REGION OF INTEREST MEDICAL IMAGE COMPRESSION USING SET PARTITIONING IN HIERARCHICAL TREES

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ABSTRACT

Medical image data (Ultrasonography, Computed Tomography, Magnetic Resonance Imaging etc.) consumes maximum storage and utilize maximum bandwidth for transmission that often results in degradation of image quality. Due to these inherent issues in such type of images, compression is the only applicable technique explored in the due course of prior research work. Currently, there exists abundant research work on medical image compression considering lossy and lossless types, but the need of medical images to be compressed efficiently with optimal compression ratio is yet a question mark. But compressing the data would mean loss of clarity in the image. This paper presents a selective image compression based on set partitioning in hierarchical trees. The selected algorithm works well in all kinds of images resulting in good compression ratios and peak signal to noise ratios.

INTRODUCTION

In the past decade, there has been a substantial progress in the area of medical science. The hospitals started findings a way to store the entire medical and radiological image in their database for further medical records. However, the scheme of storing the massive number of medical images is not that easy one as it calls for an efficient storage and retrieval technique too [1,2]. Digital medical images have potential benefits in terms of durability, portability and versatility. However, problems involving storage space and network bandwidth requirements arise when large volumes of images are to be stored or transmitted, as is the case with medical images [2]. Currently, all the big hospitals have the facilities of telemedicine’s and robotic surgery. In telemedicine, it is important that image should be compressed and sent via resource constraint network, while in robotic surgery, high definition videos are required for streaming with zero tolerance error [3-5]. However, even with such advancement in medical science, there is a gap between the medical science and technologies available to support it with an anticipated goal. It is very important that while performing compression on the medical images, the effectiveness of resolution as well as perceptual quality be restored. It is also known that compression is also accompanied by certain loss of significant information if the data are massive and channel capacity is highly limited for transmission purpose. Another difficult in the area of medical image compression is that all there are various types of bio-medical images (x-ray, CT, MRI etc) and compression ratio applicable for all these bio-medical images highly differs from each other. Therefore, it can be seen that medical image compression is an important research issue regarding the degree of compression and the preservation of the relevant information. The difficulty, however, in several applications lies on the fact that, while high CRs are desired, the applicability of the reconstructed images depends on whether some significant characteristics of the original images are preserved after the compression and decompression process has been completed [6,7].

To optimize the above requirement i.e. the high compression ratios and the preservation of the relevant information, the context based compression is one of the best choices to achieve the optimum compression ratios without any loss of useful information which is basically done by selecting different important regions of an image along with the background and then compression methodology is applied in these regions separately and not on the whole image. The low compression level is applied to the useful regions while the high compression is applied on the un-important regions and the background. During this process again different regions are combined along with the background after removal of the redundant data. As a result, very high CRs are achieved by this methodology without any appreciable loss of information and clarity of the image.

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SIGNIFICANCE OF COMPRESSION

The complexity involved in the processing of the medical images significantly differs from that of ordinary images. The ordinary natural scene images are taken from generic digital image capturing devices, while the medical images are captured from a sophisticated image capturing devices. Usually, the images are not really colored in medical samples as colored image may not carry the significant clinical attributes that are of prime importance from diagnosis viewpoint. Hence, the medical images are normally greyscale or some other specific format that bears the clinical significance of the disease. Hence, a normal image processing algorithms are not directly applicable in medical images and requires some sort of enhancement to fit for the extraction of the diagnosis origin of the medical images.

The normal compression algorithm those are directly applicable in natural scene image if applied to medical image directly may result in loss of significant clinical information. Not only this, the conventional compression algorithm may not efficient lead to compress the medical data along with retaining the significant clinical information borne by the medical image. Usually, such types of images are quite heavier as compared to the natural scene image and hence find higher degree of challenges for long term archival and retrieval process in common servers in hospitals. It was also observed that existing compression technology cannot attain a comprehensive minimization of the size of bio-medical images as well as significant minimization of bit rate for transmission purpose. The last few decades has witnessed various sorts of compression algorithms towards reducing the optimal size of the bio-medical image along with retention of significant clinical information of higher importance for physician. This paper discusses only the few significant compression techniques previously attempted for compression bio-medical images. Majority of the prior techniques are studied with respect to lossless as well as lossy compression techniques. Some studies have interestingly addressed both the issues (lossless/lossy compression) together.

It was also noticed that majority of the prior research attempts were towards the direction of the lossless approach as communities pertaining to pathology was quite hesitant to implement lossy technique due to legal and authority issues. However, such research impediment was narrowed down, once the research community started visualizing the potential attributed of lossy techniques. Reviewing the literatures, it was found that there are dual mechanism of performing lossless image compression techniques that includes i) decorrelational technique and ii) image coding technique. The issues of redundancies are minimized by adopting medical image decorrelational technique. In the area of medical image processing, the redundancies can be represented as following:

2.1 Spectral Redundancies: It is a type of image redundancies that exists between multiple different spectral bands of an image.

2.2 Spatial Redundancies: It is a type of image redundancies that exists between all the neighbouring pixels.

2.3 Temporal Redundancies: It is a type of image redundancies that exists between any adjacent frames of a video (or image sequences).

However, the literatures show adoption of various techniques to perform minimization of redundancies existing within the bio-medical images. Some of such techniques are hierarchical interpolation, differential pulse code modulation, multiplicative auto regression, and bit-plane encoding. Some of the significant image encoding standards evolved in past and still in practice are Lempel-Ziv encoding, Huffman Encoding, Arithmetic encoding, and run-length encoding [8].

One of the common features of majority of the medical images is that it has potential correlation among the neighbouring pixels and therefore the probabilities of existing image redundancies are also quite high. Solution of such issues is identified by determining the minimal correlation depiction on the medical image. It is quite important to address the redundancies issues while dealing with medical image compression as if the image is not compressed, than such redundancies will occupy more channel capacity and unnecessary storage. Although there is much advancement in the data storage, much still the area of medical image processing, the challenges
still exist and continues to provoke the research communities to solve it. As majority of the medical records are stored in sorts of image or video files, most of them are of high definition multimedia files and formats, striking more challenging scenario for performing compression technique. Table 1 exhibits such challenging scenario of multimedia files in terms of storage and channel capacity. Hence performing compression technique using conventional algorithm may result in loss of significant data or less compatible for storage and efficient bandwidth requirements.

LITERATURE REVIEW

JPEG Predictive Lossless Standard

This is one of the most frequently adopted techniques in the area of medical image processing [12,13]. It consists of a predictor that integrates the values nearly to 3 neighboring pixels (Say A, B, and C) to formulate a forecasting of the image. The computation is performing to subtract the original value of the image and the difference is coded using lossless image compression. For this purpose, either Huffman or Arithmetic entropy coding process is used. Table 1 show the list of predictors which is used in this technique. One dimensional predictors can be represented by selection value of 1, 2, and 3, while two dimensional predictors are represented as Selection 4, 5, 6, and 7. The selection value 0 is used only for the purpose of differential coding in hierarchical mode. Any significant image precision of size 2-16 bits/image can be used by the encoder and can use any of the predictors except selection-value 0. The image precision is managed by the decoders along with other predictors too. A compression of 2:1 is generated by the lossless techniques exclusively for the colour image with reasonably sophisticated scenes.

Advanced Video Coding Scheme

Advanced video coding technique provides a better way to perform lossless image compression and is specifically designed for four dimensional medical images. The technique is based on advanced video encoding scheme e.g. H.264 as well as differential coding scheme for motion vectors. The scheme uses data redundancies in all the four dimensions thereby providing a better performance of compression. The redundancies within the volume are used by initially estimating the motion-compensated residual slices, which, in turn, are encoded using motion compensation across the temporal dimension. The quantitative experimental results on a large number of medical image datasets of varying modalities show significant improvements in compression ratio of up to three times that of current 2-D and 3-D state-of-the-art compression techniques, such as JPEG2000 and 3D-JPEG2000. The technique is highly flexible and is applicable in majority of the medical image compression techniques. The upcoming image formats and networking issues are handled to large extent by it.

Symmetry-Based Scalable Lossless Compression

Symmetry based scalable lossless image compression can be seen in study performed by Sanchez et al. [21]. The author has furnished a wavelet-based technique for the purpose of compression for three dimensional medical images. Fig.5 shows the block diagram of the proposed scalable lossless compression method. Data decorrelation is performed by a 2D integer wavelet transform applied on slices within the medical image volume. The resulting sub-bands are then compressed independently by first employing a block-based intra-band prediction method to reduce their energy, followed by a modified version of the EBCOT algorithm to achieve resolution and quality scalability. The novelty of this intrabandprediction method is in that it exploits anatomical symmetries within the structural data captured to predict the value of the wavelet coefficients on a block-by-block basis.

WAVELET TRANSFORM

Wavelets are mathematical functions defined over a finite interval and having an average value of zero that transform data into different frequency components, representing each component with a resolution matched to its scale [4]. The basic concept behind the wavelet transform is to represent any arbitrary function as a superposition of a set of such wavelets or basis functions. These basis functions are called the baby wavelets and these baby wavelets are obtained from a single prototype wavelet known as the mother wavelet by dilations or
contractions (scaling) and translations (shifts) [4]. While analyzing physical situations where the signal has discontinuities and sharp spikes, they are efficient and advantageous over traditional Fourier methods. Image compression, turbulence, human vision, radar and earthquake prediction are new wavelet applications developed in recent years. In wavelet transform the basic functions are wavelets. Wavelets tend to be irregular and symmetric. All wavelet functions, \( w (2k t - m) \), are derived from a single mother wavelet, \( w (t) \). This wavelet is a small wave or pulse like the one shown in figure below.

**Scaling**

Wavelet analysis produces a time-scale view of a signal. Scaling a wavelet means stretching (or) compressing it. The scale factor is used to express the compression of wavelets and often denoted by the letter \( a \). If the scale factor is smaller, the more compressed is the wavelet. The scale is inversely related to the frequency of the signal in wavelet analysis.

**Shifting**

Shifting a wavelet means delaying (or) hastening its onset. Delaying a function \( f (t) \) by \( k \) is mathematically represented as; \( f (t-k) \) [23].

**Discrete wavelet transform**

Calculating wavelet coefficients at each possible scale is a work which generates an awful lot of data. If the scales and positions are chosen based on powers of two, the so-called dyadic scales and positions, then calculating wavelet coefficients are efficient and just as accurate. This is obtained from discrete wavelet transform (DWT).

**SPIHT (SET PARTITIONING IN HIERARCHICAL TREES)**

In [1], a wavelet-based still image coding algorithm known as set partitioning in hierarchical trees (SPIHT) is developed that generates a continuously scalable bit stream. This means that a single encoded bit stream can be used to produce images at various bit-rates and quality, without any drop in compression. The decoder simply stops decoding when a target rate or reconstruction quality has been reached. In the SPIHT algorithm, the image is first decomposed into a number of sub bands using hierarchical wavelet decomposition. The sub bands obtained for two-level decomposition are shown in figure. The sub band coefficients are then grouped into sets known as spatial-orientation trees, which efficiently exploit the correlation between the frequency bands. The coefficients in each spatial orientation tree are then progressively coded bit-plane by bit-plane, starting with the coefficients with highest magnitude and at the lowest pyramid levels. Arithmetic coding can also be used to give further compression.

In general, increasing the number of levels gives better compression although the improvement becomes negligible beyond 5 levels. In practice the number of possible levels can be limited by the image dimensions since the wavelet decomposition can only be applied to images with even dimensions. The use of arithmetic coding only results in a slight improvement for a 5 level decomposition. The embedded zero tree wavelet (EZW) coding was first introduced by J.M Shapiro and has since become a much studied topic in image coding. The EZW coding technique is a fairly simple and efficient technique for compressing the information in an image. Our focus in this project is to analyze the Set Partition in Hierarchical Tree algorithm in the EZW...
Set Partitioning Algorithm

The SPHT algorithm is unique in that it does not directly transmit the contents of the sets, the pixel values, or the pixel coordinates. What it does transmit is the decisions made in each step of the progression of the trees that define the structure of the image. Because only decisions are being transmitted, the pixel value is defined by what points the decisions are made and their outcomes, while the coordinates of the pixels are defined by which tree and what part of that tree the decision is being made on. The advantage to this is that the decoder can have an identical algorithm to be able to identify with each of the decisions and create identical sets along with the encoder.

The part of the SPIHT that designates the pixel values is the comparison of each pixel value to $2n < c_{ij} < 2n+1$ with each pass of the algorithm having a decreasing value of $n$. In this way, the decoding algorithm will not need to passed the pixel values of the sets but can get that bit value from a single value of $n$ per bit depth level. This is also the way in which the magnitude of the compression can be controlled. By having an adequate number for $n$, there will be many loops of information being passed but the error will be small, and likewise if $n$ is small, the more variation in pixel value will be tolerated for a given final pixel value. A pixel value that is $2n < c_{ij}$ is said to be significant for that pass.

By sorting through the pixel values, certain coordinates can be tagged at "significant" or "insignificant" and then set into partitions of sets. The trouble with traversing through all pixel values multiple times to decide on the contents of each set is an idea that is incident and would take a large amount of time. Therefore the SPIHT algorithm is able to make judgments by simulating a tree sort and by being able to only traverse into the tree as much as needed on each pass. This works exceptionally well because the wavelet transform produces an image with properties that this algorithm can take advantage of. This "tree" can be defined as having the root at the very upper left most pixel values and extending down into the image with each node having four (2 x 2 pixel group) offspring nodes.

The SPIHT method is not an extension from the traditional methods of image compression, and it represents an important advance in the field. The SPIHT (set partitioning in hierarchical trees) is an efficient image coding method using the wavelet transform. Recently, image-coding using the wavelet transform has attracted great attention. Among the many coding algorithms, the embedded zero tree wavelet coding by Shapiro and its improved version, the set partitioning in hierarchical trees (SPIHT) by Said and Pearlman have been very successful. Compared with JPEG which is the current standard for still image compression, the EZW and the SPIHT methods are more efficient and are able to reduce the blocking artifact [14].

The method provides the following which requires special attention:

1) Good image quality and high PSNR especially for the colour images
2) It is optimized for progressive image transmission
3) Produces a fully embedded coded le
4) Simple quantization algorithm
5) Can be used for lossless compression
6) Can code to exact bit rate or distortion
7) Fast coding/decoding (nearly symmetric)
8) Has wide applications, completely adaptive
9) Efficient combination with error protection

These properties [19] are discussed in the following. Generally, different compression methods were developed that has at least one of the following properties but SPIHT really is outstanding since it has all those qualities simultaneously.

**Image Quality**

SPIHT has the very good ability when tested to find the minimum rate in reproducing the image that is indistinguishable with the original. SPIHT is even more perfect to encode the colour images as it allocates the bits automatically for the local optimality for the colour components. Basically other algorithms encode the colour components separately following the global statistics of the individual components. But SPIHT is different from this.

**EXPERIMENTAL RESULTS**

![Image](https://example.com/image1)

![Image](https://example.com/image2)

Table 1: Comparative Study

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CONCLUSION

This paper illustrates some of the standard prior techniques that has been studied in past to overcome the issues of compressing medical images. After reviewing the prior studies, it can be said that performance of medical image compression is highly dependent on compression ratio as well as perceptible quality of a reconstructed image. Reconstructed image with better perceptual quality will retain the information of the clinical importance to higher degree and will aid the diagnostic to have better result. The compression not being performed on the entire image with the understanding of the region of diagnostic importance. We described highly scalable SPIHT coding algorithm that can work with very low memory in combination with the line-based transform, and showed that its performance can be competitive with state of the art image coders, at a fraction of their memory utilization.

REFERENCES


