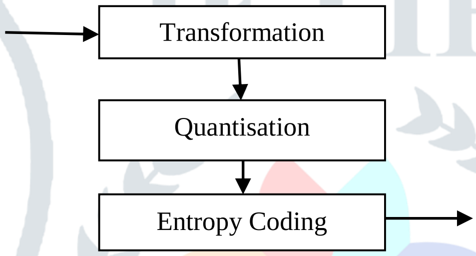

Fig.1 Lossy image compression schematic

III. CONTOURLET TRANSFORM

The Contourlet Transform is a directional transform, capable of capturing contours and fine details in images. The contourlet expansion is composed of basis function oriented at various directions in multiple scales, with flexible aspect ratios. Using this rich set of basic functions, the contourlet transform effectively capture the smooth contours that are dominant feature in images [8]. Contourlets not only possess the main features of wavelets (i.e. multi-scale and time frequency localization), but also offer a high degree of directionality and anisotropy.

Similar to wavelet, contourlet can decompose the image into different scales. So, the contourlet uses a double filter-bank structure, namely pyramidal directional filter banks (PDFB) which is composed of Laplacian Pyramid (LP) and Directional Filter Banks (DFB). LP implements multiresolution decomposition to generate multiscale representation of the image. PDFB uses DFB to process subband images from LP and reveal directional details in each scale level. This two stage filter bank is illustrated in figure 2 [8]. Efficiency of contourlet representation of image has been shown for different image processing tasks such as image denoising and compression. Using directional filter bank make it possible to capture important details of the image. In this paper we use contourlet transform as the main tool for image compression.

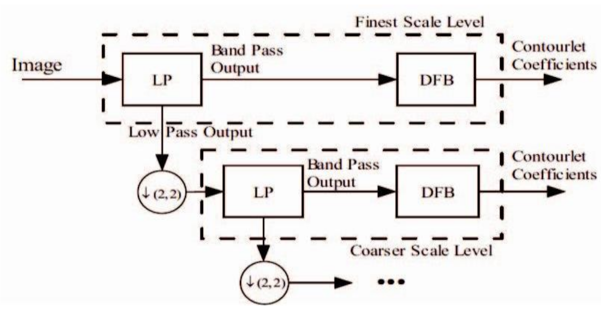

Fig.2: Contourlet Filter banks

IV. METHODOLOGY

COMPRESSION:

We present a new contourlet based image compression method. We use contourlet transform to decompose the image into coefficients. After decomposition, we choose a threshold from contourlet coefficients. Then, we apply thresholding process on the coefficients and then we perform routine quantization process. In this algorithm choosing the threshold plays a significant role. So, in order to minimize the important information loss we select the most frequently occurring contourlet coefficient of the image as the threshold. After thresholding the coefficients is quantized. Huffman coding is applied on quantized coefficients and the coded bit-stream is generated. Block diagram of this algorithm is shown in fig. 3. This threshold based process reduces the number of coefficients necessary to reconstruct the image. Scalar quantization is selected due to its simplicity and performance. The coded bit-stream includes coefficients and contourlet filter information. We can use two thresholds in thresholding stage, one for compression and another for speckle reduction. Ultrasound images suffer from the presence of speckle noise. Other methods need another pre-processing step to reduce speckle noise of the image, but our method can reduce speckle during compression process. This property makes this algorithm suitable to use in online medical image transmission systems. We can use two thresholds in thresholding stage, one for compression and another for speckle reduction. Ultrasound images suffer from the presence of speckle noise. Other methods need another pre-processing step to reduce speckle noise of the image, but our method can reduce speckle during compression process. This property makes this algorithm suitable to use in online medical image transmission systems.

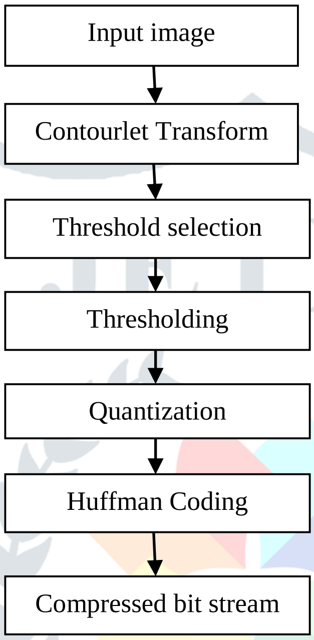

Fig.3: Compression method block diagram

2. TEXTURE REPRESENTATION:

2.1.1 Feature Extraction

The set of statistical texture features in the contourlet domain evaluated in this study, have been proposed by Liu [8]. This set consists of the first order statistical measures that follow:

i) Energy: The energy Ejk of a subband image Ijk from the CT decomposition is defined as:

$$E_{jk} = \frac{1}{M_{jk}N_{jk}} \sum_{n=1}^{N_{jk}} \sum_{m=1}^{M_{jk}} [I_{jk}(m,n)]^2$$

Where *Ijk* is the subband image of the *k*th direction in the *j*th level. *Mjk* is the row size and *Njk*, column size of the subband image *Ijk*.

ii) Standard deviation: Provides the means to capture the scale of the diversity of the image. The standard deviation *Sjk* of the subband image *Ijk* is defined as

$$S_{jk} = \sqrt{\frac{1}{M_{jk}N_{jk}} \sum_{n=1}^{N_{jk}} \sum_{m=1}^{M_{jk}} [I(m,n) - I'(m,n)]^2}$$

iii) Information entropy. For texture images, it represents the complexity of the texture information. The information entropy *Hjk* of a subband image *Ijk* is defined as

$$H_{jk} = -\sum_{n=1}^{N_{jk}} \sum_{m=1}^{M_{jk}} P_{jk}(m,n). \log P_{jk}(m,n)$$

Using the above features, the feature vector for the subband image of the *k*th direction in the *j*th level is defined as *fjk=(Ejk, Sjk, Hjk)*. If the CT is defined as *J* level and for the *j*th (*j=1,…, J*) level a *Kj* bands DFB is applied, then a total number o *K* subband images is obtained, where By combining and rearranging all the feature vectors of the *K* subband images, the feature vector *F={ fi }, i=1,2,…,K* of the input image is obtained and normalized as proposed in [9]

2.3 Feature Selection

Feature selection offers more than one significant advantages, including reduction of computational complexity, improved generalization ability and robustness against outliers. A widely adopted algorithm for feature selection is the sequential floating forward selection (SFFS) algorithm [17] which has been used in a broad range of applications [18]. The idea behind the SFFS algorithm consists of consecutive forward selection steps, followed by a number of backward steps as long as the resulting subsets are better than the previously evaluated ones at the same level. Starting from an initially empty set of features, at each forward step an additional feature for which the classification accuracy is maximized is selected. Respectively, at each backward step the maximum subset that results in improved classification accuracy is being selected.

V. RESULTS

To evaluate the performance of the proposed method we use two common metrics for performance assessment of image compression methods. We applied our method on several ultrasound images and compare the performance of our method with other compression methods. Set partitioning in hierarchical trees (SPIHT) is an image compression algorithm that exploits the inherent similarities across the sub-bands in a wavelet decomposition of an image. This algorithm codes the most important wavelet transform coefficients first, and transmits the bits so that an increasingly refined copy of the original image can be obtained progressively [5]. As SPIHT is one of the accepted compression methods, we compare our results with SPIHT. In order to evaluate the performance of the proposed method we implement our method on an ultrasound phantom image [11] and for the same compression ratios we compare the PSNR. The results are presented in figure 4 and table 1.
Peak Signal to Noise Ratio (PSNR) is one of the quantitative measures for image quality evaluation. PSNR is based on Mean Square Error (MSE)

$$PSNR = 10\log_{10}({255^2}/_{MSE})$$

Where MSE is the Mean Square Error and is used to obtain the total amount of difference between two images. MSE is calculated as below:

$$MSE = \left(\sum I(m,n) - DI(m,n)\right)^\wedge 2/(M*N)$$

Where *M*N* are the size of original image, *I(m,n)* and *DI(m,n)* are original image and decompressed image, respectively.
Compression Ratio (CR) is defined as follow:
CR= Original file size/ Compressed file size

(a) **(b)** **(c)**

Fig.4: Ultrasound phantom image (a) Original image (b) Compression by SPIHT (c) Compression by our algorithm

Table 1: Compression results of Phantom image

Method	PSNR(db)	CR
SPIHT	25.01	4.03
Proposed method	79.2566	4.51

A total of 72 thyroid ultrasound images were obtained from examinations performed on 43 patients, using a Philips HDI 5000 sonographic imaging system, with a spatial resolution of 470×470 pixels and amplitude resolution of 8 bits. During these examinations the parameters of the sonograph were kept the same. This set of ultrasound images includes hypogenic thyroid nodules, as it has been diagnosed by expert physicians. From each ultrasound image, an equal number of healthy and nodular sample blocks have been selected.
The total number of non overlapping 32x32 pixel blocks resulting from this process was 200. The classification task was implemented by means of the non parametric and generally effective *k*-NN classification approach [24]. The distance measure used by the *k*-NN was the Euclidean and parameter *k* was {3, 5}. For all experiments conducted, the classification accuracy for all experiments was estimated by 10-fold cross validation [19]. Due to the small size of thyroid nodules, the sample blocks selected are also small (32x32 pixels) and they did not allow decomposition of more than three levels with the LP and six levels with the DFB.

The first LP decomposition level supports up to six levels of DFB decomposition, decreased by one for every extra LP decomposition level. The filters applied for the LP were the filters Burt, 5-3 and 9-7 and for the DFB the 5-3 and 9-7 filters. All possible combinations of filters and decomposition levels were tested.. It was noticed that the maximum classification accuracy is 77%. This resulted from the filter 9-7 for the LP and the DFB, with two levels of LP decomposition, decomposed into sixteen and two directional subbands respectively, from finer to coarser scale. The application of the SFFS selection algorithm led to improved classification results for every experimental setup as shown in Fig. 4. In this case the maximum classification accuracy was 93% using only 36 out of 205 features and the confusion matrix is presented in Table 1. This accuracy has been obtained via 5-3 filters for the LP and the 9-7 filters for the DFB, with two levels of LP decomposition, and then decomposed into sixty four and four directional subbands respectively from finer to coarser scale. This result shows that a significantly smaller subset of CT features is necessary and sufficient to describe effectively the thyroid US texture.

In this study a methodology for the texture representation of thyroid tissue in US images has been investigated, utilizing features based on the Contourlet Transform (CT) and various types of filter banks. The experimental evaluation through supervised classification on real US thyroid images led to promising results. Furthermore, through a feature selection phase the maximum classification accuracy reached 93% for a significantly smaller set of features. These results are considered to provide evidence for the effectiveness of CT texture representation of US thyroid images. As overall conclusion, it can be argued that the combinations of 5-3 and 9-7 filters resulted in better classification accuracy for the second level of LP decomposition. Future work could include US images of higher resolution and the evaluation of different types of statistical features.

VI. CONCLUSION:

In this paper we present a new contourlet based medical image compression method. This threshold based lossy method uses contourlet transform as main tool to convert the image into contourlet coefficients. This threshold is selected due to the information content of the image and is selected among contourlet coefficients. We compare our results with other image compression methods such as SPIHT. Results show that in the same compression ratio our proposed method has acceptable performance for PSNR over SPIHT. The most significant advantage of this method is the ability of speckle reduction during compression of the image. This algorithm can reduce speckle noise of the ultrasound image during compressing it by a simple thresholding process, and this can save time in medical image transmission and archiving process. So, this simple and efficient algorithm can be very useful in the field of medical image processing and transmission.

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