



AN INTELLIGENT METHOD FOR COMPRESSION OF MEDICAL IMAGES IN TELEMEDICINE

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ABSTRACT

The medical images can be transmitted from patient room to remote medical centers for diagnosis through the wireless network in telemedicine system. In this connection, the existing methods are unable to achieve better Compression Ratio (CR) while maintaining the lower levels of distortion. An intelligent scheme has been developed for achieving a higher compression ratio and low distortion rate. The two different clusters, Region of Interest (ROI) and Non ROI are obtained by segmentation process. Integer wavelet transform technique and Bit Plane Based Parallel Set Partitioning In Hierarchical Tree (BPBPSPiHT) are applied to lower energy cluster and the curvelet transform followed by Adaptive Arithmetic Coding are applied to ROI. In the reconstruction part, the compressed higher energy cluster (ROI) is super imposed on compressed lower energy cluster by the fusion technique. The quality measures of the proposed model are compared with different techniques.

KEYWORDS: Curvelet transform, BPBPSPiHT, Compression Ratio, and PSNR.



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INTRODUCTION

Health care facilities available for everybody at any place are very difficult because of the huge population in India. Cities and towns cover 80% of secondary and tertiary healthcare facilities distant from rural area. Medical images play a vital role in accurate diagnosis with more development of modern medical industry (telemedicine) by physicians and scientists. However, the large amount of capacity of the storage devices is needed to save the medical images. The researcher researches an efficient medical image compression to solve these problems. The reconstructed image is similar to original one after compression. This scheme achieves a modest compression rate. It is used in medical applications because of no loss of image data. The block diagram of medical

image storage and transmission is given in Figure 1. The authors have proposed a compression scheme adopted for video compression¹. An optimized medical image compression algorithm based on wavelet transform and improved vector quantization has proposed by author H. Jiang². The authors have presented an image compression using digital curvelet transform³. Curtis J.Schmitt⁴ has discussed two methods of lossless compression, differential pulse-code modulation (DPCM) and arithmetic coding. Both DPCM and arithmetic coding are more computationally intensive than most other lossless compression methods and this method is not very widely used.

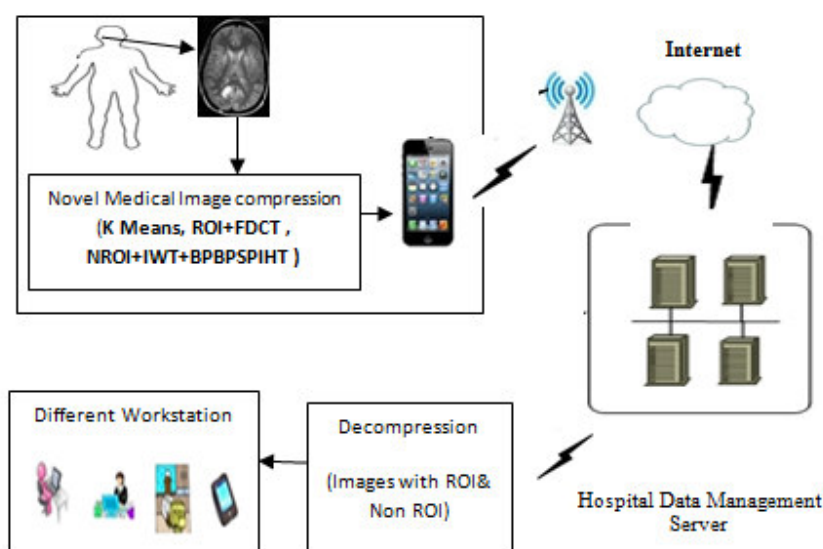


Figure 1
Usage scenario of telemedicine

Yuying⁵ have proposed a new image pre-processing for improved performance of entropy coding. Sivanantha Raja⁶ has presented the new technique of curvelet transform in combination with Lifting Scheme and Huffman coding is used to compress medical images. An advanced curvelet transform based image compression using dead zone quantization has proposed by Rammohan⁷. A novel image compression

algorithm using the second generation of curvelet transform and support vector machine (SVM) are integrated for compression of medical image⁸. First, the curvelet coefficients are obtained from original image using fast discrete curvelet transform. Then different scales of quantized curvelet coefficients were selected for lossy compression and entropy encoding.

MATERIALS AND METHODS

The algorithm⁹ is modified to increase the compression ratio (CR) and Peak signal to noise ratio (PSNR). A ROI part of an image is separated from medical image by an improved k means segmentation algorithm¹⁰. The region of interest (cancer) is compressed by Curvelet transform¹¹ and arithmetic coding. The Non region of interest (Non cancer) is compressed by Integer wavelet transform followed by BPBPSPIHT for better compression ratio. Finally the compressed higher energy cluster (ROI) is super imposed on compressed lower energy cluster by the fusion technique. The experimental result shows superior reconstruction and achieves better compression ratios.

(i) Modified K-means segmentation

Medical image segmentation¹² is the process of dividing an image into cancer (ROI) and non-cancer region to improve quality of medical diagnosis. The threshold is taken by the user, this technique is separating ROI and non ROI parts of an image which were applied to lossless and lossy compression techniques.

(ii) ROI Compression

The lossless compression algorithms¹³ is used to compress ROI part of an image. The near lossless compression algorithms consist of fast curvelet transform and adaptive arithmetic coding. The curves and edges in the medical image are enhanced by discrete curvelet transform and adaptive arithmetic coding provides a good peak signal to noise ratio value .The block diagram of encoder and decoder is given in Figure 2.

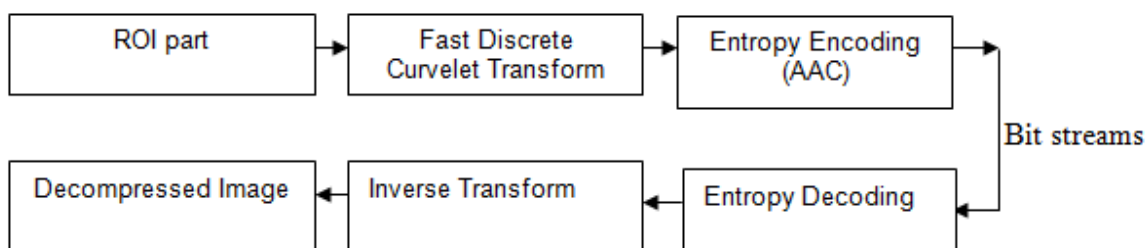


Figure 2
Encoder and decoder of ROI compression

1. Curvelet Transform

Curvelet transform is a non-adaptive technique which is different from other transforms with respect to degree of localization in orientation and variation of scale. A primary task is to

extract the features such as points, lines, edges, and textures from an image. The Curvelet function in frequency domain is given by equation 1.

$$\Phi_{j,k,l}(\xi) = U_j(R_{\theta_{j,l}}, \xi) \cdot e^{-i(b_k^{j,l}, \xi)} \quad (1)$$

It is supported inside the polar wedge with radius $2^{j-1} < r \leq 2^{j+1}$ and

angle $2^{-\frac{l}{2}}\pi(-1-l) < \omega \leq 2^{\frac{l}{2}}\pi(-1-l)$.

where $U_j(R_{\theta_{j,l}}, \xi)$ represent scaled window function, $R_{\theta_{j,l}}$ represent rotational matrix, $b_k^{j,l}$ represent position in the curvelet transform. The inverse Curvelet transform is defined by equation 2.

$$f = \sum_{j,k,l} \langle f, \Phi_{j,k,l} \rangle \Phi_{j,k,l} \quad (2)$$

The term $\langle f, \Phi_{j,k,l} \rangle = c_{j,k,l}(f)$ is called as curvelet coefficient which is given by equation 3.

$$c_{j,k,l}(f) = \int_{\mathbb{R}^2} \hat{f}(\xi) U_j(R_{\theta_{j,l}}, \xi) \cdot e^{i(b_k^{j,l}, \xi)} \quad (3)$$

The transform coefficients are encoded by AAC.

2. Adaptive Arithmetic Encoder

The curvelet coefficients are applied to lossless coding (AAM). It is the method of representing frequently occurring pixel values into fewer bits. In arithmetic coding¹⁴, single codes are used to represent a string of character, thereby reducing the file size.

(iii) NROI Compression

The Integer wavelet transform followed by BPBPSPiHT and Adaptive arithmetic encoder are used to compress the Non ROI part of an image. The non-importance of the medical image is fully compressed by this technique. The block diagram of encoder and decoder is given in Figure 3.

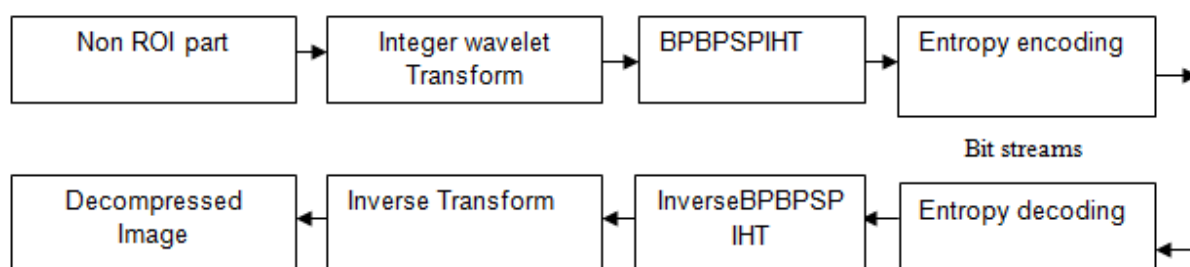


Figure 3
Encoder and decoder of Non ROI compression

1. Integer wavelet Transform

The bio-orthogonal wavelet transform have been used because it is symmetric, almost orthogonal and gives the best results for medical images. The image is decomposed into different frequency components. The Lifting is performed to give a precise output coefficient. Integer wavelet Transform coefficients are applied to lossy image coder.

2. Lossy Image coder

a. Bit Plane Based Parallel Set Partitioning In Hierarchical Tree (BPBPSPiHT)

The widely used compression algorithm for wavelet transformed images is Set-partitioning in hierarchical trees (SPIHT). Slow processing speed is the main drawback of SPIHT due to its dynamic processing order that depends on the

image contents. The original SPIHT algorithm processes wavelet coefficients in a dynamic order that depends on the values of the coefficients. Thus, it is not easy to process multiple coefficients in parallel and consequently, it is difficult to improve the throughput of the original SPIHT. In order to increase the throughput, a bit-plane parallel SPIHT encoder architecture¹⁵ was proposed. This modified SPIHT (BPBPSPiHT) decomposes integer wavelet coefficients bit-plane by bit-plane and then processes multiple bit-planes independently in a parallel manner. Then, the results of multiple bit-planes are merged into a single bit stream. The proposed algorithm for a single 4 × 4-bit block is described in Figure.4.

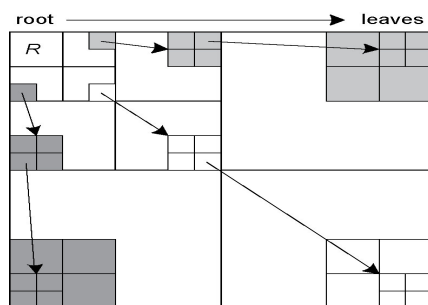


Figure 4
Structure of BPBPSPIHT encoding method

The 4×4 -bit block is denoted by A that is decomposed into four 2×2 blocks. B represents a 2×2 -bit block and n represents the bit-plane number. BPBPSPIHT consists of three passes that output refining bits, sorting bits, and first refining bits, respectively.

According to the type of generated bits, these three passes are called refinement pass (RP), sorting pass (SP), and first refinement pass (FRP), respectively. The algorithm of proposed method is given below

Refinement Pass(RP)

for each $B \in A$ such that $S_{n+1}(B)=1$ do
 for each $w(i) \in B$ do
Output $S_n(w(i))=$ the n^{th} bit of $w(i)$ magnitude bit
If $S_{n+1}(w(i))=0 \wedge S_n(w(i))=1$ **then**
output the sign of $w(i)$ sign bit
Set $S_n(B)$ equal to 1

Sorting Pass(SP)

If $S_{n+1}(A \cup D(A))=0 \sim (\text{parent}(A) \wedge S_n(\text{parent}(A))=0)$ **then**
Output $S_n(A \cup D(A))$ sorting bit
If $S_n(A \cup D(A))=1$ **then**
for each $B \in A$ such that $S_{n+1}(B)=0$ **do**
output $S_n(B \cup D(B))$
if $S_n(B \cup D(B))=0$ **then**
Set $S_n(B)$ equal to 0
Else
Set $S_n(B)$ equal to 1
Else
for each $B \in A$ such that $S_{n+1}(B)=0$ **do**
Set $S_n(B)$ equal to 0

First Iteration Refinement Pass(FIRP)

for each $B \in A$ such that $S_n(B)=1$ and $S_{n+1}(B)=0$ **do**
Set $S_n(B)$ equal to 1
for each $w(i)$ in B **do**
Output the n^{th} bit of $w(i)$ magnitude bit
If $S_n(w(i))=1$ **then**
output the sign of $w(i)$ sign bit

(iv) Fusion

Finally the compressed higher energy cluster (ROI) is super imposed on compressed lower energy cluster by the fusion technique. This technique reduces the size of medical image and increases the quality of the medical image by preserving the detailed information.

RESULTS AND DISCUSSIONS

The real time medical images acquired from patients were tested by proposed algorithm. The each medical image size was 256x256 pixels. The quality of the medical images ¹⁶ is improved by proposed algorithm. The performance of the proposed algorithm is evaluated in terms of quality measures such as MSE, PSNR, CR, compression time and Decompression time results for different medical images. The PSNR in terms of decibels (dBs) is given by:

$$PSNR=10 \text{ Log}_{10}\left(\frac{255^2}{MSE}\right) \quad (4)$$

Figure 5 show the plot of PSNR for each image with different methodology. The PSNR values of the proposed method for different medical images from plot are very high as compared to the existing method. The time period for compression and decompression and CR for medical images using proposed method are

shown in Table 1. The decompression time period for the existing algorithm and the proposed algorithm are almost same. Thereby the quality was maintained without any loss. The capability of compression system is characterized by compression ratio which is calculated as

$$\text{Compression Ratio} = \frac{\text{size of the compressed image}}{\text{size of the original image}} \quad (5)$$

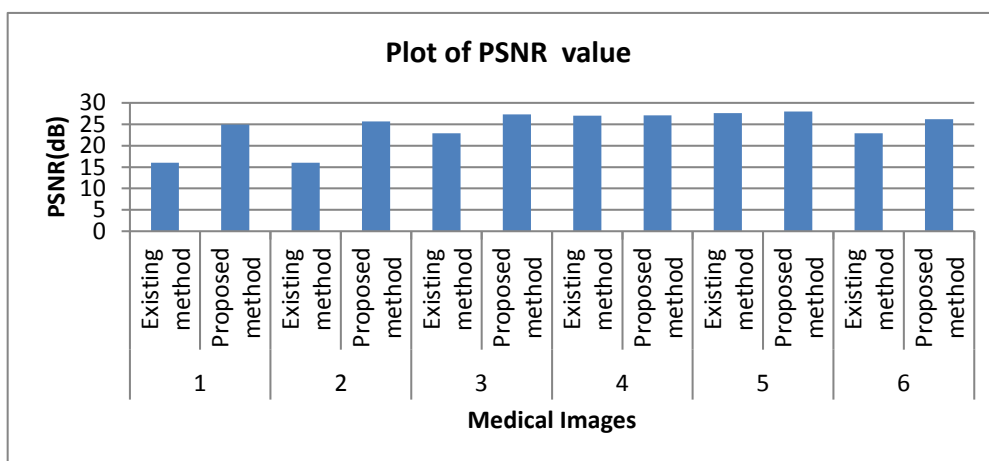


Figure 5
Plot of PSNR and time period for different methods

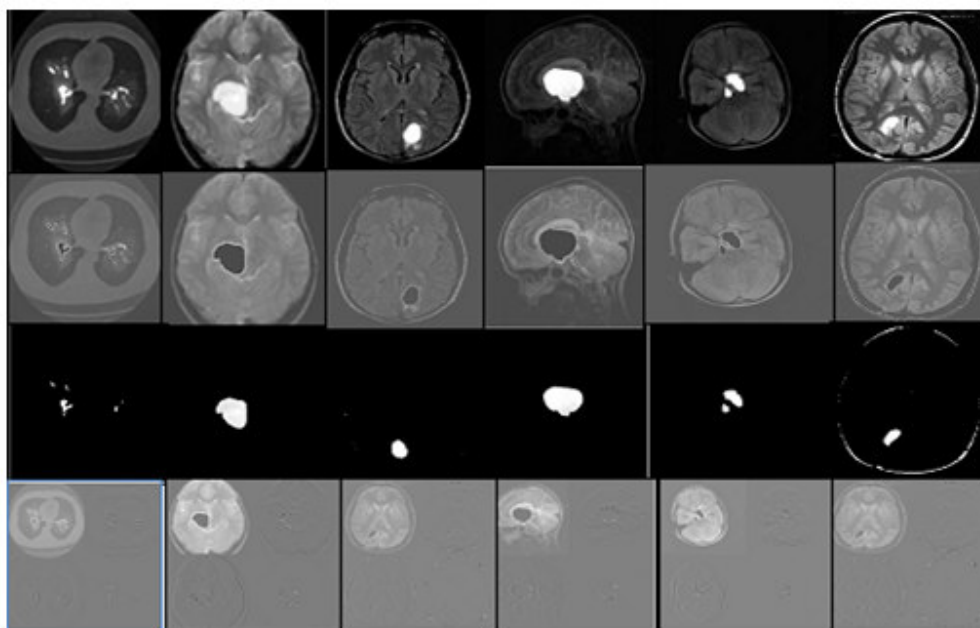


Figure 6

Input medical images, Non ROI parts of medical images, ROI parts of medical images, Integer wavelet transform of NROI parts of medical images, Reconstructed medical images

The simulated outputs of proposed method are discussed below; Figure 6 shows the input medical images for the compression, ROI and Non ROI parts of an image, Integer wavelet transformed image and finally the reconstructed images using the proposed method.

Table 1

Comparison of proposed method on different medical images in terms of quality parameters

S.No	Methods	CR	PSNR (dB)	CT (sec)	DCT (sec)
1	ROI+DPCM,NROI+Contourlet+HC	2.0	16.0	02.08	08.32
	ROI+ Contourlet+AC,NROI+BPBPSPIHT	1.2	24.9	12.16	10.72
2	ROI+DPCM,NROI+Contourlet+HC	1.1	16.0	02.12	08.34
	ROI+ Contourlet+AC,NROI+BPBPSPIHT	1.1	25.7	12.12	10.94
3	ROI+DPCM,NROI+Contourlet+HC	1.0	22.9	02.08	08.75
	ROI+ Contourlet+AC,NROI+BPBPSPIHT	1.1	27.3	11.41	10.18
4	ROI+DPCM,NROI+Contourlet+HC	1.0	27.0	02.12	10.34
	ROI+ Contourlet+AC,NROI+BPBPSPIHT	1.1	27.1	12.60	11.38
5	ROI+DPCM,NROI+Contourlet+HC	2.0	27.6	2.05	8.87
	ROI+ Contourlet+AC,NROI+BPBPSPIHT	1.2	28.0	11.15	09.98
6	ROI+DPCM,NROI+Contourlet+HC	2.0	22.9	2.15	11.0
	ROI+ Contourlet+AC,NROI+BPBPSPIHT	0.7	26.2	19.8	18.7

* HC-Huffman, AC-Arithmetic coding, CT-Compression time, DCT-Decompression time

The compression results of the proposed method is shown that it provides better compression ratio with good quality compared to existing methods¹⁶.

CONCLUSION

Thus, K means algorithm is used for effective detection of the ROI and Non ROI part of an image. The newly developed scheme based on curvelet transform followed by lossless coding (AAC) for ROI image compression and integer wavelet transform followed by BPBPSPIHT coder for lossy compression. The implementation results gives better

reconstruction and high compression ratios compared to the existing methods. The parameters like compression and decompression time and compression rate are evaluated. It shows that the PSNR is much higher in the proposed method than the existing methods. The system proved to be very efficient and accurate with the highest compression rate as compared to the various techniques employed in the literature.

REFERENCES

1. Vander Heyden, J.E. K.Inkpen, M.S.Atkins, and M.S. T.Carpendale, Exploring presentation methods for tomographic medical image viewing, *Artificial Intelligence. Med.*, 22(.2), 89-109,(2002).
2. Huiyan.HJiang, ZhiyuanZMa,Yang YHu Benqiang BYang ,LiboLZhang, Medical image compression based on vector quantization with variable block sizes in wavelet domain, *Comput Intell Neurosci*, doi:10.1155/2012/541890,1-8,(2012).
3. Awais Mansoor and AtifBin Mansoor,On image compression using digital curvelet transform, in *Proc. IEEE Crown Com*, 1–6,(2012).
4. Curtis J. Schmitt, Lossless Image Compression,in *Proc. IEEE Globe com*, 19–24(2009).
5. Yuying Zhen¹, Chun Qi, Guanzhen Wang, A New Image Pre-processing for Improved Performance of Entropy Coding, in *Proc. IEEE DySPAN*, 259–268,(2005).
6. Sivanantha Raja A.,D.Venugopal,S.Navaneethan, An Efficient Colored Medical Image Compression Scheme using Curvelet Transform, in *Euro Journals Publishing*, 80(3),416-422,(2012).
7. Rammohan T., K. Sankaranarayanan, An Advanced Curvelet Transform Based Image Compression using Dead Zone Quantization, *Euro Journals Publishing*,79(4).486-496,(2012).
8. Yuancheng Li, Qiu Yang, Runhai Jiao,A Novel Image Compression Algorithm Using the Second Generation of Curvelet Transform and SVM, *Global Congress on Intelligent Systems*, IEEE, 117-119,(2009).
9. Kiran Bindu, Anita Ganpati, Amankumarsharma , A Comparative Study of Image Compression Algorithms, *International Journal of Research in Computer Science*,2(5), 37-42, (2012).
10. Bai X., J.S. Jin, and D. Feng , Segmentation-based multilayer diagnosis lossless medical image compression,in *Proc. ACM Int. Conf.*,100(1),9-14,(2004).
11. Emmanuel J. Candptes and David L. Donoho, Curvelets, Multiresolution Representation, and Scaling Laws, *Wavelet Applications in Signal and Image Processing*,Proc.SPIE, 4119-4124,(2004).
12. Chunfei Zhang, Zhiyi Fang, An Improved K-means Clustering Algorithm, *Journal of Inf & Comp Sci*,.10(1), 193–199,(2013).
13. Gonzalez R.C.,Woods R.E, *Digital Image Processing*, 3rd Edition, Pearson Education,484-820,(2002).
14. David Salomon ,Data Compression: *The Complete Reference*, 3rd Edition, Springer,300-600,(2004).
15. Jin, Yongseok, and Hyuk-Jae Lee., A Block-Based Pass-Parallel SPIHT Algorithm, *IEEE Transactions on Circuits and Systems for Video Technology*, 22(7):1064-1075, (2012).
16. Vora V.S., Prof. A.C.Suthar, Y.N.Makwana and S.J.Davda,Analysis of Compression Image Quality Assessments, *International journal of Advanced Engineering and Applications*,.4(5), 2230-2235,(2000).