PERFORMANCE EVALUATION OF IMAGE COMPRESSION FOR MEDICAL IMAGE

Loganathan R.
Research Scholar, Sathyabama University
Chennai, INDIA
logu73@yahoo.com

Dr.Y.S.Kumaraswamy
Sr. Prof & HOD, Dept. of MCA (VTU)
Dayananda Sagar College of Engineering
Bangalore, INDIA

Abstract

Most hospitals store medical image data in digital form using picture archiving and communication systems due to extensive data digitization of data and increasing telemedicine use. Data storage needs and bandwidth requirements have necessitated use of lossy compression techniques. Wavelet transforms successful use in image compression was extensively studied in literature. Image segmentation aims to partition an image domain into many mutually exclusive subdomains over which some image properties are homogeneous. In medical images, an object represents a diseased organ called a region of interest (ROI). Though literature suggested many procedures ROI are efficiently segmented through active contour use. ROI are compressed with lossless compression to maintain medical image integrity. This paper investigates Biorthogonal spline wavelet performance as a possible mode for medical image compression. Active Contour segments ROI in medical images. The performance of Set Partitioning in Hierarchical Trees (SPHIT) and Embedded zerotree wavelet algorithm (EZW) to compress images is evaluated.

Keywords**:** Medical Image Compression, Region of Interest (ROI), Active Contour, Biorthogonal Wavelet, Set Partitioning in Hierarchical Trees (SPHIT) and Embedded zerotree wavelet algorithm (EZW)

1. Introduction

A digital image obtained by sampling and quantizing a continuous tone picture requires huge storage. For example, a 24 bit color image with 512x512 pixels occupies 768 Kbyte space on a disk. Image compression aims to reduce data amount required to represent sampled digital images and thus reduce storage and transmission cost. Image compression is important in many important applications, including image database, image communications, remote sensing (use of satellite imagery for weather and other earth-resource applications), document and medical imaging, and so on [1]. Expanding number of applications need efficient manipulation, storage, and transmission of binary, gray-scale, or color images.

A common image characteristic is that neighbouring pixels are correlated and so have redundant information [2]. The task then is location of less correlated image representation. Redundancy and irrelevancy reduction are two fundamental compression components. Redundancy reduction is removal of duplication from signal source (image/video). Irrelevancy reduction omits signal parts that will be unnoticed by signal receiver, ie; the Human Visual System.

There are three types of redundancies which are used to compress file size in images, which include an image sequence [3]. They are:

a. Coding redundancy: Fewer bits to represent symbols occurring frequently.
b. Interpixel redundancy: Neighbouring pixels have similar value.
c. Psycho visual redundancy: Human visual system cannot distinguish colours simultaneously.

Usually, coding is classified into Lossless and Lossy [4]. With lossless coding, original sample values are retained and compression is through exploring signal statistical redundancies. Lossy coding on the other hand alters the signal to achieve higher compression ratios.

Image segmentation aims to partition an image domain into mutually exclusive subdomains on which some image properties are homogeneous. Image fragmentation is done so that every fragment is linked with a distinct class, and is distinguished as an object or background. In medical images, an object represents a diseased organ [5], [6]. Over decades many image segmentation methods were proposed in the literature.

Despite diversity, segmentation methods follow similar algorithmic patterns, the latter involving hypotheses creation relating to image structure/properties needing segmentation. An image is a features set based on discriminated segmentation classes applying for a decision threshold in an explicit/implicit manner [7]. An image feature can be a random variable described by a set of conditional likelihood functions. Segmentation is based on local/global analysis [8], whether using deformable contours [9] or polygons [10]. Successful segmentation methods minimize misclassification error probability. As probability constitutes a universal criterion image segmentation methods are designed on this.

Unsupervised texture segmentation came under intensive research recently, when attempts were made to discriminate between different textures regions [11]. Texture is hard to analyse in image processing and computer vision because: first, segmentation is not a clear cut issue even in un-textured images. Second, there are no universal mathematical real world textures models though attempts were made to create them [12].

Medical imaging impacts medicine specially diagnosis and surgical planning. But imaging devices generate huge data amounts for every patient requiring storage and efficient transmission. Current compression schemes have high compression rates thereby affording some quality loss. But physicians cannot afford image region deficiencies known as regions of interest (ROIs). An approach which has high compression rates and good ROI quality is required. A common idea preserves quality in diagnostically critical regions but allows lossy encoding in other regions. The research focuses on ROI coding to ensure multiple/arbitrarily shaped ROIs use in images, with arbitrary weights describing each ROI's importance including the background to ensure that such regions are represented by varying quality levels [13].

Various compression ratios with maximum energy were proposed in literature, improving compression ratio and retaining the maximum energy hit road blocks as medical images are highly noise sensitive [14, 15]. To overcome lossy compression limitations, various compression techniques on same image based on ROI are investigated in this paper. The following sections deal with related works, materials and methods used and the experimental results.

2. Related Works

Li Zhu et al., [16] introduced an image compression algorithm based on object segmentation. Shape-adaptive discrete wavelet transforms transform arbitrary shaped objects to attain greater coding efficiency. To minimize background coding redundancy human head regions and its background are compressed independently. This paper details two lossless image contour coding based on differential chain, and modified arbitrary shape set partitioning in hierarchical trees (SPIHT) algorithm. Experimentation with the proposed method showed results that when 0.078 bit per pixel (bpp) was achieved, peak signal-to-noise ratio (PSNR) reconstructed photograph exceeded to 4dB than regular SPIHT. Hence, the proposed object segmentation based image compression algorithm outperformed conventional methods.

Sakalli et al., [17] proposed a different contour search algorithm with faster convergence to object contours. This algorithm is quicker than both greedy snake algorithm (GSA) and fast greedy snake (FGSA) algorithm. Search is performed in an alternate skipping way among a snake's odd and even nodes (snaxels) with various step sizes to ensure a twisting movement to a likely local minimum. The snake is unlikely to be trapped in a pseudo-local minimum with adjusted alternative step sizes. To enhance convergence, iteration is a coarse-to-fine approach. The proposed algorithm is compared to FGSA algorithm implementing two alternating search patterns without altering search step size. To extract face profiles in a hierarchical way, the algorithm is used along with subband decomposition. Experiments reveal maximizing speed compared to FGSA in first stage coarse convergence by more than 40%, and in fine-tuning stage by more than 20%. GG snake approach is employed in a hierarchical manner lowering preprocesing burden by implementing small images and smoothing filters. Gradient information is obtained at every level from wavelet decomposed images and convergence of snake model is investigated for all probable behaviors with and without skipping with alternate patterns.

Wavelet transform's multi-resolution properties are exploited by Embedded zero tree wavelet (EZW) coding in contrast to pre-existing wavelet transforms. Artificial Neural Network is applied for image processing problems, and superior performance over traditional techniques is seen when addressing issues of noisy/incomplete data for image compression applications. Jilani et al., [18] proposed a novel fuzzy optimization design for image processing based on neural networks. A novel fuzzy neuron network (FNN) able to adjust input/output values and improve stability, robustness and network working speed help attain high compression ratio is done by this combination system. Hence EZW provides better performance with less computation, not requiring complicated bit allocation procedures like sub-band coding and prior image source knowledge like JPEG, to optimize quantization tables. Approximately 30% more accuracy was got in image retrieval by the Embedded zero tree wavelet coding with fuzzy Backpropagation artificial networks compared to existing EZW coding system.

Shingate et al., [19] suggested compressing images into a bit stream with improving accuracy through a EZW encoder based on progressive encoding. It has properties similar to JPEG encoded images in that decoded images include additional details when additional bits are added to the stream. It is also equal to Π, a number representation, whose accuracy progresses when adding a digit with accuracy being stopped when not required. Progressive encoding is also known as embedded encoding. Using EZW image coding is undertaken with a few optimizations results in an image compressor efficient at possessing compressed data stream property with a preferred bit rate. Information loss causing lossy in compressor achieves a bit rate. Using EZW encoder, lossless compression is possible but with less spectacular results. So the proposed approach uses wavelets coefficients zero tree structure effectively, resulting in superior compression ratio and good PSNR/SNR. Compared to other coders, this coder reveals superior performance.

Babu et al., [20] suggested using Partial EZW Algorithm for enhanced image compression. The difficulty of EZW which loses effectiveness in lower bit planes transmission is overcome by the proposed Partial EZW Algorithm. Also this paper includes incorporation of wavelet transformation and ROI coding to Partial EZW and therefore a top coder is obtained with both EZW and SPIHT Algorithms. Results prove and validate this. The proposed coder in terms of PSNR and CR reveals better medical image performance.

3. Methodology

3.1. Biorthogonal Wavelets

The Cohen, Daubechies, and Feauveau produced biorthogonal wavelets compactly support biorthogonal spline wavelets with compactly supported duals. In biorthogonal wavelets, separate decomposition/reconstruction filters are defined and so responsibilities of analysis/synthesis are assigned two different functions (in the biorthogonal case) as against a single function in orthonormal case [21, 22, 23].

The biorthogonal scaling function is given by

$$\phi(t) = 2\sum_{n=-\infty}^{\infty} h(n)\phi(2t-n) \qquad \underline{dual}\ \tilde{\phi}(t) = 2\sum_{n=-\infty}^{\infty} \tilde{h}(n)\tilde{\phi}(2t-n)$$

$$\left\langle \phi(t), \tilde{\phi}(t-k) \right\rangle = \delta(k) \qquad \left\langle \phi(2^{-k}t), \tilde{\phi}(2^{-k}t-n) \right\rangle = 2^k \delta(n)$$

where $h(n)$ and $\tilde{h}(n)$ serve as impulse response of FIR filters and two sets of scaling functions $\phi(t)$ and $\tilde{\phi}(t)$ generate subspaces V_k and $\tilde{V}_k$ respectively. Unlike orthogonal case, biorthogonal wavelets can be synthesized and scaling functions that are symmetric/anti-symmetric can be supported compactly.

Wavelet analysis procedure adopts a wavelet prototype function, called analyzing wavelet/mother wavelet. Temporal analysis is through a contracted, high-frequency prototype wavelet version, while the same wavelet performs frequency analysis with a dilated, low-frequency version. As original signal/function is represented with regard to wavelet expansion (using coefficients in a linear combination of wavelet functions), data operations are done with corresponding wavelet coefficients alone. And if best data adopted wavelets or truncated coefficients below threshold are chosen, data representation is sparse, ensuring that such sparse coding makes wavelets good data compression tools.

The proposed mother wavelet is derived as:

$(2/(\sqrt{5} * pi^{1/4})) \times e^{(-t^2/2)} \times \sin h(2 \times pi \times t)$ *[sin (pi*(2*x-1))-sin(pi*(x-0.5))/(pi*(x-0.5))]

An initial threshold is chosen

$$t_0 = 2^{\lfloor (\log_2(max|h(x,y)|)) \rfloor}$$

where h(x, y) denotes a coefficient.

3.2. Active contour model

Mumford and Shah [24] formulated a segmentation algorithm, Active contour model (also called snakes), to delineate an object outline from a noisy 2D image. The contours minimize associated energy as a sum of an internal and external energy:

- Minimal external energy is achieved when snake is at object boundary position.
- Minimal internal energy is achieved when snake acquires shape of the object.

Energy types rely on boundary curve smoothness and image features. Segmentation begins with an automatic contour or through user interaction. The contour is evolved in object boundaries direction under forces derived from energy with energy minimization being obtained through gradient descent. The active-contour methods are edge-based, using functionals depending on image response to an edge filter [25].

The basic Active model is given by

$$F(c^+, c^-, C) = \mu . Length(C) + \lambda^+ \int_{inside(C)} |\mathcal{U}_0(x,y) - c^+|^2 dxdy$$
$$+\lambda^- \int_{outside(C)} |\mathcal{U}_0(x,y) - c^-|^2 dxdy$$

where c+ and c- are constant unknowns representing the average value of u0 inside and outside the curve, respectively. The parameters $\mu > 0$ and $\lambda^{+}, \lambda^{-} > 0$ are weights for the regularizing term and the fitting term, respectively. The above model can be rewritten as

$$F(c^{+}, c^{-}, \emptyset) = \mu . Length\{\emptyset = 0\} + \lambda^{+} \int_{\emptyset \geq 0} |\mathcal{U}_0(x,y) - c^{+}|^2 dxdy$$
$$+\lambda^{-} \int_{\emptyset < 0} |\mathcal{U}_0(x,y) - c^{-}|^2 dxdy$$

for the level set formation where $c = \{(x,y) \in \Omega : \emptyset(x,y) = 0\}$

3.3. Set Partitioning in Hierarchical Trees (SPIHT)

Set Partitioning in Hierarchical Trees (SPIHT) is a common wavelet-based image compression coder that converts the image into its wavelet transform transmitting information about wavelet coefficients. Inverse transform is done through a decoder for image reconstruction. SPIHT improves still image compression greatly when compared to vector quantization, and with wavelets combined with quantization. Its advantage is that it does not need bit stream training and embedding. SPIHT displays exceptional characteristics like lossless compression, quicker coding/decoding, better image quality with higher PSNR, and exact bit rate coding.

SPIHT algorithm divides wavelets into Spatial Orientation Trees where every pixel is related to a tree node. Four pixels from same sub band form a pixel offspring at the wavelet's next scale. Tree leaves consist of pixels at the finest wavelet scale with no children.

3.4. Embedded ZeroTree wavelet (EZW)

Embedded ZeroTree wavelet (EZW) coding is effective and computationally inexpensive to compress images. The principles of computation algorithm are (1) wavelet pyramid image decomposition, (2) partial ordering of transform coefficients by highest bit plane of magnitude, with ordering information being encoded by a decoder reproduced set partitioning algorithm, (3) ordered bit plane transmission of refinement bits, and (4) exploitation of image self-similarity of wavelet pyramid decomposition across various scales.

An EZW encoder is designed for use with wavelet transforms and so it includes 'wavelet' in its name. It basically operates on images (2D-signals) but can also be used for other dimensional signals.

The EZW encoder is based on progressive encoding to compress images into bit streams with greater accuracy; meaning that when more the stream gets more bits, the decoded image will contain more details, a JPEG encoded image characteristic. Embedded zerotree wavelet algorithm (EZW) is a simple and effective image compression algorithm, with a characteristic that bit stream bits are generated in an order to yield a fully embedded code representing a sequence of binary decisions differentiating an image from a "null" image. With an embedded coding algorithm, an encoder can terminate encoding at any time allowing target rate/target distortion metric to be met correctly. A bit stream, a decoder can stop decoding any time and still produce an exact image that will have been encoded at a bit rate matching a truncated bit stream. In addition to production of a fully embedded bit stream, EZW provides competitive compression results with compression algorithms on test images. This is achieved through a technique which needs no training, no pre-stored tables or codebooks, and no prior image source knowledge.

4. Result and Discussion

Two sets of experiments were carried out: (i) Biorthogonal Wavelet and SPHIT and (ii) Biorthogonal Wavelet and EZW for compressing the image. The proposed methods were evaluated in MATLAB platform. Figure 1 shows input/output for different medical images where ROI mask between important space and unimportant space is computed. Figure 2 reveals extracted ROI and Non ROI image parts.

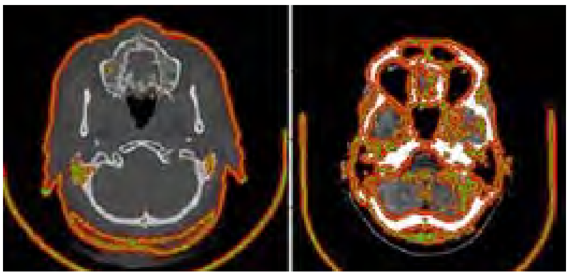

Figure 2: The edges detected using proposed method

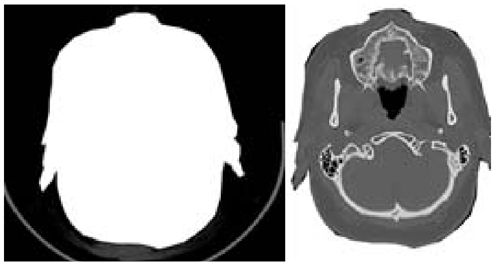

Figure 2: Extracted ROI and Non ROI part of the image.

Figure 3 shows the Non ROI image after compression.

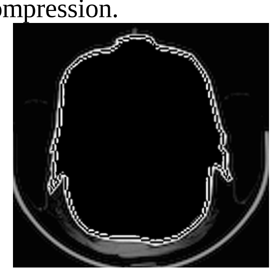

Figure 3: Highly compressed Non Region of interest

The bits per pixel obtained are tabulated as shown in Table 1.

Table 1: Bits per pixel for different Medical Images

SPIHT		EZW	
Bits per pixel	PSNR	Bits per pixel	PSNR
2.628	40.6536	2.9642	41.4124
2.614	39.973	2.8765	40.1032
2.623	40.7972	2.8124	40.2122
2.654	40.6559	2.8376	39.7982
2.617	40.5055	3.0112	39.9965

With this proposed method, medical images are segmented into ROI and non ROI, resulting in highly improved Peak Signal to Noise Ratio (PSNR). A higher PSNR value means that ratio of Signal to Noise is higher, ‘signal’ here referring to the original image, and 'noise' to the error in its reconstruction. It is observed that the EZW achieves better results than SPIHT.

5. Conclusion

Various compression methods for retaining maximum energy have been proposed in literature, improving the compression ratio. To overcome the limitations of lossy compression, ROI of the image is compressed using different techniques. It was proposed to segment ROI using Active Contour in this paper. It was also proposed to use a novel biorthogonal wavelet with Set partitioning in Hierarchical Trees (SPHIT) and Embedded ZeroTree wavelet (EZW) for compressing the image. Experimental results obtained from the proposed methods were encouraging. After testing the algorithm on different image it was seen that the Peak Signal to Noise Ratio (PSNR) is consistently in the region of 40 which is very feasible. EZW performs better than SHIPT.

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