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Medical Image Compression using Modified Curvelet Transform

Saravanan.S*
Dept of Information Technology,
Karunya University, Coimbatore, India
saranrulz671@gmail.com

D.Sujitha Juliet
Dept of Information Technology,
Karunya University, Coimbatore, India
sujitha_juliet@yahoo.com

K. Shiby Angel
Dept of Information Technology,
Karunya University, Coimbatore, India
shiby_angel@yahoo.co.in

Abstract: An adaptive image-coding algorithm for compression of medical images in the wavelet domain is determined using a modified curvelet transform with a SPIHT encoder. The objective results tested for different medical images show that the proposed scheme attains high PSNR and high compression ratio as compared with existing image compression methods.

Keywords: Haar Wavelet transform, Curvelet transform, Medical Image compression, SPIHT

I. INTRODUCTION

Medical images are much important in the field of medicine. The trend in medical imaging is increasing toward direct digital image acquisition. Currently, many modalities such as CT (computed tomography), MRI (magnetic resonance imaging), PET (positron emission tomography) and SPECT (single-photon emission computed tomography) produce images directly in digital form. These digital images carry prohibitive amounts of data. For storage and communication purposes, compression is necessary.

Image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible. Many current compression schemes provide a very high compression rate but with considerable loss of quality. But in the case of medical field there is a need to achieve no deterioration in image quality. Since there are many schemes which provides lossless compression for medical images, modified curvelet transform is able to efficiently represent two dimensional (2D) singularities along arbitrarily shaped curves [1]. In this paper an efficient method for compression of medical images is proposed, which uses a modified curvelet transform with a SPIHT encoder.

II. REVIEW OF LITERATURE

Compression is meant for storage and communication purposes. Even though there are many compression schemes which provide a very high compression rate but there is considerable loss of quality. Medical imaging which has a great impact on the diagnosis of diseases and surgical planning need long-term storage and efficient transmission.

Wavelet transform is able to efficiently represent a function with 1D singularities. Although the discrete wavelet transform (DWT) has established an excellent reputation for mathematical analysis and signal processing, the typical wavelet transform is unable to resolve two dimensional (2D) singularities along arbitrarily shaped curves. The curvelet transform has been very efficient for many different applications in image processing because it can resolve 2D singularities along smooth curves. It uses parabolic scaling law to achieve anisotropic directionality. The first 3D discrete Curvelet transform preserves the important properties, such as parabolic scaling, tightness and sparse representation for singularities of codimension one [1]. It is evident that curve functions are effective in representing functions that have discontinuities along straight lines [2]. Normal wavelet transforms fail to represent such functions effectively. A multiresolution geometric analysis (MGA), named Curvelet transform [6], was proposed in order to overcome the drawbacks of conventional two-dimensional discrete wavelet transforms.

The introduction of wavelets gave a different dimension to the compression. But there are some limitations of wavelets while handling the line and curve singularities in the image [3]. Wavelet performs the least and is also affected by the blocking artifacts. Curvelet Transform gives the best performance for PSNR [3,4] and the subjective visual inspection shows that the Curvelet is the best for Compression when compared to wavelet [4].Curvelet Transforms are more suitable for the image data to represent the singularities over geometric structures in the image.

Curvelet provides stable, efficient, and near-optimal representation of smooth objects having discontinuities along smooth curves [5]. Curvelet, a multiscale directional transform allows an almost optimal non adaptive sparse representation of objects with edges. Its applications include image/video processing, seismic exploration, simulation of partial different equations, and compressed sensing [6].

M.J. Fadili and J.L. Starck have analyzed an image with different block sizes, using curvelet transform [7]. This analyses imposes a relationship between the width and length of the important frame elements so that they are anisotropic and obey approximately the parabolic scaling law width ≈ length^2 [7,8]. Thus Curvelets are a multiscale system [10, 9] in which the elements are highly anisotropic at fine scales, with effective support shaped according to the parabolic scaling principle. An extension to the 2D transform was developed recently known as the 3D curvelet transform. This resulting curvelet frame preserves the important properties, such as parabolic scaling, tightness and sparse representation for singularities [11].

Over the past few years, a variety of sophisticated wavelet-based methods for image compression have been developed and implemented. Haar wavelet transform is simplest wavelets transform [12]. Compression with this wavelet transform is scalable as the transform process can be applied to an image as many times as wanted and hence very high compression ratios can be achieved [13]. . It bears various properties like orthogonality, linear phase, compact support, perfect reconstruction, high imperceptibility and robustness [14,24].

Set partitioning in hierarchical trees (SPIHT), an efficient implementation of EZW [16] provides even better performance [15] than the other extensions of EZW. The main advantage of SPIHT is that it is fully progressive [17]. It provide significantly better quality and compression with spatial scalability [19]. In the recent years a 3D lossless SPIHT encoder was developed which produces up to 30-38% decrease in compressed file sizes compared to 2D lossless image compression algorithms [18]. SPIHT provides salient features such as better quality, visually superior and low computational effect when compared with other encoding algorithms such as JPEG, EBCOT, and BISK [20,21,22]. Thus SPIHT encoder provides features for simple and effective method for grayscale image compression [23].

III. BACKGROUND

A. Haar Transform:

The Haar transform proposed in 1910 by a Hungarian mathematician Alfred Haar [25] is one of the earliest transform functions used in image processing. The haar transform (HT) is one of the simplest and basic transformations from a space domain are a local frequency domain. This method reduces the calculation work and it is compact, dyadic and orthonormal [26].HT decomposes each signal into average and difference components. The first level of approximation $\boldsymbol{a}^1 = \left(a_1, a_2, \cdots, a_{N/2}\right)$ is defined as

$$a_m = \frac{X_{2m-1}+X_{2m}}{\sqrt{2}} \qquad (1)$$

for $m = 1,2,3,\cdots,N/2$, where X is the input signal. The basic vector of haar matrix bears various properties like orthogonality, linear phase, compact support, perfect reconstruction.

B. Modified Curvelet Transform:

Curvelet, a multiscale transformation is to represent a curve as a superposition of functions of various lengths and widths obeying the parabolic scaling law width » length^2 [7,8]. Curvelet transform works by first decomposing the image into sub bands, i.e., separating the object into a series of disjoint scales and each scale is then analyzed by means of a local ridgelet transform.

In the modified curvelet transform this decomposing is done with a haar wavelet where the image is decomposed into approximation and detail. These sub bands are then analyzed by ridgelet transform. Haar transform is the simplest of the wavelet transforms. Decomposing with haar wavelet transform is scalable and hence very high compression ratios can be achieved.

C. SPIHT Encoding:

Once the decomposition using modified curvelet is done, the next phase is to code the resulting coefficients into an efficient result. Even though there are many encoding algorithms for image compression, one of the most efficient algorithms that provides salient features such as better quality, visually superior, fast coding and decoding, low computational effect and low-bit rate performance, is SPIHT algorithm .

The coefficients are further encoded using SPIHT algorithm which exploits the dependencies between the location and value of the coefficients across sub bands. The sub band coefficients are then grouped into sets known as spatial-orientation trees, which exploits efficiently over the correlation between the frequency bands. Then the coefficients in each spatial orientation tree are then progressively coded from the most significant bit-planes (MSB) to the least significant bit-planes (LSB), starting with the coefficients with the highest magnitude and at the lowest pyramid levels. This pyramid structure is commonly known as spatial orientation tree. The SPIHT algorithm proceeds the top coefficients in the pyramid structure using a progressive transmission scheme. This method allows obtaining a high quality version of the original image from the minimal amount of transmitted data.

IV. PROPOSED METHOD

In the proposed method as shown in figure 1 the input image is decomposed using a modified curvelet transform which works in four steps: (1) Sub band Decomposition using haar-wavelet (2) Smooth Partitioning (3) Renormalization (4) Ridgelet Analysis. After the curvelet transform is applied to an image, the proposed algorithm works by partitioning the decomposed image into significant and insignificant partitions [25] based on the following function:

$$s_n(T) = \begin{cases} 1, \max |C_{i,j}| \geq 2^n \\ 0, otherwise \end{cases} \qquad (2)$$

where $S_n(T)$, is the significance of a set of co-ordinates , $C_{i,j}$ represents the combination of curvelet transformed coefficients and the coarsest coefficients at coordinates (i,j) .it is classified into three sets, namely the list of insignificant points (LIP), the list of significant points (LSP), and the list of insignificant sets (LIS) based on the threshold value.

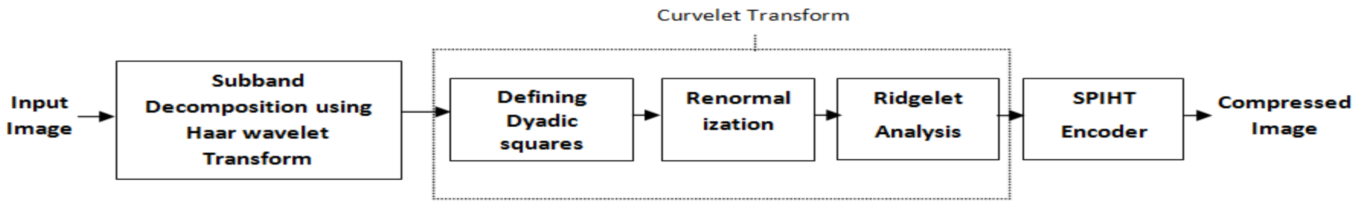
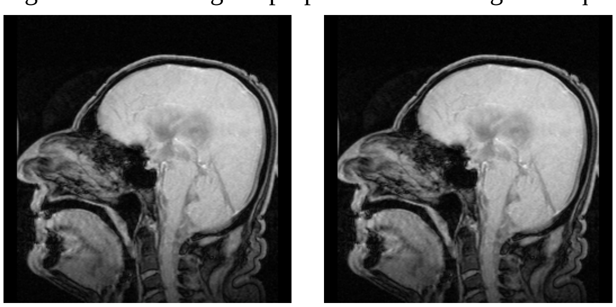


Figure 1. The block diagram of the proposed compression method

V. PERFORMANCE EVALUATION

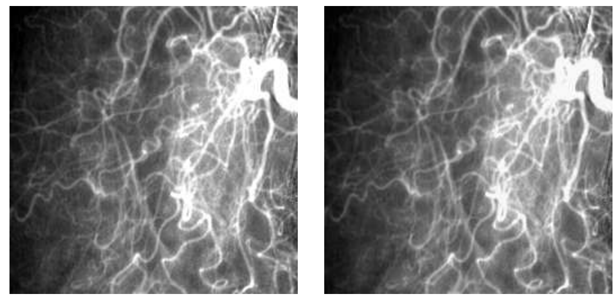
The performances are evaluated for the proposed algorithm using a set of 3 medical images of size (256X256).The quality of the compressed images has been attained using different metrics and the efficiency of the proposed method is evaluated by comparing it with Curvelet SPIHT [2]method and Haar SPIHT [26] based compression method. Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Bits per Pixel (BPP), Compression ratio (CR) and Computational time (CT) are used as different metrics. Table1 shows the performance comparison of different parameters for various techniques. Original and compressed images are shown in Figure 2.

Figure 4 and Figure 5 show the average values of PSNR (dB) and MSE (dB) obtained for the several medical images as stated in Table 1. Figure 6 depicts the CR of compressed images obtained using the proposed and existing techniques.



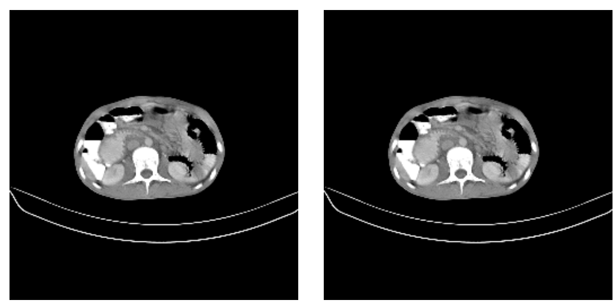
a) Original Image b)compressed Image

i) Sagittal MRI of Head



a) Original Image b)compressed Image

ii) Sagittal STIR –axial View of cerebral



a) Original Image b)compressed Image

iii) Pancreas

Figure 2 shows the Set of medical images used for evaluation. i) Sagittal MRI of Head. ii) Sagittal STIR –axial View of cerebral. iii) Axial CT Image of Pancreas.

Table 1 Performance comparison of different parameters for various techniques

Images	Compression methods	PSNR	CR	MSE	BPP	CT
	Curvelet –SPIHT	43.88	11.07	2.59	0.89	0.57
	Haar- SPIHT	44.38	08.71	2.37	**0.70**	**0.45**
Pancreas	**Proposed**	**45.09**	**13.11**	**2.01**	1.05	0.62
	Curvelet -SPIHT	42.69	10.56	3.5	0.84	0.56
Cerebral	**Haar- SPIHT**	42.13	08.42	3.98	**0.62**	**0.52**
	Proposed	**43.21**	**14.82**	**3.1**	1.19	0.65
Head	**Curvelet -SPIHT**	47.50	8.87	1.16	**0.71**	0.62
	Haar- SPIHT	45.65	7.09	1.77	0.87	**0.59**
	Proposed	**48.10**	**12.02**	**0.96**	1.06	0.67

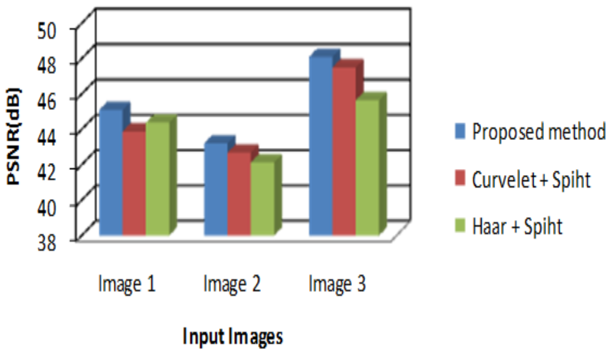


Figure 4 Comparison of PSNR's of compressed images obtained using the proposed and existing techniques

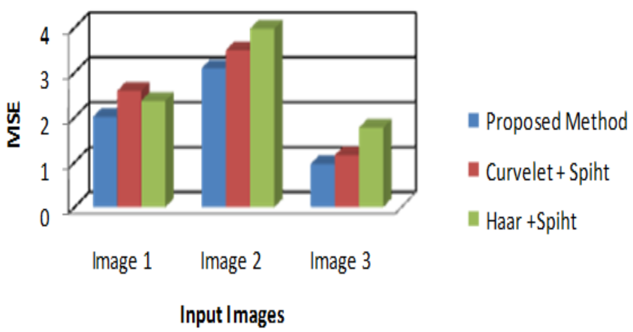


Figure 5 Comparison of MSE's of compressed images obtained using the proposed and existing techniques

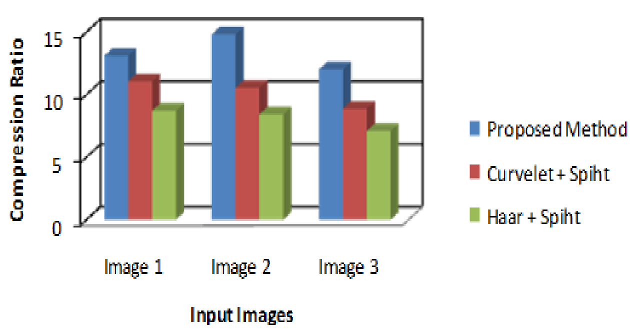


Figure 6 Comparison of CR values of compressed images obtained using the proposed and existing techniques

VI. CONCLUSION

An efficient method for compression of medical images is proposed. From the experimental results it is clear that the optimal sparse representation of objects with edges is well defined and the resulting image is visually superior. The proposed method is compared with other efficient methods and results show that the proposed method achieves a significant improvement in high PSNR and compression ratio.

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