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MEDICAL IMAGE COMPRESSION USING ANAMORPHIC STRETCH TRANSFORM

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ABSTRACT

Medical image compression have an important role in medical field because they are used for future reference of patients. Medical imaging poses the great challenge of having compression algorithms that reduce the loss of fidelity as much as possible so as not to contribute to diagnostic errors and yet have high compression rates for reduced storage and transmission time. A new method for medical image compression is introduced. It uses a new physics-based mathematical transformation that increases spatial coherency by causing feature selective stretch. Anamorphic Stretch Transform is used for compressing the medical images. The transformation increases the spatial coherence resulting in superior compression without sacrificing the image quality. AST can be considered as the generalized (or nonlinear) time-wavelength mapping. It minimizes the number of samples needed for a digital representation of the signal; in other words, it reduces the record length or the digital data size.

KEYWORDS: Image Compression, Discrete Cosine Transform, Discrete Wavelet Transform, Anamorphic Stretch Transform.

INTRODUCTION

Image compression addresses the problem of reducing the amount of data required to represent a digital image. It is a process intended to yield a compact representation of an image, thereby reducing the image storage/transmission requirements. There are several different ways in which image files can be compressed. For internet use, the two most common compressed graphic image formats are the Joint Photographic Experts Group (JPEG) [4, 5] format and the Graphics Interchange Format (GIF) format. The JPEG method is more often used for photographs, while the GIF method is commonly used for line art and other images in which geometric shapes are relatively simple.

Compressing an image is significantly different than compressing raw binary data. General-purpose compression programs can be used to compress images, but the result is less than optimal. This is because images have certain statistical properties, which can be exploited by encoders specifically designed for them. Also, some of the finer details in the image can be sacrificed for the sake of saving a little more bandwidth or storage space. The commonly used algorithms for the compression are Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) [11] etc.

A DCT is a fourier related transform similar to the discrete fourier transform (DFT), but uses only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the fourier transform of a real and even function is real and even), where in some variants the input and/or output data are shifted by half a sample. There are eight standard DCT variants, of which four are common. The most common variant of discrete cosine transform is the type-II DCT [2, 14, 15] which is often called simply “the DCT” and its inverse is the type-III DCT, is correspondingly often called simply “the inverse DCT” or “the IDCT”. Two related transforms are the discrete sine transform (DST), which is equivalent to a DFT of real and odd functions, and the modified discrete cosine transform (MDCT), which is based on a DCT of overlapping data.

Discrete wavelet transform (DWT) [2] is a wavelet transform in which the wavelets are discretely sampled. An advantage of DWT is temporal resolution because it captures both frequency and location information. It is a linear transformation that operates on a data vector whose length is an integer power of two and transforming it into a numerically different vector of the same length. The main feature of DWT is multiscale representation of function.

Using the wavelets a given function can be analyzed at various levels of resolution. The DWT is also invertible and can be orthogonal. Wavelets are effective for analysis of textures that recorded with different resolution. It is very important problem in nuclear magnetic resonance imaging because high-resolution images require long time of acquisition. This causes an increase of artifacts caused by patient movements which should be avoided.

Fractal encoding is a mathematical process used to encode any given image as a set of mathematical data that describes the fractal properties of the image. Fractal encoding relies on the fact that all objects contain information in the form of similar, repeating patterns called an attractor. Fractal encoding is largely used to convert the image into fractal codes. In the decoding it is just the reverse, in which a set of fractal codes are converted to image. The encoding process has intense computation, since large number of iterations is required to find the fractal patterns in an image. The decoding process is much simpler as it interprets the fractal codes into the image.

Another technique for the compression of images is Anamorphic Stretch Transform (AST) [1]. AST is a physics based transform that emerged from photonic time stretch and dispersive fourier transform and can be applied to analog temporal signals such as communication signals and digital data such as images. It reshapes the data such that its output has properties conducive for data compression and analytics and the reshaping consists of warped stretching in fourier domain. The compression is lossless and is achieved through a same domain transformation of the signal's complex field and performed in the analog domain prior to digitization. AST can be used as a standalone algorithm or can be combined with existing digital compression techniques to enhance speed or quality or to improve the amount images can be compressed. AST can also be used in analog applications because it can capture and digitize signals that are faster than the speed of the sensor and the digitizer and also minimizes the volume of data generated in the process.

RELATED WORKS

D. Malarvizhi et al. [6] proposed a new entropy coding algorithm for the compression of images using discrete cosine transform. This algorithm uses quantized coefficients of discrete cosine transform. Image transformation, quantization and encoding are the main steps in compression. Inverse transformation dequantization and decoding are the steps in reconstruction. An N X M image is taken and the intensity of pixels are calculated. DCT coefficients of the images are generated using dct matrix. The pixels in the array are in the form of gray scale level. This algorithm also provides good quality images.

Andras Cziho [13] proposed a technique for image compression using region of interest vector quantization. The algorithm is based on the vector quantization and adopts the idea of region of interest. The image to be compressed is first segmented into regions and a separate codebook is used for compressing every region. The size and the number of codewords may be different in the codebooks according to the diagnostic importance of the corresponding image region. This permits to create appropriate codebooks with representative codewords and to obtain good reconstruction quality in relevant zones, while reinforcing the compression in less important regions. The reconstructed image has good quality. Not only a good rate or distortion performance is obtained, but also the quality is preserved.

Deepak Kumar Jain et al. [3] proposed a technique for image compression using discrete cosine transform and adaptive huffman coding. The original image is divided into blocks. DCT is applied to each block by multiplying the modified block with DCT matrix on the left and transpose of DCT matrix on its right. Each block is then compressed through quantization. A quantization matrix is used in combination with a DCT coefficient matrix to carry out transformation. Quantization is the step where most of the compression takes place. Quantized matrix is then entropy encoded. The compressed image is reconstructed through reverse process i.e., by using inverse DCT. This technique has good performance as compared to other algorithms.

Lei Wang et al. [8] proposed a lossy to lossless image compression based on reversible integer DCT. A progressive image compression scheme is investigated using reversible integer discrete cosine transform (RDCT). DCT has bad performance in lossy image compression as compared with wavelet transform. Lossy to lossless image compression can be implemented in the proposed scheme which consists of RDCT, coefficients reorganization, bit plane encoding, and reversible integer pre and post-filters.

Aaron T. Deever et al. [10] proposed a method called lossless image compression with projection-based and adaptive reversible integer wavelet transforms. A projection based scheme is introduced to reduce the first-order entropy of transform coefficients and to increase the performance of reversible integer wavelet transforms. Also the projection

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method has been framed for predicting a wavelet transform coefficient. This technique promotes optimal fixed prediction methods for the lift based wavelet transforms. On the other side the projection technique was emphasized for an adaptive prediction method which differentiates the final prediction process of lift based transform on basis of modeling context.

B. Ramakrishnan et al. [9] proposed a medical image compression technique called internet transmission of digital imaging and communications in medicine (DICOM) images with effective low bandwidth utilization. A wavelet based encoder called set partitioning in hierarchical trees (SPIHT) has been used for the progressive transmission of DICOM images. The process goes this, the header of the DICOM image has to be transmitted firstly, the compressed image secondly and then the images are reconstructed from low quality to high quality at the receiver's side.

Vijendra Babu [7] et al. proposed a wavelet based image compression using region of interest (ROI) embedded zerotree wavelet (EZW). This algorithm is capable of coding each arbitrary shape ROI regions independently. In this case, region-based coding for better utilization of the available bit rate ,since the high quality should be maintained only for the aforementioned diagnostically significant regions and the rest of the image can be encoded at a lower bit rate. Once the region of interest is selected efficiently, the significant region is transformed using lossless integer wavelet transform filter and diagnostically unimportant region with lossy Daubechies 5/3 tap filter. Then the transformed images are encoded using partial EZW algorithm. Arithmetic encoder is used to reduce the redundancy and to improve the efficiency of compression. The procedure for decoding is exact reverse of the encoding.

MEDICAL IMAGE COMPRESSION

The medical community has been very reluctant to adopt lossy algorithms in clinical practice. The images are compressed by lossless compression methods because each bit of information is important. The stages of the proposed method is shown in Fig.1. The original endoscopic medical image is taken first and anamorphic stretch transform is applied to original image. Discrete wavelet transform is then applied to the AST transformed image. For further compression runlength encoding is applied to the DWT transformed image. In the reconstruction phase inverse of these steps can be done, i.e., runlength decoding, inverse DWT and inverse AST.

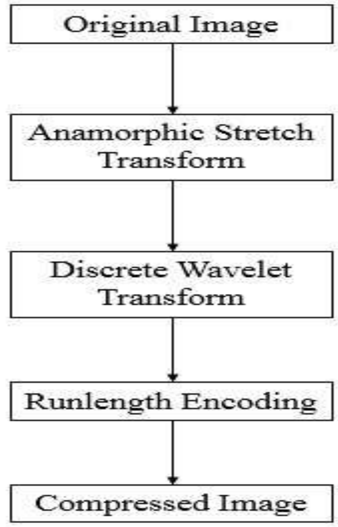

Fig.1. System Flow Chart

Anamorphic Stretch Transform

Anamorphic stretch transform (AST) is a mathematical transformation in which analog or digital data is stretched and warped in a specific fashion such that it results in non-uniform fourier domain sampling. Main steps of AST are:

- Flip the image to an xy co-ordinate system.
- Map the image onto an xy mesh-grid.
- Reshape the xy mesh-grid and create a 3 X N array of coordinate data.
- Convert the 3 X N matrices to 4 X N matrices.
- Translate and rotate the image.

- Interpolate the RGB components.
- Project the image onto a fictitious screen.

Discrete Wavelet Transform
Discrete wavelet transform (DWT) converts the image into a set of basic functions and these functions are the wavelets. The DWT is a highly efficient and flexible method for sub band decomposition of signals. Wavelets convert the image into a series of wavelets that can be stored more efficiently than pixel blocks. Wavelets have rough edges, they are able to render pictures better by eliminating the blockiness. In DWT, a time scale representation of the digital signal is obtained using digital filtering techniques.

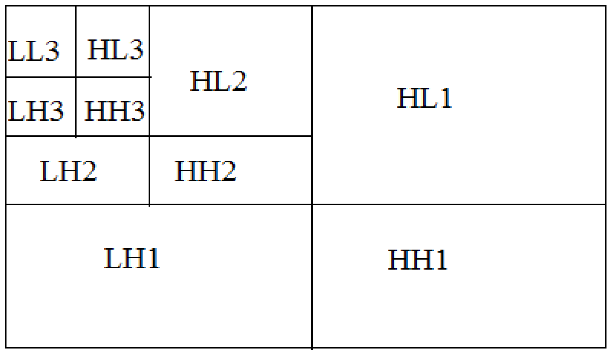

Fig. 2. Structure of wavelet Decomposition

The approximation (LL) sub-signal shows the general trend of pixel values and other three detail sub-signals show the vertical (LH), horizontal (HL) and diagonal (HH) details or changes in the images. The hierarchical structure shown in Fig. 2. If these details are very small then they can be set to zero without significant change in the image. The greater number of zeros the greater compression ratio. If the energy retained (amount of information retained by an image after compression and decompression) is 100 percent then the compression is lossless as the image can be reconstructed exactly.

Runlength Encoding
After discrete wavelet transform, runlength encoding is performed. RLE works by reducing the physical size of a repeating string of characters. This repeating string, called a run, is typically encoded into two bytes. The first byte is the value of the character in the run, which is in the range of 0 to 255, and is called the run value. The second byte is the represents the number of characters in the run and is called the run count. An encoded run may contain 1 to 128 or 256 characters; the run count usually contains as the number of characters minus one (a value in the range of 0 to 127 or 255).

EXPERIMENTAL RESULTS
The experimental results of the proposed image compression method and comparison with other techniques is discussed in this section. The proposed method has been compared with two well-known compression techniques- JPEG and Fractal Compression. In order to verify the quality of reconstructed image Peak to Signal Ratio (PSNR) is used as an estimate. The time efficiency and speed has been compared by estimating encoding time of the algorithms using features in MATLAB.

The proposed medical image compression technique has been applied against different types of endoscopic medical images such as stomach, esophagus and larynx. The system have been tested over different size of endoscopic medical images like 155 X 180, 378 X 480, and 405 X 480. The tested medical images are shown from figure 1 to figure 3. The peak signal to noise ratio and encoding time of different images are computed and compared it with other compression techniques such as JPEG and fractal compression. The table 1, table 2, table 3 and table 4 shows the different values of these measures for the medical images shown in 1 to 3.

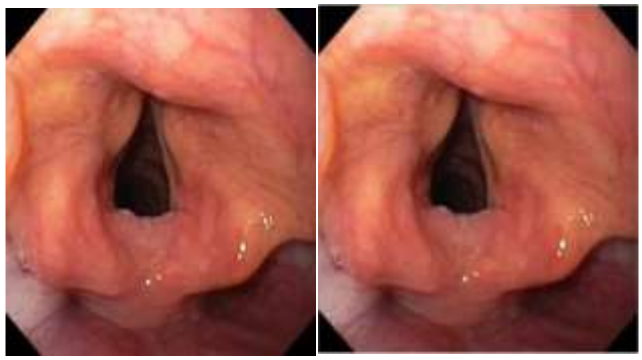

Figure 3. (a). Original Image (b). Reconstructed Image

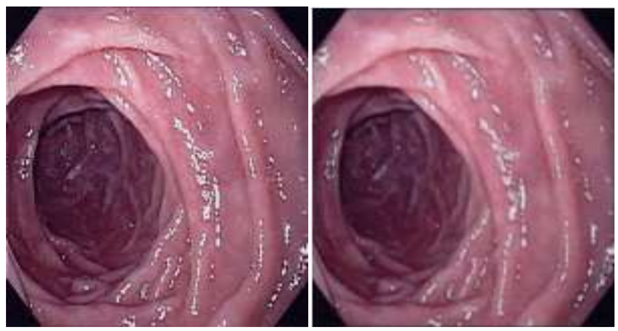

Figure 4. (a). Original Image (b). Reconstructed Image

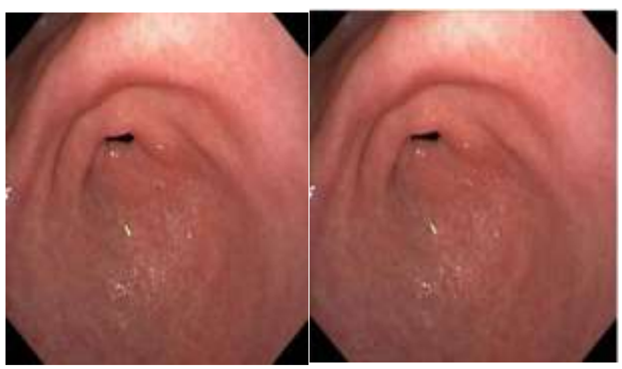

Figure 5. (a). Original Image (b). Reconstructed Image

Table 1. Comparison of PSNR values for various methods

IMAGE	AST	JPEG	FRACTAL
Larynx1	28.33	28.30	28.30
Larynx 2	28.25	28.20	28.21
Larynx 3	28.32	28.29	28.29
Larynx 4	28.61	28.59	28.60
Larynx 5	28.40	28.37	28.38
Larynx 6	28.39	28.35	28.35
Larynx 7	27.76	27.72	27.73
Larynx 8	28.76	28.71	28.72
Stomach 1	31.05	30.99	31.01
Stomach 2	29.05	29.05	29.03
Stomach 3	29.14	29.10	29.06

Stomach 4	28.78	28.75	28.77
Stomach 5	28.11	28.08	28.10
Stomach 6	28.84	28.86	28.85
Stomach 7	28.14	28.10	28.10
Stomach 8	28.31	27.65	27.65
Esophagus 1	28.06	28.03	28.04
Esophagus 2	29.01	28.98	28.99
Esophagus 3	28.40	28.37	28.33
Esophagus 4	28.82	28.75	28.80
Esophagus 5	29.10	29.07	29.07
Esophagus 6	28.23	28.21	28.23
Esophagus 7	29.02	28.37	28.98
Esophagus 8	30.00	29.93	29.95

Table 2. Encoding time for various methods

IMAGE	AST	JPEG	FRACTAL
Larynx1	1.26	0.38	2.72
Larynx2	1.24	0.09	2.50
Larynx3	1.24	0.09	3.19
Larynx4	1.27	0.09	3.38
Larynx5	1.16	0.09	2.01
Larynx6	1.14	0.09	1.85
Larynx7	1.14	0.12	4.33
Larynx 8	1.17	0.13	3.89
Stomach1	1.61	0.11	2.00
Stomach2	1.59	0.12	3.16
Stomach3	1.64	0.12	3.52
Stomach4	1.61	0.12	2.62
Stomach5	1.62	0.12	3.51
Stomach6	1.63	0.12	3.87
Stomach7	1.61	0.12	2.96
Stomach8	1.62	0.12	3.59
Esophagus 1	1.66	0.18	3.32
Esophagus 2	1.61	0.12	2.88
Esophagus 3	1.61	0.12	4.33
Esophagus 4	1.60	0.12	4.41
Esophagus 5	1.62	0.12	3.73
Esophagus 6	1.62	0.12	2.64
Esophagus 7	1.63	0.12	2.64
Esophagus 8	1.62	0.11	3.11

These results prove that the proposed technique provide better compression and the original images can be retrieved without any degradation in quality after compression. Anamorphic Stretch Transform provides better compression than the other two techniques. The PSNR value for AST is better than that of JPEG and Fractal.

However AST needs more time to perform encoding than JPEG, with the advantage of being far better than fractal encoding. It is interesting to see that decoding is comparatively faster for AST. Studies can further be conducted on incorporating other coding techniques along with Anamorphic Stretch Transform and making it an acceptable compression standard. Also, experiments can be further conducted on reducing the encoding time.

CONCLUSION

Anamorphic Stretch Transform is a new technique that overcome drawbacks of other techniques and also enhance the reconstructed quality of compressed image with high compression rate for medical image. AST is used to compress both analog and digital data. It is a mathematical transformation in which data is stretched and warped in a specific fashion. By using AST the volume of data is reduced without losing any information. AST is more advantageous as compared to the existing compression techniques. AST is used as a pre compression process in this technique.

As a future work AST can be used as a standalone algorithm for the compression of medical images. Compression can be done by convolving the kernel points of the image.

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