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Proficient Image Compression for Retinal Fundus Images

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ABSTRACT: This paper presents a new image compression technique for the coding of retinal images. Retinal images are used to detect diseases like diabetes or hypertension. In this work, the contourlet transform of the retinal image is taken first. The coefficients of the contourlet transform are quantized using adaptive multistage vector quantization scheme. The number of code vectors in the adaptive vector quantization scheme depends on the dynamic range of the input image. The simulation result analysis of the proposed scheme provides the levels of preserved contourlet based edge image with a better compression ratio and encoding time of encoded image.

KEYWORDS: ContourletTransform(CT), Directional Filter Bank(DFB),Laplacian Pyramid(LP), Adaptive Multistage Vector Quantization.

I. INTRODUCTION

Digital images are ubiquitous in many application areas as diverse as internet browsing, medical sciences, astronomy and remote sensing. Once personal computers gained the capacity to display sophisticated pictures as digital images, people started to seek methods for efficient representation of these digital pictures in order to simplify their transmission and save disk space. At this point image compression became very important and highly applicable and since then it has been the researchers favorite. The field of image compression has a wide spectrum ranging from classical lossless techniques and popular transform approaches to the more recent segmentation based (or second generation) coding methods. Further, compression techniques can be classified into lossless and lossy techniques. The lossless techniques allow compressing an image without losing any information while the images reproduced by the lossy techniques are not very perfect.

In spite of providing excellent results in terms of rate-distortion compression, the transform-based coding methods do not take an advantage of the underlying geometry of the edge singularities in an image. From the mid 80s there have been many attempts to design second generation image coding techniques that exploit the geometry of the edge singularities of an image. Recently, many image compression algorithms such as the Bandelets, the Prune tree, the Prune-Join tree, and the GW image coding method based on the sparse geometric representation have been introduced.

The present study is envisaged to improve the image coding method by using the contourlet transform. The Contourlet transform has better performance in representing edges than wavelets for its anisotropy and directionality; hence it is well suited for multi-scale image representation. The Contourlet coefficient has less computational complexity with the vector dimension. For this reason, low dimensionality VQ is typically used in image compression, but such the corresponding sub-bands are quantized using adaptive multi-stage vector quantization. Vector quantization (VQ) has been proven a powerful compression scheme for coding of images and image sequences. Multistage Vector Quantization (MSVQ) is a structured VQ scheme in which the search time and codebook complexity reduction with respect to optimal VQ is obtainable.

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II. EXISTING WORK

1. Compression schemes are available with DCT, DWT, contourlet transforms for common images like famous images like LENA, BARBARA etc.

2. None of the works have been very less encoding and decoding time.

In the past decades, the discrete cosine transform (DCT) has been the most popular for compression because it provides optimal performance and can be implemented at a reasonable cost. Several compression algorithms, such as the JPEG standard for still images and the MPEG standard for video images are based on DCT. However, the EZW, the SPIHT, the SPECK , the EBCOT algorithms and the current JPEG 2000 standard are based on the discrete wavelet transform (DWT). DWT has the ability to solve the blocking effect introduced by DCT; it also reduces the correlation between the neighboring pixels and gives multi scale sparse representation of the image.

A. Draw Backs In Existing Work:

1. While in any conventional compression methods like DCT, DWTs, the META information is not preserved during transformation and encoding process. This is a major drawback.

2. So any existing compression will never work for loss less compression, so that will not be suitable for bio medical applications. Also if we try to reduce the encoding time, then accuracy in reconstruction comes down.

B. What are the principles behind compression?

A common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information. The foremost task then is to find less correlated representation of the image. Two fundamental components of compression are redundancy and irrelevancy reduction. **Redundancy reduction** aims at removing duplication from the signal source (image/video). **Irrelevancy reduction** omits parts of the signal that will not be noticed by the signal receiver, namely the Human Visual System (HVS). In general, three types of redundancy can be identified:

1. **Spatial Redundancy** or correlation between neighboring pixel values.
2. **Spectral Redundancy** or correlation between different color planes or spectral bands.
3. **Temporal Redundancy** or correlation between adjacent frames in a sequence of images (in video applications).

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. Since we will focus only on still image compression, we will not worry about temporal redundancy.

C. What are the different classes of compression techniques?

Two ways of classifying compression techniques are mentioned here.

(a) Lossless vs. Lossy compression: In lossless compression schemes, the reconstructed image, after compression, is numerically identical to the original image. However lossless compression can only achieve a modest amount of compression. An image reconstructed following lossy compression contains degradation relative to the original. Often this is because the compression scheme completely discards redundant information. However, lossy schemes are capable of achieving much higher compression. Under normal viewing conditions, no visible loss is perceived (visually lossless).

(b) Predictive vs. Transform coding: In predictive coding, information already sent or available is used to predict future values, and the difference is coded. Since this is done in the image or spatial domain, it is relatively simple to implement and is readily adapted to local image characteristics. Differential Pulse Code Modulation (DPCM) is one particular example of predictive coding. Transform coding, on the other hand, first transforms the image from its spatial domain representation to a different type of representation using some well-known transform and then codes the transformed values (coefficients). This method provides greater data compression compared to predictive methods, although at the expense of greater computation.

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III. PROPOSED SCHEME

A. Contourlet Transform:

Contourlets form a multiresolution directional tight frame designed to efficiently approximate images made of smooth regions separated by smooth boundaries. The Contourlet transform has a fast implementation based on a Laplacian Pyramid decomposition followed by directional filter banks applied on each band pass subband.

A filter bank structure that can deal effectively with piecewise smooth images with smooth contours, was proposed by Minh N Do and Martin Vetterli. The resulting image expansion is a directional multiresolution analysis framework composed of contour segments, and thus is named contourlet. This will overcome the challenges of wavelet and curvelet transform. Contourlet transform is a double filter bank structure. It is implemented by the pyramidal directional filter bank (PDFB) which decomposes images into directional subbands at multiple scales.

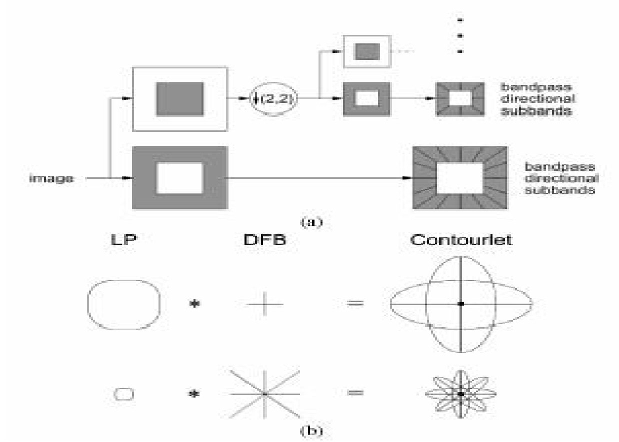

Figure 1.(a) Block diagram of a PDFB and (b) Supports for Contourlets

In terms of structure the contourlet transform is a cascade of a Laplacian Pyramid and a directional filter bank. In essence, it first use a wavelet-like transform for edge detection, and then a local directional transform for contour segment detection. The contourlet transform provides a sparse representation for two-dimensional piecewise smooth signals that resemble images.

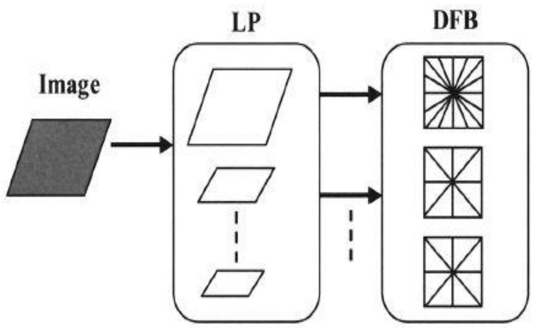

Figure 2. A flow graph of the Contourlet Transform

The flow graph of the contourlet transform is depicted in below Fig 2. The LP decomposition at each level generates

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a down sampled low pass version of the original and the difference between the original and the prediction, resulting in a band pass image. Band pass images from the LP are fed into a DFB so that directional information can be captured. The DFB is efficiently implemented through an I-level binary tree decomposition that leads to 2/ subbands with wedge-shaped frequency partitioning as illustrated below. The cascading of LP and DFB results in Pyramidal Directional Filter Bank (PDFB).

B. Directional Filter Bank:

In 1992, Bamberger and Smith introduced a 2-D directional filter bank (DFB) that can be maximally decimated while achieving perfect reconstruction. The directional filter bank is a critically sampled filter bank that can decompose images into any power of two's number of directions. The DFB is efficiently implemented via an l-level tree structured decomposition that leads to '2l' subbands with wedge-shaped frequency partition as shown in Fig.3. The original construction of the DFB involves modulating the input signal and using diamond shaped filters.

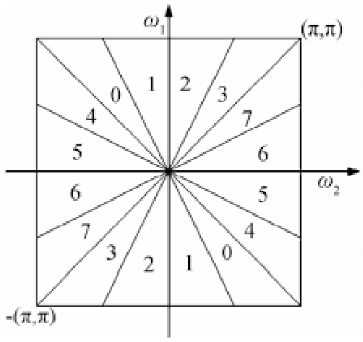

Figure 3. DFB frequency partitioning

Furthermore, to obtain the desired frequency partition, an involved tree expanding rule has to be followed. The DFB is designed to capture the high frequency components (representing directionality) of images. Therefore, low frequency components are handled poorly by the DFB. In fact, with the frequency partition low frequencies would leak into several directional subbands, hence DFB does not provide a sparse representation for images. To improve the situation, low frequencies should be removed before the DFB. This provides another reason to combine the DFB with a multiresolution scheme.

C. Laplacian Pyramid:

One way of achieving a multiscale decomposition is to use a Laplacian pyramid (LP), introduced by Burt and Adelson. The LP decomposition at each level generates a down sampled low pass version of the original and the difference between the original and the prediction, resulting in a band pass image as shown in Fig. In **this figure, 'H' and 'G' are called analysis and synthesis filters and 'M' is the sampling matrix.** The original image is convolved with a Gaussian kernel. The resulting image is a low pass filtered version of the original image. The Laplacian is then computed as the difference between the original image and the low pass filtered image.

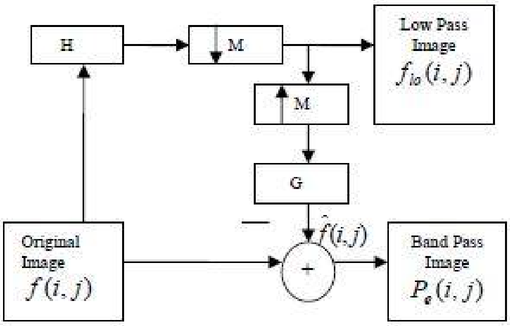

Figure 4. LP Decomposition (one level)

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This process is continued to obtain a set of band-pass filtered images (since each one is the difference between two levels of the Gaussian pyramid). Thus the Laplacian pyramid is a set of band pass filters. By repeating these steps several times a sequence of images, are obtained. If these images are stacked one above another, the result is a tapering pyramid data structure, as shown in Fig.5 and hence the name.

The Laplacian pyramid can thus be used to represent images as a series of band pass filtered images, each sampled at successively sparser densities. It is frequently used in image processing and pattern recognition tasks because of its ease of computation. A drawback of the LP is the implicit oversampling. However, in contrast to the critically sampled wavelet scheme, the LP has the distinguishing feature that each pyramid level generates only one band pass image (even for multidimensional cases), which does not have **"**scrambled**"** frequencies. This frequency scrambling happens in the wavelet filter bank when a high pass channel, after down sampling, is folded back into the low frequency band, and thus its spectrum is reflected. In the LP, this effect is avoided by down sampling the low pass channel only.

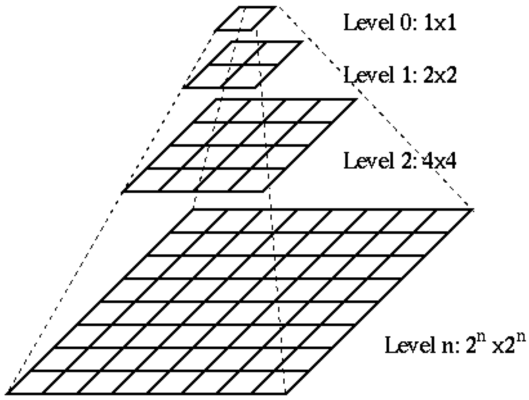

Figure 5: Laplacian pyramid structure

D.Adaptive Multistage Vector Quantization:

Vector Quantization is the extension of scalar quantization to a higher dimensional space which is lossy in nature. In this paper, we have proposed an adaptive vector quantizer which is based on the dynamic range of the input image. A vector quantizer is defined as a mapping 'Q' of 'L' dimensional Euclidean space into a finite subset Y which is given by

$$Q: R^L \rightarrow Y \qquad \text{.... (1)}$$

where 'V' is the set of reproduction vectors, which is generally termed as VQ codebook

$$Y = (xi; i = 1,2, 3....N) \qquad \text{.... (2)}$$

Here x represents the code vectors and 'N' is the number of vectors in the code book 'V'. The first step in the proposed adaptive vector quantization scheme is to split the image into a set of 'L' dimensions. Two important factors which decide the size of the code book are rate (R) and dimension (L). The number of code vectors in the code book is 2RL. In our algorithm, the dynamic range of the input image is determined first. The dynamic range is given by

$$\text{Dynamic range} = \text{Maximum gray level value} - \text{Minimum gray level value} \qquad \text{.... (3)}$$

This dynamic range is used to fix the interval of the vector space to be partitioned. The interval is calculated as

$$\text{Interval} = \frac{Dynamic\ Range}{R \times L} \qquad \text{.... (4)}$$

The interval determines the quality of the reconstructed image. If the interval is narrow, then the quality of the

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reconstructed image will be good; on the other hand if the interval is wide, then the quality of the reconstructed image will be poor. After determining the interval, the subsequent step is to form the code vectors. In our approach, the general expression of code vector for L=2 is given by

$$C_{ij} = \left[\left([i \times Interval] + \frac{Interval}{2}\right), \left([j \times Interval] + \frac{Interval}{2}\right)\right] \quad \text{.... (5)}$$

where i, j are integers (i, j = 0,1,2..). Successive vectors are formed by adding the interval in both dimensions to the initial code vector. After forming the code vectors, the next step is to project the input vector into the code vector. Each input vector is matched with a closest codeword in the codebook, and then the index of the codeword is transmitted instead of the code vector itself the matching of the input vector to the nearest code vector is based on minimum distortion. A distortion measured is used to assign the cost of reproducing any vector as reproduction. A quantizer is optimal if it minimizes the average distortion. The squared error distortion is

$$d(x,\bar{x}) = \|x - \bar{x}\| \quad \text{.... (6)}$$

Multistage adaptive vector quantization scheme is used in this work. The multistage vector quantization scheme is shown in Fig. 4. In the figure, 'X' represents the input vector, LUT stands for Look up table, i1, i2 represents the indices from different stages.

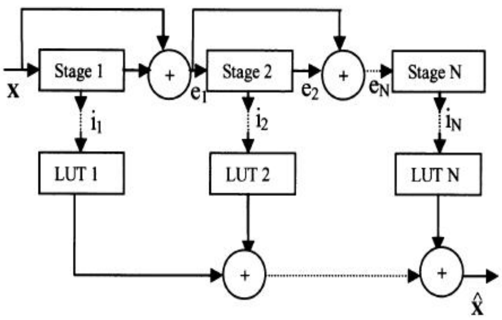

Figure 6. Multistage Vector Quantization Scheme

The overall index is the concatenation of indices chosen from each of the two codebooks. It is evident from the figure that the input vector is given only to the first stage, whereas the input to the successive stages is the error vectors from the previous stage.

E. Proposed Algorithm:

The proposed retinal image coder scheme is summarized below

Step 1: The correlation present in the input retinal image is minimized by taking the Contourlet transform of the input retinal image. Different pyramidal and directional filters are taken into consideration in this work.

Step 2: The transform coefficients obtained in step 1 are adaptively vector quantized in a multistage manner where the residual coefficients due to quantization are iteratively feedback and vector quantized. The number of code vectors depends on the dynamic range of the input image; hence it is adaptive in nature.

Step 3: The output indices from step 2 are lossless coded using static Huffman code. In decoding, the decoder basically performs the reverse process of the above steps.

$$C_{ij} = \left[\left([i \times interval] + \frac{interval}{2}\right), \left([j \times interval] + \frac{interval}{2}\right)\right]$$

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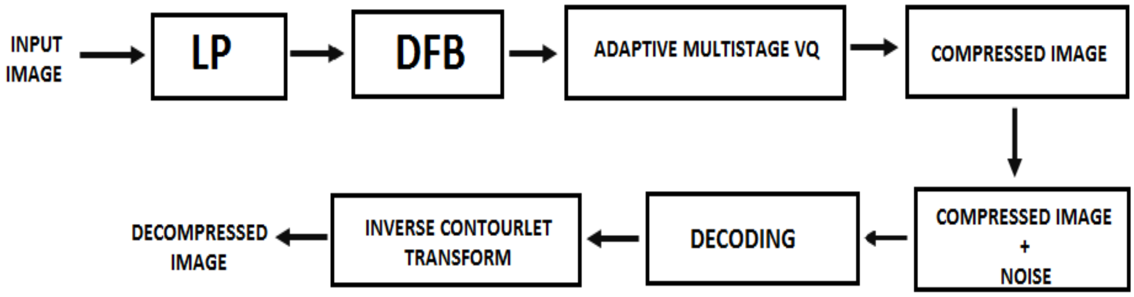


Fig 7. Block diagram of proposed system

F. Error Metrices:

Two of the error metrics used to compare the various image compression techniques are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are

$$MSE = \frac{1}{MN}\sum_{Y=1}^{M}\sum_{X=1}^{N}[I(X,Y) - I'(X,Y)]^{2} \qquad ....(1)$$

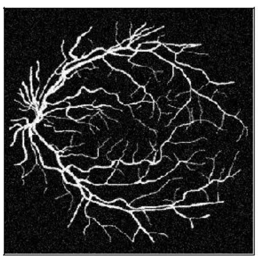
$$PSNR = 20 * \log10\,(255 / \mathrm{sqrt}\,(MSE)) \qquad ....(2)$$

Where,

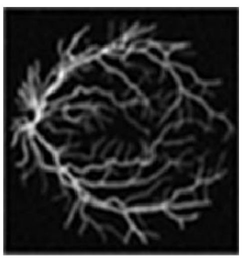
I(x,y) is the original image,
I'(x,y) is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images.

A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, if you find a compression scheme having a lower MSE (and a high PSNR), you can recognize that it is a better one.

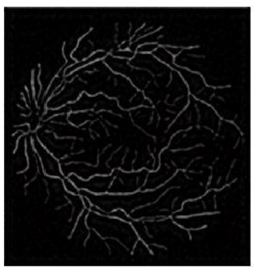
IV. SIMULATION RESULT & ANALYSIS



Input Image



Contourlet coefficient Level 1



Contourlet coefficient Level 2

Contourlet coefficient Level3

The performance of the proposed scheme is tested on 256 x 256 bit retinal image and the results are given in Table 1. The different pyramidal filters taken into consideration are 'Haar', 'biorthogonal 9/7'. The different directional filters taken into consideration are 'pkva' and 'biorthogonal 9/7'. In the case of wavelets, the different wavelet filters chosen are 'Haar', 'biorthogonal 9/7' and 'la8'. Table 1 shows the performance of the proposed algorithm for the first, second and third level of decomposition by varying the bits per dimension (bpd) from 0.125 to 1.0. From the table it is obvious that in the case of contourlets, as the level of decomposition increases, the Peak Signal to Noise Ratio (PSNR) value slightly increases. This is due to the fact that the hidden information available in different subbands is exploited

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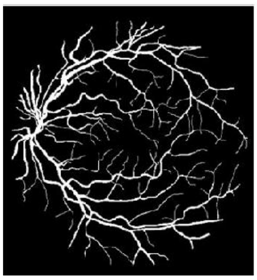
properly giving rise to an increased PSNR value. From the table, it is clear that the performance of the proposed scheme varies with the choice of the filter. In the case of contourlet, the 'biorthogonal 9/7' as pyramidal filter and 'pkva' as directional filter gives better reconstruction image quality when compared to other choice of filters. The edges of the original and the reconstructed retinal images using Canny Edge detector for different bits per dimension is discussed in this paper. From the figure, it is clear that the edges are properly reconstructed at higher bits per dimension. In the case of contourlet, the pyramidal and directional filters taken into consideration are 'Haar' and 'pkva' respectively.



Original image

Reconstructed image

V. CONCLUSION

From the simulation results, it can be observed that for the same bits per dimension, the PSNR obtained using contourlet transform is better than that of the wavelet transform. Hence, a better image reconstruction is possible with less number of bits using contourlet transform. In retinal images, the optic nerves are having higher amount of contoured patterns hence contourlet performs superior than wavelet. Higher PSNR results can be obtained by including more number of stages in multi-stage vector quantization, which will result in increased computational complexity.

VI. FUTURE ENHANCEMENT

The future works carried out for the proposed system are
1. To prove that the Decoding process preserves the Meta information of an original image.
2. Determine the Quality of image and compare with other Existing techniques.

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