



Ripplet Transform Type II for Medical Image Compression

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ABSTRACT: Hospitals produce a number of images per diagnosis and this can lead to produce the 5GB to 15 GB data. It increases the difficulties for a hospital storage system to store, manage and to transmit these images. Among the proposed compression methods, much interest has been focused on achieving good compression ratios and high Peak Signal to Noise Ratio (PSNR), and little work has been done on resolving 2D singularities along image edges with efficient representation of images at different scales and different directions. Grounded on this fact, this paper proposes a compression method for medical images by representing singularities along arbitrarily shaped curves without sacrificing the amount of compression. This method uses a recently introduced family of directional transforms called Ripplet transform. Usually the coarser version of an input image is represented using base, but discontinuities across a simple curve affect the high frequency components and affect all the transform coefficients on the curve. Hence these transforms do not handle curve discontinuities well. By defining the scaling law in a more broader scope and more flexible way, Ripplet Transform is formed as a generalisation of Curvelet transform, by adding two tunable parameters i.e support of Ripplets and degree of Ripplets. The inherent properties of Ripplet transform in conjunction with the coding of coefficients using Huffman Encoder provide efficient representation of edges in images and thereby achieving a high quality compressed image.

KEYWORDS: Ripplet Transform Type I, Type II, Compression, Huffman Encoding, PSNR, Compression Ratio, Discrete Ripplet Transform

I. INTRODUCTION

Mobile where high compression ratios are gained by sacrifice of the original data within certain allowable degradation limits. However, many important and diverse applications, including medical imaging, satellite, aerial imaging image archiving, and precious fine arts and documents preserving, or any application demanding ultra high image fidelity, require lossless compression (i.e., reconstruct the compressed data without any loss of information). In Image processing, Fourier transform is usually used for image representation in tradition. However, Fourier transform can only provide an efficient representation for smooth images but not for images that contain edges. Edges or boundaries of objects cause discontinuities or singularities in image intensity. But singularities in a function (which has finite duration or is periodic) destroy the sparsity of Fourier series representation of the function, which is known as Gibbs phenomenon [1].

In contrast, wavelet transform is able to efficiently represent a function with 1D singularity. Currently, the most popular choice is wavelet transforms. However, typical wavelet transform is unable to resolve two dimensional (2D) singularities along arbitrarily shaped curves. In order to overcome this weakness, a new system of representations namely ridgelet which can effectively deal with linelike phenomena in 2D, was proposed. However, to overcome the limitations of these transforms, a theory called Multiscale Geometric Analysis (MGA) theory has been developed for high dimensional signals and several MGA transforms are proposed such as contourlet, curvelet, bandelet, etc. The ridgelet transform also fails to resolve 2D singularities. In order to analyze local line or curve singularities, there is an idea to partition the image, similar to block processing and then to apply ridgelet transform to the obtained sub-images. This multiscale ridgelet transform is proposed by Starck and named as curvelet transform [2]. The curvelet transform represents two dimensional functions with smooth curve discontinuities at an optimal rate. Contourlets, as proposed by Do and Vetterli [3] form a discrete filter bank structure that can deal effectively With piece-wise smooth images with



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smooth contours. Contourlet has less clear directional features than curvelet, which in turn leads to artifacts in image compression.

Anisotropic directionality is achieved by using parabolic scaling law in the case of Curvelets. By generalizing the scaling law, Jun Xu, Lei Yang and Dapeng Wu proposed a new transform called Ripplet transform Type I (Ripplet-I) [4]. Ripplet-I transform adds two parameters, i.e., support c and degree d to the Curvelets. Ripplet-I is provided with anisotropic capability of representing 2D singularities along arbitrarily shaped curves, by the introduction of these parameters. Images are approximated from coarse to fine resolutions and is represented hierarchically by the Ripplet transform. Higher energy compaction is achieved as the transform coefficients decay faster than any other transforms. Good localization in both spatial and frequency domains makes it compactly supported in the frequency domain and fastly decaying in the spacial domain. The ripplet functions orient at various directions as the resolution increases. The anisotropy of ripplet functions is a result of the general scaling and support that guarantees to capture singularities along various curves

II. RELATED WORKS

A. VECTOR QUANTIZATION BASED METHODS

Binit Amin, Patel Amrutbhai proposed a method based on Vector Quantization and by using wavelets. This work informs a survey on vector quantization (5) based lossy image compression using wavelets. Vector quantization has the potential to greatly reduce the amount of information required for an image because it compresses in vectors which provides better efficiency than compressing in scalars. Vector quantization based coded images then encoded for transmission by using different encoding technique like Huffman encoding, Run Length Encoding etc.

B. REGION OF INTEREST METHOD

Manpreet Kaur and Vikas Wasson (6) proposed a compression method based on Region of Interest (ROI) of an image. In medical field only the small portion of the image is more useful. The reason behind for including the regions other than ROI is to make user as more easily to locate the position of critical regions in the original image. But for medical images this will be a risk as the vital information cannot be preserved using ROI method.

III. BACKGROUNDS

A. RIPPLET TRANSFORM TYPE I

Ripplets can get multi-resolution analysis of data. The ripplet transform generalizes the curvelet transform by adding two parameters, namely, support c and degree d . These parameters provide the ripplet transform with anisotropy capability of representing singularities along arbitrarily shaped curves, and the curvelet transform is just a special case of the ripplet transform with $c=1$ and $d=2$. Ripplets localizes the singularities more accurately because for each scale, ripplets have different compact supports. The directionality of ripplets ensures capturing orientations of singularities.

B. RIPPLET TRANSFORM TYPE II

Ripplet transform Type II (riplet-II) (9), which is based on generalized Radon transform. The generalized Radon transform converts curves to points. It creates peaks located at the corresponding curve parameters. Intuitively, our ripplet-II transform consists of two steps: 1) Use generalized Radon transform to convert singularities along curves into point singularities in generalized Radon domain. 2) Use wavelet transform to resolve point singularities in generalized Radon domain. Radon transform is widely applied to tomography. Classical Radon transform is defined in 2D space as the integral of an input 2D function over straight lines. Using this transform, four parameters, i.e. scale, orientation, degree and translation can be tuned as required. Examples of ripplet-II functions with different parameter settings are shown below.

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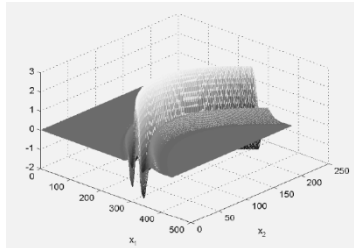


Fig.1. Ripplet II functions $a=1, b=0, d=2, \theta=0$

IV. PROPOSED COMPRESSION METHOD

The block diagram of the proposed compression method based on Ripplet Transform is illustrated in Fig.2. The proposed method can be used for the compression of grey scale medical images as well as colour medical images. This method uses Ripplet Transform Type II for the compression. To further improve the quality of the compressed image, the conventional SPIHT encoder (10) is replaced by a Huffman encoder in the proposed method. In this method, colour medical image of size 256×256 is taken as input. The colour image is split into three bands (R,G,B). The wavelet transform is applied using biorthogonal CD F 9/7 wavelet, separately for each band. Thus, the input image is decomposed into multiresolution subbands. The low frequency subbands are directly encoded. But for the high frequency subbands, ripplet transform II is taken and then encoded. Ripplet II sub bands are partially constructed from the decomposed wavelet subbands. The low frequency sub bands are directly encoded using Huffman encoding algorithm. The high frequency sub bands are dissected into small partitions by the procedure called smooth partitioning and the resulting dyadic squares are then renormalized. The effective region is analyzed in the ripplet domain.

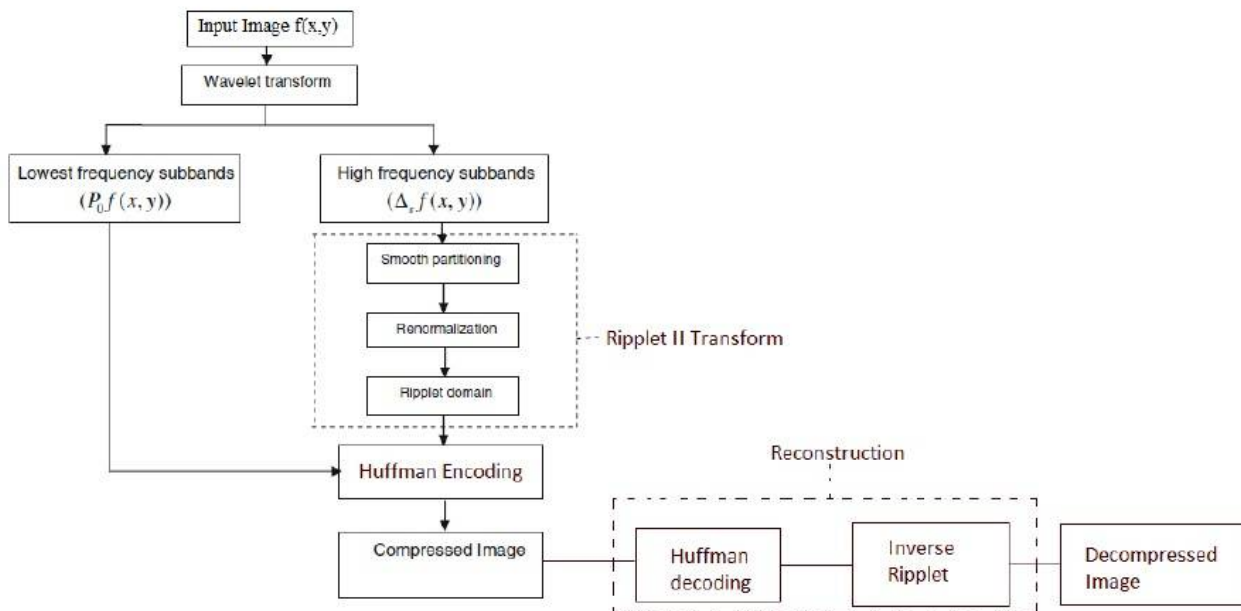


Fig.2. The Proposed Compression method

Thus finally the resulting ripplet coefficients are further encoded using Huffman encoder. The compressed image is obtained and the compression ratio is calculated. A Huffman coding method based on Ripplet transform for compression of colour medical images is proposed. The Ripplet transform breaks the inherent limitations of wavelet

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transform. It represents the image in different scales and directions in order to provide high quality compressed images. Then Huffman decoding and inverse ripplet transform are taken in order to reconstruct the original image. Fig.3 shows the reconstruction part or the decompression part of the compression system. The Huffman decoding and inverse ripplet transform are taken in order to reconstruct the original image.

V. SIMULATION RESULTS

The performances of the proposed method can be evaluated on a medical images of size 256 x 256 (8 bits per pixel) and the quality of the compressed images has been assessed in terms of PSNR (dB), Bitrate, compression ratio

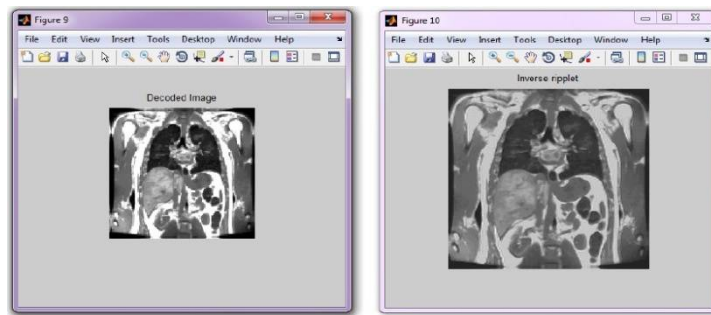


Fig.3.Huffman Encoding and Inverse Ripplet Transform

VI. PERFORMANCE EVALUATION

The major design objective of compression method is to obtain the best visual quality with minimum bit utilization. PSNR is one of the most adequate parameters to measure the quality of compression. If the PSNR values are higher, the quality of compression is better and vice versa.

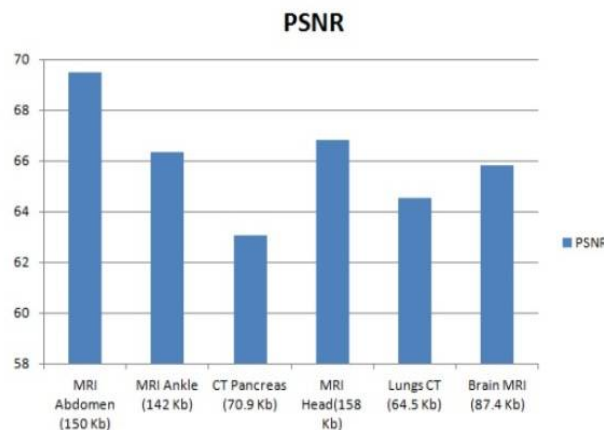


Fig.4.Comparison of PSNR values

PSNR is one of the most adequate parameters to measure the quality of compression. If the PSNR values are higher, the quality of compression is better and vice versa. From the table showing the experimental results on PSNR and MSE, it is clear that this method outperforms all other methods and achieves high PSNR with low MSE. In the proposed method, the non-negative windowing function and the subband filtering procedures yield exact reconstruction, resulting in high PSNR. The average PSNR value obtained on these six sets of medical images is 65.99 dB and the average MSE obtained is 0.1310. Compression ratio is used to enumerate the minimization in image representation size produced by the compression algorithm. This method provides an average compression ratio of 35.56 and an average bitrate of 0.0280.

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Bitrate is defined as the ratio of the size of the compressed image in bits to the total number of pixels. It can be inferred that in the proposed method, the non-negative windowing function and the subband filtering procedures yield exact reconstruction, resulting in high PSNR

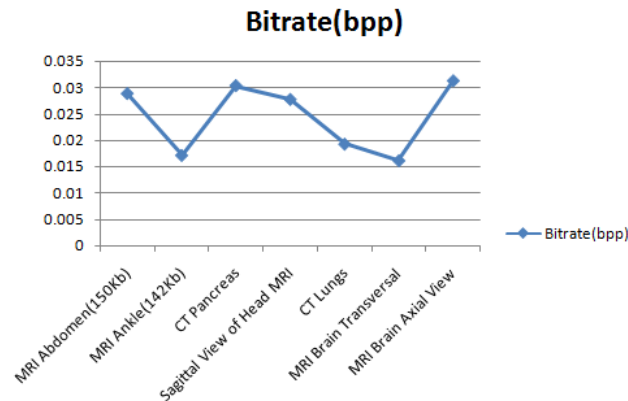


Fig.5.Comparison of Bitrate values

Compression ratio (CR) is used to enumerate the minimization in image representation size produced by the compression algorithm. It is defined as the ratio of the number of bits in the original image to that of the compressed image. It can be predicted that the proposed method will outperform other methods on the compression of medical images.

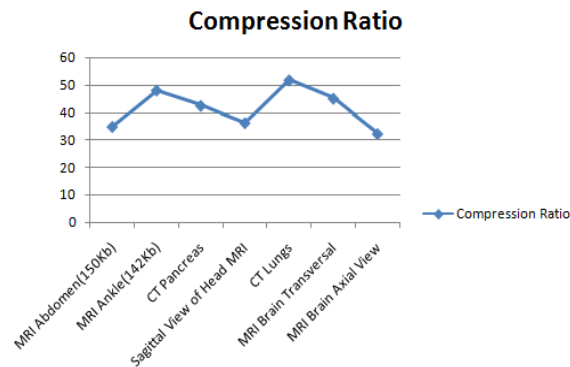


Fig.6.Comparison of CR values

VII. CONCLUSION AND FUTURE WORK

Current image representation schemes have limited capability of representing two-dimensional (2D) singularities (e.g. edges in an image). To further improve the capability of representing 2D singularities, this study proposes a new transform called ripplelet transform type II (ripplelet-II). Both forward and inverse ripplelet-II transforms were developed for continuous and discrete cases. Ripplelet-III transform with $d=2$ and achieve sparser representation for 2D images, compared to ridgelet. Hence, ripplelet-II transform can be used for feature extraction because of its efficiency in representing edges and textures. Ripplelet-II transform also enjoys rotation invariant property, which can be leveraged by applications such as texture classification and image retrieval. The ripplelet transforms used in this compression method are Type I and Type II. The ripplelet transform also has Type III, which are based on cubic radon transform, which will be further used in the compression method for future works. The new transform called ripplelet transform for resolving 2D singularities proves to be a promising one for feature extraction. Ripplelet-II transform is basically generalized Radon transform followed by 1D wavelet transform. Both forward and inverse ripplelet-II transform were developed for continuous and discrete cases. Ripplelet-II transform with $d = 2$ can achieve sparser representation for 2D images, compared to ridgelet. Hence, ripplelet-II transform can be used for feature extraction due to its efficiency in representing edges and textures. As wavelet analysis is very effective at representing objects with isolated point singularities,



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ridgelet analysis can be very effective at representing objects with singularities along lines. Curvelet is based on multiscale ridgelets combined with a spatial bandpass filtering operation. The ripples as the generalization of curvelet have almost all the properties of curvelet except the parabolic scaling. The novelty of this method is that it uses Ripplet transform with anisotropy capability to represent singularities along arbitrarily shaped curves and combines with a Huffman encoder to improve the compression performance

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BIOGRAPHY

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