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SPECIAL ISSUE ON RECENT RESEARCH CHALLENGES IN BIO-MEDICAL APPLICATIONS

Improvement of Public Healthcare System through Band Effective Storage and Transmission of Color Medical Images

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Public healthcare system rely on medical images like magnetic resonance images, computed tomography, etc for effective diagnosis. Also remote expert's advice plays a significant role in improvement of the healthcare solutions. Thus, medical images acquired from radiological equipments and their storage play a major role in healthcare applications such as diagnosis of diseases, telemedicine and telecare. Storage and transmission of color medical images require compression which is a challenging task. In this paper, the compression algorithm for color medical images using ripplet transform and huffman coding is proposed. The objective of the proposed method is to obtain good quality compressed images by representing images at different scales and directions and to achieve high compression ratio (CR) with reduced transmission time. The simulation experiments have been conducted with the database consisting of variety of color medical images with varying sizes and resolutions. From the simulation results it is confirmed that the proposed algorithm yields better CR than existing algorithms and JPEG 2000 and also proves to be efficient in reduction in transmission time also. Hence, this algorithm will pave the path for improved system of telemedicine and band effective storage.

Key words: Public healthcare system, color medical image compression, compression ratio, Huffman coding, ripplet transform, transmission time.

The diagnosis based on the resultant medical images obtained by numerous radiological techniques from various portions of the body plays a vital role to save the life and cure diseases Due to this, the utility of medical images have been drastically increasing the memory requirements in healthcare centres. The advanced development in medical imaging systems such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET) and computed radiography (CR) produces huge amount of medical images of various anatomical structures. Emerging technological advancements to meet the memory requirements of day to day life seems not to fulfil the requirement of storage since data storage is proportionately increasing. Image compression is the ultimate solution to fulfil the storage requirements which may result in loss of some detail. In case of medical images, any lapse or loss in detail leads to a big issue in surgical, diagnostic and telemedicine applications. There exists need for lossless compression of these images for storage and communication purposes. Hence, an effective lossless compression algorithm is preferred.

Literature review

Different transforms proposed in literatures for compression and many of them do not concentrate on color medical images. Joint Photographic Experts Group (JPEG) 2000 is the best performance algorithm for compression[1] but it reduces the color value in images. Fourier transform is suitable only for an efficient representation of smooth images but not for images that contain edges. The 1D singularity in a function destroys

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the sparsity of Fourier series representation of the function. To overcome this, there came the wavelet transform which is able to efficiently represent a function with 1D singularity[2]. But the wavelet transform is unable to resolve two dimensional (2D) singularities along arbitrarily shaped curves. Since 2D wavelet transform is just a tensor product of two 1D wavelet transforms, it resolves 1D horizontal and vertical singularity respectively. The poor directionality of wavelet transform has undetermined its usage in medical images. To overcome the limitation of wavelet several other transforms are proposed such as contourlet[3], ridgelet[4] Discrete Cosine Transform (DCT)[5], shearlet[6], surfacelet[7], bandlet[8], block based hadamard [9], adaptive hadamard,[10]. All these transforms suffer from handling the curvy portions of medical images effectively well. In[11] curvelet transform represents two dimensional functions with smooth curve discontinuities at an optimal rate. In order to optimize the scaling law, the ripplet transform is proposed. The proposed ripplet transform[12] provides better performance than the directional transforms because it localizes the singularities more accurately and is highly directional to capture the orientations of singularities. In the previous work, the image compression for the gray scale medical images of various sizes is implemented using the ripplet transform with the combination of huffman coding algorithm[12] The proposed work aims at compressing color medical images and to achieve good CR with reduced latency. Faster evolution of wavelet lifting coefficients for fingerprint image provide better PSNR for various bit rates with set partitioning in hierarchical trees coder(SPIHT)[16] but it is alossy one. The discrete wavelet transform, 3D integer wavelet transform, Daubechis wavelet transform and lifting wavelet transform in combination with the entropy encoding are used to compress medical images[17]. These wavelet transforms are not so complex to compute but compression ratio is less. The lifting wavelet transform provides better results over other wavelet transforms[18]. The lifting transform in combination with the 1D-daubechis wavelet transform provides a better compression ratio and bits per pixel value but tested only for the natural Images[19]. These combinations of transforms didn't efficiently reconstruct the exact image after decompression process. Even though there is increased compression ratio but produce diminishing quality of the original Image[20]. Medical images like MRI images are having large amount of details in the curved surfaces. The application of existing transforms did not able to reproduce proper information about these curved surfaces and edge information[21]. Fractal image compression and other algorithms are presented here[22,23]. They don't focus much on PSNR, CR and other quality metrics. The problem with these literatures enumerate that the experimentation were not done with color medical images.

The rest of the paper will be organized as follows. After brief description about the transforms and encoding algorithm in section 2, the proposed model for compression is discussed in section 3.The experimental results and performance analysis are presented in section 4 and finally in section 5, the paper is concluded.

Technical background

Ripplet Transform

The ripplet transform proposed by Xu *et al*[13] is an attempt to break the inherent limitations of wavelet transform. It is a higher dimensional generalization of wavelet transform capable of representing images or two dimensional signals at different scales and different directions. Similar to curvelet, ripplet is also optimal for representing objects with C^2 singularities. Thus, edges within images have a sparse representation in ripplet space. Ripplet generalizes curvelet by adding two important parameters support c and degree d. The introduction of support c and degree d provides anisotropy capability of representing Singularities along arbitrarily shaped curves[12]. Each coefficient in the ripplet expansion of an image is the result of convolution of the associated ripplet and the image. The ripplet function can be generated as

$$\rho_{a\vec{b}\theta}(\vec{x}) = \rho_{a\vec{0}0}\left(R_\theta\left(\vec{x} - \vec{b}\right)\right) \quad ...(1)$$

where $R_\theta = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix}$ is the rotation matrix, which rotates h radians. $\vec{x}$, $\vec{b}$ are 2D vectors. The major axis referred as effective length pointing in the direction of ripplet and the minor axis referred as effective width which is orthogonal to the major axis represent the effective region. The effective region satisfies the property for its length and width as width $\approx$ c* length^d where c defines the support of ripplets and d determines the degree of ripplets. This property provides ripplets the capability of capturing singularities along arbitrary curves. In the ripplet system, effective region describes the characteristics of pixels at various scales, locations and directions.

The effective region tuned by support c and degree d is an evidence for the most distinctive property of ripplets known as general scaling. For c = 1 and d = 1, both axis directions are scaled in the same way. So, ripplet with d = 1 will not have the anisotropic behavior. For d >1, the anisotropic property is reserved for the Ripplet transform. For d = 2, ripplets have parabolic scaling, for d = 3, ripplets have cubic scaling and so forth. Therefore, the anisotropy provides ripplets the capability of capturing singularities along arbitrary curves. For each scale, ripplets have different compact supports such that ripplets can localize the singularities more accurately. Ripplet transform provides a hierarchical representation of images and can successively approximate images from coarse to fine resolutions. They have compact support in frequency domain and decay very fast in spatial domain and are well localized in both spatial and frequency domains. The magnitudes of their coefficients decay faster than other transform and provide higher energy concentration ability.

Encoding Process

SPIHT is good compression algorithm, but it requires image-level access and cannot eliminate the correlation inside the sub bands[14] Huffman coding is a statistical lossless coding technique that consists of techniques guaranteed to generate an exact replicate of input data stream. This could be used when storing database records, spreadsheets, or word processing file and image formats where the loss of even a single bit could be catastrophic. Medical images in which loss of detail leads to severe diagnostic failures could be compressed using this huffman coding and it is best suited[15]

Proposed work

The proposed work is interpreted as a block diagram in figure 1.In proposed methodology, an efficient algorithm of ripplet transform in combination with huffman coding is used to compress color medical images. Various color medical images such as MRI, CT and PET with different sizes have been acquired from the radiology sections of the reputed hospitals. All those images are the real anatomical structures of the humans taken at different portions of the body. Initially, the decomposition is done using the wavelet filter and the input color image is decomposed into low and high frequency sub bands.

$P_0 f(x,y)$

$$f(x,y) \mapsto (P_0 f(x,y), \Delta_1 f(x,y), \Delta_2 f(x,y), ...) \quad ...(2)$$

where is the high detailed component and low detailed components are denoted by

$$(\Delta_1 f(x,y), \Delta_2 f(x,y)....) \in \Delta_s f(x,y)$$

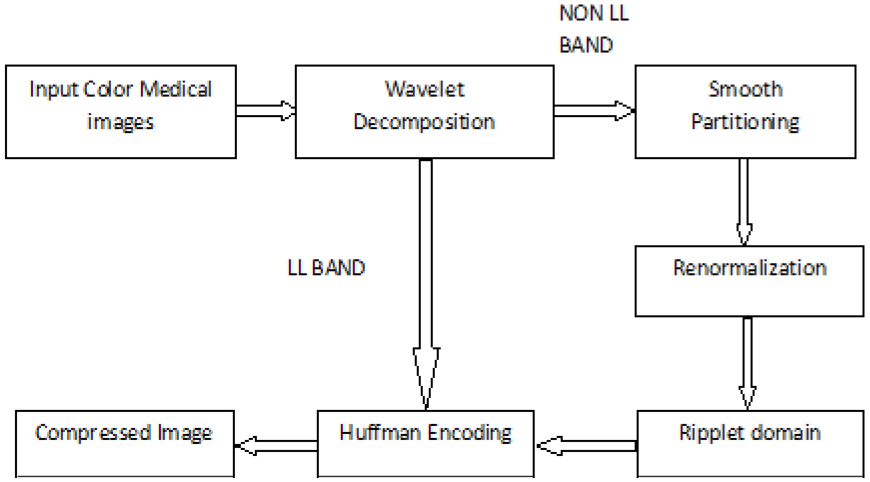

Fig. 1. Block diagram of proposed method

Normally there will result eight sub bands after decomposition by discrete wavelet teansform like d=0,1,2,3,4,5,6,7. Further, they undergo ripplet transformation via smooth partitioning, renormalization. Smooth partitioning divides the frequency bands into three subband groups denoted by S = 1, 2, 3. These S values corresponds to d values and they are related as follows. S = 1, d = 0, 1, 2, 3 ; S = 2 , d = 4, 5; and S = 3, d=6,7. Thus, the decomposed wavelet bands are partially converted into ripplet sub bands S1,S2 and S3 . Then the high frequency low detailed components are divided into smaller portions which are accomplished by multiplication of them with the smoothening function normally windows located around dyadic squares Q that will result in smooth division of the functions into squares. Multiplying the low frequency band with a windowing function produces a smooth dissection of the function into squares of side $2^{-s} * 2^{-s}$. These steps will produce the fruitful desired output while doing the inverse operation during reconstruction. The necessary condition for effective energy partition is the requirement of non-negative function and now each sub band is smoothly partitioned into squares. They are all squares and they should not intersect each other. There should not be any overlapping even at the edges or in the fragment. Then the squares are checked for the valid data and if there exists empty valued squares that are identified separately. They will have no energy and can be ignored and the remaining dyadic squares are then renormalized. Through renormalization, each dyadic square is centred and made into the unit square and all the pixels in these squares are ripplets in spatial domain. The direction and width of ripplets are determined by major and minor axes respectively. Width is always greater than length and this will provide the support for capturing singularities along arbitrary curves well in ripplet doamain. The natural capability of ripplet coefficients make the edges preserved quite effectively. Afterwards the huffman coding is applied to the ripplet coefficient to compress. The low frequent high detailed components are directy encoded by huffmann coder so as to avoid any loss of useful data.

The proposed compression procedure is shown in Figure 1 and is formulated as follows:

- Acquisition of color medical images $f(x, y)$ and use of text removal step, whenever required.
- The wavelet decomposition is applied to the filtered image using bi-orthogonal 9/7 filter. The input image is decomposed into a set of frequency sub bands.

$$f(x,y) \rightarrow (P_0 f(x,y), \Delta_1 f(x,y), \Delta_2 f(x,y), \ldots\ldots)$$

Where $P_0(x, y)$ is the lowest frequency component, $\{\Delta_1 f(x,y), \Delta_2 f(x,y), \ldots\} \in \Delta_s f(x,y)$ is the high frequency component. Decomposed wavelet bands j are partially reconstructed into ripplet sub bands as $j \in \{2s, 2s+1\}$.

Smooth partitioning

Dissects the low frequency band into small partitions by defining a grid of dyadic squares.

$$Q(s,k1,k2) = \left[\frac{k1}{2^s}, \frac{k1+1}{2^s}\right] * \left[\frac{k2}{2^s}, \frac{k2+1}{2^s}\right] \bullet Q\ s \quad \ldots(3)$$

Multiplying the low frequency bands with the windowing function produces smooth dissection of function into squares of side $2^{-s} \times 2^{-s}$.

$$S_Q\ h_Q = w_Q \times P_0 f(x,y) \quad \ldots(4)$$

Renormalization

Renormalize each resulting dyadic square by centering each square to unit squares $[0,1] \times [0,1]$

$$(T_Q f(x,y))(x_1, x_2) = 2^s f(2^s x_1 - k_1, 2^s x_2 - k_2) \quad \ldots(5)$$

Ripplet domain

Analyze each square in ripplet domain and encode resulting coefficients using Huffman algorithm.

Performance evaluation

The performance of proposed algorithm is carried out in MATLAB with 34 sets of medical images acquired from recognized medical centres and only four among them for sample are shown in figure 2.All the tested images are taken from the real anatomical structure of humans. In Figure 3, the intermediate stage wise results are shown and the experimental results are presented in tables 2 and 3. The experimentation is carried out at 1.2 bits per pixel (bpp).

From the results of experimentation at 1.2 bpp, it is clear that there is increment in compression ratio and decrement in transmission time when compared with the combinations of ripplet-SPIHT, ripplet-RLE and JPEG 2000. It outperforms the standard JPEG 2000 in terms of transmission time and consumption of bandwidth.

CONCLUSION

As there is a rapid development in telemedicine, the storage bandwidth requirement especially for color images also increases rapidly.

Table 1. Comparison of compression ratio at 1.2 bits per pixel (bpp)

Color Medical images	Ripplet +SPIHT	Ripplet +RLE	JPEG 2000	Proposed work Ripplet + Huffman
Rib cage MRI	12.03	14.69	14.98	15.726
Lungs MRI	12.27	18.34	18.96	19.575
Kidney MRI	9.76	15.06	16.24	15.977
Brain MRI	11.78	8.198	12.50	15.590
CT images (10 sets)	Average of 10.75	Average of 11.3	Average of 11.7	Average of 12.25
Ultrasound, PET images (10 sets)	Average of 11.5	Average of 11.8	Average of 11.98	Average of 12.80
DICOM images (10 sets)	Average of 10.53	Average of 11.50	Average of 11.90	Average of 13.00

Table 3. Comparison of Transmission Time

Color Medical Images	JPEG 2000(sec)	Proposed work (Ripplet + Huffman)(sec)	Decrease in time(%)
Rib cage	3.765	3.125	16.99
Lungs MRI	4.125	3.978	3.51
Kidney	3.976	3.766	5.24
Brain	4.452	4.321	2.93
CT images (10 sets)	Average of 4.2	Average of 4.05	3.57
Ultrasound, PET images (10 sets)	Average of 3.9	Average of 3.56	8.72
DICOM images (10 sets)	Average of 4.12	Average of 4.03	2.18

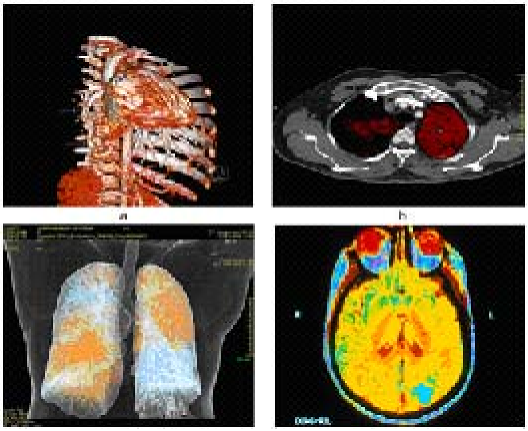

Fig. 2. Sample Input medical images a.Ribcage MRI b. Kidney MRI c. Lungs MRI d. Top view brain MRI

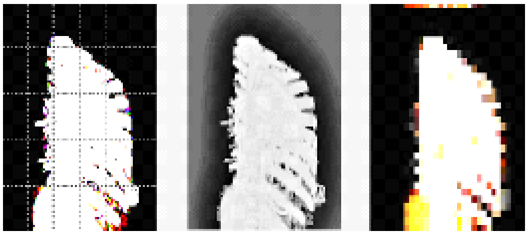

Fig. 3. Ripplet transform for rib cage MRI 3a. smooth partitioning,3b renormalization,3c. ripplet domain

The proposed efficient color medical image compression method helps to alleviate this problem with the increased compression ratio values and reduced time. Both are well improved than the other methods and are best suited to cater the requirements of telemedicine and band effective storage applications which will certainly improve the healthcare system.

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