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Ripplet Transform based Medical Image Compression

A Novel Efficient Method with Huffman Encoding

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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 and II,Discrete Ripplet Transform, Image compression, Huffman Encoding, Compression ratio, PSNR.

INTRODUCTION

From early days to now, the basic objective of image compression is the reduction of size for transmission or storage while maintaining suitable quality of decoded images. Compression not only minimizes channel capacity and storage requirements but also reduces time required to transmit data. Consequently, the methods of compressing data prior to storage and transmission are of significant practical and commercial interest. Most compression schemes are lossy, 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 effient 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 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

RELATED WORKS

Vector Quantization based Methods

Binit Amin, Patel Amrutbhai proposed a method based on Vector Quantisation 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.

Region of Interest (ROI) based methods

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.

Projection based methods

Sujitha Juliet, Blessing Rajsingh and Kirubakaran Ezra proposed a compression method based on projection [7]. This method takes advantage of the Radon transform and its basis functions are effective in representing the directional information. The technique computes Radon projections in different orientations and captures the directional features of the input image. But the method fails to represent edge features effectively.

Prediction based methods

Pensiri and Surapong introduced a compression method based on Predictive coding [8].Predictive coding has proven to be effective for lossless image compression. Predictive coding estimates a pixel color value based on the pixel color values of its neighboring pixels. It is based on the quantized pixel colors of three neighboring pixels. The prediction scheme can help minimize the upper bound of the residual errors from the prediction. This method is less effective in capturing high frequency information.

BACKGROUNDS

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=1and 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.

Ripplet Transform Type II

Ripplet transform Type II (ripplet-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. . To present ripplet-II transform, we need to define ripplet-II functions first. Given a smooth univariate wavelet function $\emptyset$ we define a bivariate function and the Ripplet II transform is calculated as follows.

$$\psi_{a,b,d,\theta}(\rho,\phi) = a^{-1/2}\psi((\rho cos^{d}((\theta-\phi)/d)-b)/a$$

Where a denotes scale, b denotes translation, d denotes degree and θ denotes orientation. The LHS of the above equation is called ripplet-II function. Here d values greater than 0 is only considered so that positive open curves.Examples of ripplet-II functions with different parameter settings are shown below.

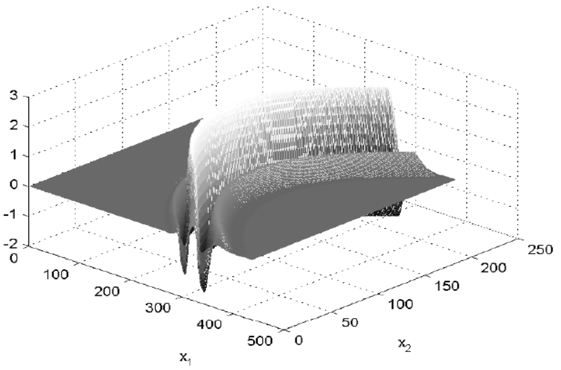

Fig.1. Ripplet II functions a=1, b=0, d=2,θ=0

A. *Forward Ripplet II Transform*

Ripplet-II transform of a real-valued 2D function f is defined as the inner product between the function f and ripplet-II functions. Ripplet-II transform has the capability of capturing structure information along arbitrary curves by tuning the scale, location, orientation, and degree parameters. Ripplet-II transform can be obtained by inner product between GRT and 1D wavelet, which is the 1D wavelet transform (WT) of GRT of function f; i.e., the ripplet-II transform of function f can be obtained by first computing GRT of f, and then computing 1D WT of the GRT of f as below:

$$f(\rho,\phi) \Longrightarrow GR_d[f](r,\theta) \Longrightarrow R_f(a,b,d,\theta)$$

B. *Inverse Ripplet II Transform*

Reversing the process in the above equation the inverse of the ripplet-II transform of function f can be obtained by first computing Inverse Wavelet Transform (IWT) and then computing inverse GRT (IGRT) as below:

$$R_f(a,b,d,\theta) \Longrightarrow GR_d[f](r,\theta) \Longrightarrow f(\rho,\phi)$$

Ripplet-II transform can be implemented as a 1D wavelet transform along the radius of the generalized Radon domain. A possible future direction is to apply 2D wavelet transform to the generalized Radon coefficients. The additional wavelet transform along angle θ holds the potential of improving the sparsity of transform coefficients.

C. *Properties of Ripplet II Transform*

Localisation :Ripplet II with degree d decays fast along curves of polynomial degree

Directionality:Ripplet II can be oriented toward arbitrary.

Flexibility: Compared to ridgelet, ripplet II provides flexible choice for degrees.

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.

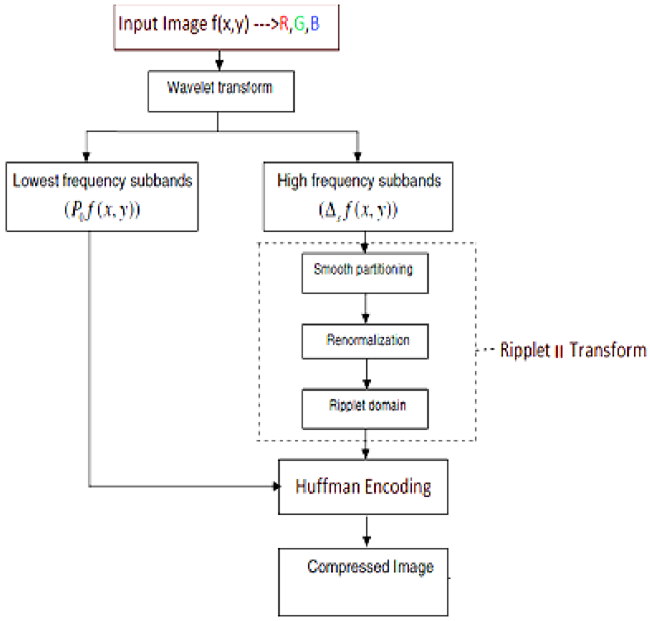

Fig.2.The Proposed Compression method

In this method, colour medical image of size 256 x 256 is taken as input. The colour image is split into three bands(R,G,B).The wavelet transform is applied using biorthogonal CDF 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.

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 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.

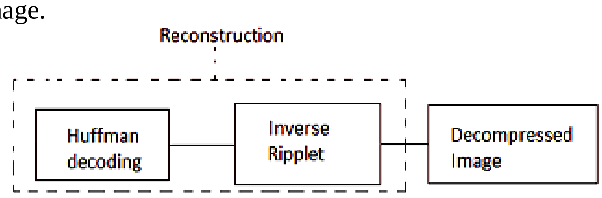

Fig.3.Reconstruction part of the Compression system

V.RESULTS AND DISCUSSIONS

The performances of the proposed method can be evaluated on a medical images of size 256x 256 (8 bits per pixel) and the quality of the compressed images has been assessed in terms of PSNR (dB), Bitrate, compression ratio. 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. 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. 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. This is due to the fact that the Ripplet transform successively approximates images from coarse to fine resolutions and is highly directional to capture the orientations of singularities. For some images, Haar wavelet will perform better because the approximation component contains most of the energy and the coefficients are reduced with input permutation of variables.

VI.FUTURE WORKS

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 ripplet transform type II (ripplet-II).Both forward and inverse ripplet-II transforms were developed for continuous and discrete cases. Ripplet-II transform with d=2 and achieve sparser representation for 2D images, compared to ridgelet. Hence, ripplet-II transform can be used for feature extraction because of its efficiency in representing edges and textures. Ripplet-II transform also enjoys rotation invariant property, which can be leveraged by applications such as texture classification and image retrieval. The ripplet transforms used in this compression method are Type I and Type II. The ripplet transform also has Type III, which are based on cubic radon transform, which will be further used in the compression method for future works.

VII.CONCLUSION

The new transform called ripplet transform for resolving 2D singularities proves to be a promising one for feature extraction.Ripplet-II transform is basically generalized Radon transform followed by 1D wavelet transform. Both forward and inverse ripplet-II transform were developed for continuous and discrete cases. Ripplet-II transform with d = 2 can achieve sparser representation for 2D images, compared to ridgelet. Hence, ripplet-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, 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 ripplets 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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