WAVELETS AND THEIR USAGE ON THE MEDICAL IMAGE COMPRESSION WITH A NEW ALGORITHM

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ABSTRACT

Technically, all image data compression schemes can be categorized into two groups as lossless (reversible) and lossy (irreversible). Although some information is lost in the lossy compression, especially for the radiologic image compression, new algorithms can be designed to minimize the effect of data loss on the diagnostic features of the images. Wavelet transform (WT) constitute a new compression technology that has been described in natural and medical images. In this study, the well known Shapiro's embedded zerotree wavelet algorithm (EZW) for image coding is modified. It is designed to optimize the combination of zerotree coding and Huffman coding. It is shown that the multi-iteration algorithms and particularly the two-iteration EZW for a given image quality produce lower bit rates than Shapiro's. It is applied for the medical images and here, the thorax radiology is chosen as a sample image and the good performance is codified.

1. INTRODUCTION

Image compression is essential for applications such as transmission and storage in data bases. 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 archiving and communication systems (PACS) enviroment [1]. It is well known that all image data compression schemes can be categorized into the lossless (reversible) and lossy (irreversible) groups. Although lossless one is especially preferred in medical images , it makes necessary the use of lossy schemes due to the having relatively low achieved compression ratios. This musn't cause to have the less diagnostic features. Therefore the new algortihms can be developed to minimize the effect of data loss on the diagnostic features of the image [2]. Although the JPEG (Joint Photographic Experts Group) compression technique has essentially become a standard [3], it suffers from blocking artifacts that becomes more evident with increasing compression ratios [4]. To minimize or prevent artifacts new compression techniques are still studying. Since 1987, Wavelets transform (WT) constitute a new compression technology that has been described in natural and medical images [5, 6]. The most popular compression techniques Shapiro's technique [7] is based on the WT [8] and on the self similarity inherent in the images [9] where the wavelet coefficients are partially ordered in magnitude by comparison to a set of decreasing thresholds which determine their significance [9,10]. In this study, It is developed a modified version of the original Shapiro's EZW algorithm which produces better image qualities at the same compression ratios, especially, at low bit rate. The details of this algorithm will be described in further section.

This paper is organized as follows. In Section 2, A short description of Wavelet transform and Image compression. In Section 3, It is described the new algorithm together with the basic EZW algorithm. Finally, summary the major findings and outline our future work is given.

2. WAVELET TRANSFORM AND IMAGE CODING

2.1 A Short Description of Wavelet Transform

A wavelet is a "small wave" having the oscillating wavelike 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 $\psi(t)$

$$\psi_{a,b}(t) = |a|^{-1/2}\, \psi\left(\frac{t-b}{a}\right) \qquad (1)$$

The *mother or basic wavelet* ψ must satisfy $\int \psi(x)\, dx = 0$, (i.e. The condition on ψ should be $C_\psi = \int |\omega|^{-1} |\Psi|^2 d\omega < \infty$, where Ψ is the Fourier transform of ψ; if $\psi(t)$ decays faster than $|t|^{-1}$ for $t \to \infty$, then this condition is equivalent to the one above). The continuous wavelet transform of f(t) with respect to the wavelet $\psi(t)$ is then

$$W_f\,(a,b) = \langle f(t), \psi_{a,b} \rangle = \int_{-\infty}^{\infty} f(t)\, \psi_{a,b}(t)\, dt \qquad (2)$$

The wavelet transform coefficients are given as inner products of the function being transformed with each of the basis functions.

The inverse continuous wavelet transform is defined [11] as

$$f(t) = \frac{1}{C_\psi} \int_0^{\infty} \int_{-\infty}^{\infty} W_f\,(a,b)\, \psi_{a,b}\,(t)\, db\, \frac{da}{a^2} \qquad (3)$$

This continuous wavelet transform and inverse of it can be expressed for the functions of two-dimensions.

The second type of wavelet transform is defined as *the wavelet series expansion*. Again, a basic wavelet is scaled by binary scaling and translated by a dyadic translations to form a set of basis functions. For the wavelet expansion, a two-parameter system which is defined for a signal f(t) becomes

$$f(t)=\sum_k \sum_j a_{j,k}\,\psi_{j,k}(t) \qquad (4)$$

and the $\psi_{j,k}(t)$ formed from the mother wavelet $\psi(t)$ are the wavelet expansion functions that usually form an orthogonal basis of L^2 (R) defined as

$$\psi_{j,k}(t)=2^{j/2}\,\psi(2^j t-k) \qquad (5)$$

where both j and k are integer indices where j determines the dilation while k specifies the translation. The two-dimensional set of coefficients $a_{j,k}$ is called the *discrete wavelet transform (DWT)* of f(t). A more specific form indicating how the $a_{j,k}$'s are calculated by writing inner products as

$$a_{j,k}=<\psi_{j,k}(t)\,,\,f(t)> \qquad (6)$$

(Note that $<\psi_{j,k}(t)\,,\psi_{l,m}(t)>=\delta_{j,l}\,\delta_{k,m}$ where l and m are integers, $\delta_{j,k}$ is the Kronecker delta function, and <. , .> indicates inner product.) [11-13].

2.2 Image Compression

A DWT which provides a compact multiresolution representation of the image where multiresolution supplies a simple hierarchical framework for interpreting the image information. The DWT decomposes an image into a set of successively smaller orthonormal images.

in order to obtain a set of biorthogonal subscales of images, the original image is decomposed at different scales. The hierarchical wavelet decomposition will be used for images suggested by Mallat [14]. The lowpass (L) and high pass (H) filters are applied to the image in both the horizontal and vertical directions, and the filter outputs subsampled by a factor 2, generating three orientation selective high-pass subbands HH, HL, LH and a lowpass subband LL. The process is then repeated on the LL band to generate the next level of the decomposition, etc. The 3-level hierarchical subband decomposition which separates the information of the image at different scales and orientations is shown in Figure 1 to represent the *parent-child* dependencies of subbands. In this figure the arrows point from parents to child for a 3-scale wavelet. This scheme can be extended to larger number of subbands [15].

3. THE NEW 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.

In 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.

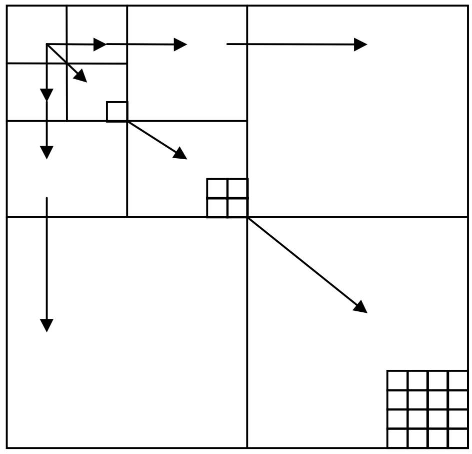

Figure 1.Parent-child dependencies of subbands.

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 analysed. 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 also 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 [7].

Therefore, we studied the symbol distribution in the dominant list for several images. Thus our 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.

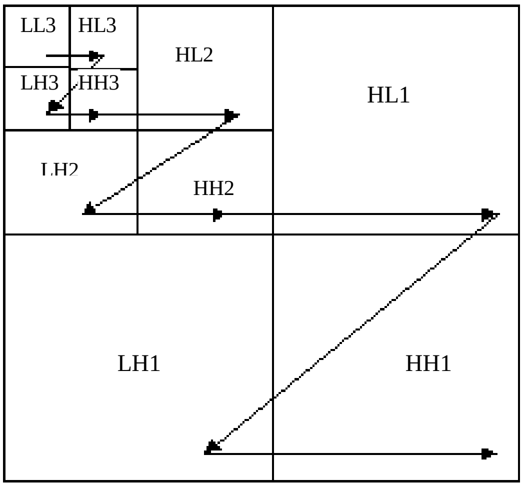

Figure 2. Scanning order of the subbands for encoding of a significant map.

In this way, we still take advantage of the data reduction achieved by ZTR symbol while, at the cost of introducing extra symbols, we are able 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 tresholds: 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 we will see 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 [7] 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.

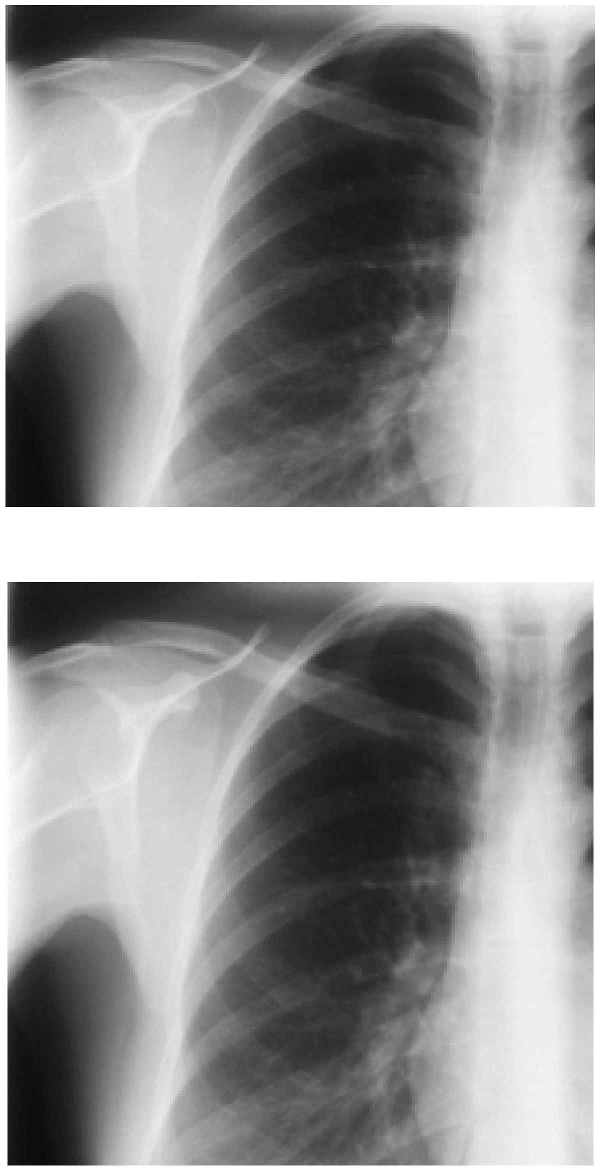

Figure 3.Thorax radiography: Original image at the top and the image coded at 0.5 bpp at the bottom.

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.

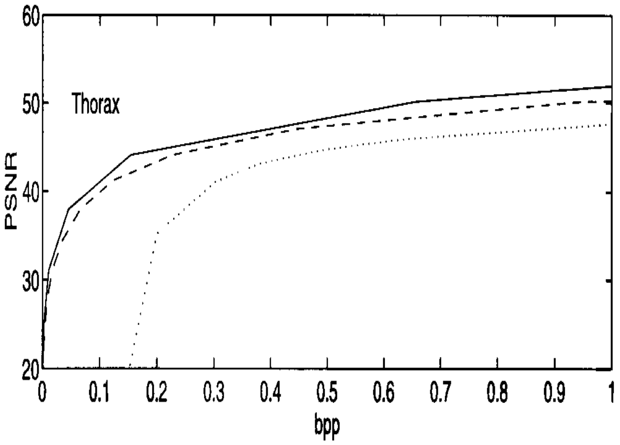

Figure 4. PSNR versus bpp for the thorax radiography

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. SUMMARY AND 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 Perman [16] and apply for the other wavelet transforms [17,18].

6. REFERENCES

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