THE MEDICAL IMAGE COMPRESSION WITH EMBEDDED ZEROTREE WAVELET

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ABSTRACT
The rapid growth of digital imaging applications, including desktop publishing, multimedia, teleconferencing and high definition television, (HDTV) has increased the need of effective image processing. While processing any data, it requires large memory space for storage, which ultimately increases the transmission time. In order to save memory space and speed up the rate of transmission of data over networks, data compression is essential. Technically all image data Compressed into two groups as lossless and lossy. Some information is lost in the lossy compression, especially for radiological images. To minimize the effect of data loss on the diagnostic features of the images a new algorithm can be designed. Wavelet transform (WT) constitute a new compression technology that has been used in natural and medical images. In this study, the embedded zerotree wavelet algorithm (EZW) is used for image coding. It is designed to optimize the combination of zerotree coding and Huffman coding. It is shown that the multi-iteration algorithm and particularly the two iteration EZW for a given image quality produce lower bit rate. It is applied for medical images and here, the thorax radiology is chosen as a sample image and the good performance is codified. This compression technique can be used for Office automation, Bio-medical, Remote Sensing, Criminology, Astronomy and space applications, Information technology and Military applications.

KEY WORDS – Wavelet Transforms, DWT, EZW, Threshold, Huffman Coded

1. INTRODUCTION
Uncompressed multimedia data (graphics, audio and video) requires considerable storage capacity and transmission bandwidth. Despite of rapid progress in mass storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data-transmission bandwidth continues to outstrip the capabilities of available technologies. The recent growth of data intensive multimedia based applications have not only sustained the need for more efficient ways to encode signals and images but have made compression of such signals central to storage and communication technology.[1]

A major application domain of medical imaging technology is radiology where some of the imaging modalities include computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and positron emission tomography (PET), in the picture achieving and communication system environments [1]. It is well known that all image data compression schemes can be categorized into the lossless and lossy groups. Although lossless, one is especially preferred in medical images. It makes necessary the use of lossy schemes due to compression relatively low compression ratio is lossless method. This mustn’t cause to have the less diagnostic features. Therefore, the new algorithms can be developed to minimize the effect of data loss on the diagnostic features of the image [2]. For still image compression, the JPEG [2] standard has been established. The JPEG compression encoding is based on Discrete Cosine Transform scheme [3]. First the image is divided into 8 x 8 block size and then DCT is applied. Due to this block based DCT scheme, the performance of these encoders generally degrades at low bit rates.

Over the past few years, a variety of powerful and sophisticated scheme for image compression with high compression ratio and good image quality have been developed and implemented. More recently, the wavelet transform has emerged as a cutting edge technology. Wavelet based coding provides substantial improvements in picture quality at higher compression ratios [4]. This paper introduces some basic concepts on image compression and the more popular wavelet based image-coding schemes.

2. WAVELET TRANSFORMS
A wavelet is a ‘small wave’ having the oscillating wave like characteristic and the ability to allow
simultaneous time and frequency analysis by the way of a time-frequency localization of the signal. Wavelet systems are generated by dilating and translating a single prototype function or wavelet ψ(t).

A two-dimensional scaling function, φ (x, y), and three two-dimensional wavelets, ψ_H(x, y), ψ_V(x, y), and ψ_D(x, y), are required. Each is the product of a one dimensional scaling function φ and corresponding wavelet ψ. Excluding products that produce one-dimensional results, like φ (x), ψ (x), the four remaining products produce the separable scaling function [4].

φ (x, y) = φ (x) φ (y)                           (1)
and separable, "directionally sensitive" wavelets

ψ_H(x, y) = ψ (x) φ(y)                              (2)
ψ_V(x, y) = φ (x) ψ (y)                          (3)
ψ_D(x, y) = ψ (x) ψ (y)                          (4)

These wavelets measure functional variations - intensity or gray level variation for images along different directions. ψ_H measures variations along column’s (horizontal edges), ψ_V respond to variations along rows (vertical edges), and ψ_D corresponds to variations along diagonals. The directional sensitivity is a natural consequence of the separability imposed by eqs. (1 to 4) and it does not increase the computational complexity of the two-dimensional transform.

3. THE ALGORITHM

The wavelet decomposition is an alternative representation of image data but the number of bits used to store it has not changed. To compress the image data, it must be decided which coefficients to send and how many bits to use to code them. The Shapiro’s EZW algorithm is based in the construction of dominant and significant lists for a given image, which is decorrelated with a wavelet transform. In the dominant list, the information about the significance of a coefficient is coded, while in the significant list only the values for the significant coefficients are kept up to a given degree of precision.

In Shapiro’s scheme, the significance of a coefficient at a given iteration is determined based on its comparison with a threshold (T): If the value of the coefficient is greater than T, the coefficient is significant while, if it is smaller than T, it is considered insignificant. In either case, two possibilities are considered and coded by a different symbol. When the coefficient is significant, its sign is coded: POS for positive values and NEG for negative values. When the coefficient value is below threshold, the values of the coefficient descendants, which are the corresponding coefficients in lower scales are analyzed. If all the descendants are insignificant, we have a ZTR and there is no need to code them. When some of the descendants are significant, however, we have an isolated zero (IZ), and the descendants have to be codified individually. Thus, 4 symbols (2 bits) are enough to code completely the dominant list. The same procedure is performed in all scales with a prefixed order until the dominant list is completed. The ordering procedure is described in Figure 2 for a 3-scale wavelet. When the dominant list is completed, the magnitudes of the significant coefficients are refined one additional bit of precision (coded by 0’s or 1’s). The same scheme is repeated iteratively alternating a dominant pass and a subordinate pass and then, reducing the threshold. In this way, the values of the coefficients are successively approximated at each iteration. As a final stage, the dominant list is Huffman coded to obtain further data compression [5]. Therefore, in the symbol distribution in the dominant list for several images, the idea is to code information about the coefficient value along with information about the value of its descendants, by diversifying the ZTR symbol into several other symbols.
Figure 2. Scanning order of the subbands for encoding of a significant map.

In this way, here is the advantage of the data reduction achieved by ZTR symbol while, at the cost of introducing extra symbols, it is possible to convey more information about the coefficient value. We propose a method that combines two or more iterations of the original algorithm into one, comparing the coefficient values simultaneously to two different thresholds: T1 and T2, with T1>T2. Then, two alternatives have been considered depending on the number of symbols used to code the significance of a coefficient. In both cases, the symbols for the ZTR and IZ are still used to code those coefficients insignificant relative to T2. In the first case, the four symbols PIZ2, NIZ2, PZTR2 and NZTR2 code simultaneously the sign of coefficients in [T1,T2] i.e. those whose value is significant relative to T2, but insignificant relative to T1, and also the significance of their descendants. Thus, PIZ2 and NIZ2 code respectively positive and negative coefficients with some significant descendants, while PZTR2 and NZTR2 code positive and negative coefficients whose descendants are insignificant. In this case, 8 symbols (3 bits) are needed to code the significant list. In the second case, each of the symbols used to code coefficients significant relative to T1 is also split into two new symbols to distinguish those significant coefficients whose descendants are significant relative to T2 from those whose descendants are insignificant. Therefore, POS splits into PIZ1 and PZTR1, and NEG into NIZ1 and NZTR1. Thus, for this second alternative 10 symbols (4 bits) are needed to code the dominant list.

In summary, both alternatives need more bits (3 or 4 bits) than the original algorithm (2 bits) to code the dominant list but, as indicated in the Results, the total number of symbols is reduced as many of the old ZTRs are now coded with other symbols conveying more information in a single step.

4. RESULTS

A test image is chosen a 512x512 thorax radiography. Firstly, the image is transformed using a 6-scale biorthogonal wavelet [5] and then, coded with each of the algorithms described above. They are followed by adaptive Huffman coding which is one of the noiseless coding scheme. After an entropy analysis, it is found that the best performance is obtained when only two iterations are combined although higher compression ratio than original algorithm is obtained for three or more iterations but lower one is achieved for two iterations. Figure 3 illustrates the good performance of EZW algorithms for the thorax radiography codified at 0.5 bit Per pixel (bpp) with peak signal-to-noise ratio (PSNR) of 49 dB.

Figure 3 (a) Thorax radiography: Original image

Figure 3 (b) Thorax radiography: The image coded at 0.5 bpp.

It is chosen a compression ratio for which the images display good visual quality, similar to original, although with different PSNRs. It is found that, in general, the signal-to-noise ratio for the medical image needs to be higher by
approximately 6 dB than the natural image (for example Lena) to be visually acceptable (i.e. without blurry appearance or block-like artifacts), although the number of steps necessary to reach this level of visual quality is the same for the both kind of images. To reach the same PSNR with Shapiro’s algorithm, 0.65 bpp are necessary for the radiography.

![Figure 4. PSNR versus bpp for the thorax radiography.](image)

To give a quantitative idea of the behaviour of the EZW algorithms at different bit rates, it is computed the PSNR and the bits per pixel necessary to code the image at each iteration, and plotted it in Figure 4 for Shapiro’s (dashed line), the modified algorithm (solid line) and standard JPEG algorithm (dotted line). For a given PSNR, the compression ratio obtained with modified algorithm is always higher than the results obtained from the others. It is obviously seen that the performance of the JPEG is below both EZW algorithms. The difference in performance between the EZW algorithms and JPEG is larger at very low bit rates (0.1-0.3 bpp) for which JPEG produces images with very low PSNRs. In addition, images coded at low bit rates with JPEG are hardly recognizable, while those coded with either of the EZW algorithms show a better visual quality.

5. CONCLUSION

In this study, it is presented a modified version of the embedded zerotree wavelet basic algorithm introduced by Shapiro that can be applied to natural and medical images codec. The modified algorithm shows a clear advantage in the compression ratio achieved for a given SNR over traditional EZW and it works at higher speed. It is concluded that for a given image quality the modified one produced lower bit rates than Shapiro’s EZW. The new approach is more efficient for applications demanding high visual quality, which often happens in medical image compression rather than an embedded representation of the image. Then, the new technique can be adapted to provide a final image with a given visual quality by performing n-iterations combined in a single step. A 512x512 thorax radiograph image is chosen as a sample image. The results show that image quality is better than the one obtained by JPEG and EZW. Preliminary results in medical images show that the new algorithm gives better visual qualities than other lossy methods traditionally used. As a further research, the algorithm can be oriented to determine the advantages of it in an improved version of Shapiro’s algorithm recently introduced by Said and Pearlman [10] and apply for the other wavelet transforms.

6. REFERENCES


