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Adaptive Medical Image Compression Based on Lossy and Lossless Embedded Zerotree Methods

Sid Ahmed Elhannachi*, Nacéra Benamrane*, and Taleb-Ahmed Abdelmalik**

Abstract

Since the progress of digital medical imaging techniques, it has been needed to compress the variety of medical images. In medical imaging, reversible compression of image's region of interest (ROI) which is diagnostically relevant is considered essential. Then, improving the global compression rate of the image can also be obtained by separately coding the ROI part and the remaining image (called background). For this purpose, the present work proposes an efficient reversible discrete cosine transform (RDCT) based embedded image coder designed for lossless ROI coding in very high compression ratio. Motivated by the wavelet structure of DCT, the proposed rearranged structure is well coupled with a lossless embedded zerotree wavelet coder (LEZW), while the background is highly compressed using the set partitioning in hierarchical trees (SPIHT) technique. Results coding shows that the performance of the proposed new coder is much superior to that of various state-of-art still image compression methods.

Keywords

LEZW, Medical Images, ROI, RDCT, SPIHT

1. Introduction

Currently, medical image compression is done with lossless or near-lossless of information, to ensure data integrity and avoid misdiagnosis due to degradation of image quality especially in parts called regions of interest (ROI). However, this type of compression (lossless) doesn't offer significant reduction in the volume of such data. In this context, the lossy compression also has many advantages for applications other than the diagnosis.

To find a good compromise between compression ratio and validation of diagnostic quality of compressed images, it seems an advantage of combining the two techniques on a medical image. So after an extraction step of the region of interest ROI in the image (e.g., tumor area in a brain magnetic resonance image [MRI]), a lossless compression can be applied to the region of interest while the remaining part called background will be compressed with loss.

In a medical image, a region of interest can be selected manually or else detected in a semi-automatic or automatic manner. Detecting of the ROI part has been studied for several years and the existing

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algorithms include ROI extraction are based on low-level features or geometric properties [1-4].

JPEG2000 standard is a compression technique that can cover the needs of compression of medical images. This method can perform a lossless compression in regions of interest and lossy compression elsewhere [5].

In the literature, several existing works discussed the use of the ROI to improve medical image compression. In [6], a multi-ROIs algorithm for medical image compression is proposed. Based on the segmentation of Canny operator, the image is divided into ROIs and non-ROIs. In the ROIs, lossless compression is applied, based on JPEG2000 algorithm. The set partitioning in hierarchical trees (SPIHT) encoder was used to encode non-ROIs.

In [7], an approach based context-regions of interest to compress vascular images for peripheral arteries, has been proposed. The vascular image is divided into primary regions (PROI), secondary regions (SROI) and the background. Based on the JPEG2000 algorithm, these multiple ROIs was compressed at various degrees of interest.

A study [8] presented a ROI based method with SPIHT algorithm. The scheme used a flexible method to determine the ROI into the DWT and accepts multiple regions by defining the ROI mask on the low frequency sub-band which reduces the amount of bits needed to the mask. In [9], a compression method is proposed to compress the liver cancer computed tomography (CT) images. The ROIs are compressed using the lossless Huffman encoder, while the remaining irrelevant region of image is compressed using the near-lossless image compression techniques: SPIHT, embedded zerotree wavelet (EZW), and DCT-RLE.

A study [10] has investigated an approach for medical image compression using ROI-EZW. Lossless integer wavelet transform was included to partial EZW to encode the ROI part. The partial EZW uses conventional EZW when the frequency of one's is less than 0.2 and two new options are used otherwise, making it more superior to EZW and SPIHT algorithm.

Another ROI coding scheme has been presented in [11] where the ROI part is selected by the user. Using the fractal encoding, the ROI part is encoded by employing wavelet transform based on listless SPECK (LSK), giving high compression ratio and better peak signal-to-noise ratio (PSNR) values.

The authors in [12], proposed a ROI coding approach for abdominal CT image. Divided manually, the region of no interest was coded by a hybrid technique based on fractal and improved SPIHT. The Huffman technique was used to compress the region of interest, for lossless requirements.

In [11,12], measure performance showed that the PSNR values obtained with ROI compression are not so high compared with those obtained in compression without ROI, this is probably due to the use of fractal method which in some cases, cannot get enough information from the detail images of the wavelet transform. Also, the Huffman coding does not always permit to obtaining high PSNR values.

A solution consists to use a robust lossless compression technique on the ROI part. This is an important requirement for medical imaging domains, where, mainly high quality is demanded. The algorithms for lossless compression can be further categorized into predictive coding and transform coding algorithms.

Predictive coding requires intensive computation and relies on extensive side information to implement the sophisticated predictors such as clustered differential pulse-code modulation (C-DPCM) [13] and context-based adaptive lossless image coding (CALIC) [14,15].

Transform coding algorithms are more computationally efficient, but typically do not equal the

lossless compression performance of predictive algorithms. Since the wavelet transform holds the properties of the multi-resolution analysis and energy compactness, most transform based compression algorithms are based on these. Therefore, transform based coding has become the popular approach because of its high efficiency, as well as other advantages including progressive transmission, random access to the bit stream, ROI coding.

Particularly, several works have shown that EZW wavelet-based embedded image coders help to provide an excellent rate-distortion performance since dependencies of wavelet coefficients in subbands are well exploited for high resolution images [16-18]. However, in very low bit rate image coding using low resolution images (e.g., ROI size of 100×145) the embedded zerotree coding performance is prominently reduced due to the insufficient wavelet decomposition.

For this purpose, beside wavelets, DCT based zerotree coding applications were investigated and used by several researchers [19-22]. These works showed that DCT-based embedded coders can provide competitive compression rates with a good image quality compared to the wavelet based embedded coders.

In this paper, the aim of the proposed medical image compression approach is to compress the important region strictly without loss, and to compress the remaining regions of the image with loss. The pixels appertaining to the ROI part are encoded efficiently by using a reversible DCT-based lossless embedded zerotree coder, thus yielding an overall high compression ratio and conserving the relevant data diagnostic. To use the zerotree encoder with DCT coefficients, these coefficients are rearranged into a hierarchical structure similar to the wavelet subbands. We obtain better compression results, comparing to the DWT embedded zerotree and conventional DCT that use regular quantizer.

The remainder of this paper is organized as follows: Section 2 exhibits the proposed approach for adaptive medical image compression. Section 3 illustrates and discusses the experiments results, while last section concludes the paper.

2. Proposed Approach

We remind that the objective of the proposed approach is to make medical image coding more efficient by preserving the content of the ROI part used in all diagnosis treatment. The proposed method is based on the EZW algorithm, which is modified and combined to a reversible DCT (RDCT), to improve its performance for lossless compression. The background is highly compressed with the SPIHIT method. In the following paragraphs we will briefly present the basic tools having been used and then we will detail our proposed compression system.

The RDCT has a good energy compaction property and gives better results for image compression by providing an excellent rate-distortion [23-25]. Therefore we propose to use RDCT as a substitute for the DCT with a lossless embedded compression to encode the ROI part of image without loss of decoding accuracy.

Integer DCT performs as well as the DCT by employing lifting structures and rounding operations, which convert signals from real values to integer values [26,27].

The lifting-structured method maps an integer input vector to also an integer output vector as done for integer wavelet transform [28]. The integer approximation is achieved by applying a rounding function after each addition. Various integer DCTs have been greatly innovated for lossy-to-lossless

image coding [29-32]. The authors in [33] present a comparative study on many kinds of Int-DCT, they referred to five algorithms of integer DCT type II (namely, the BinDCT-IIC, -IIL, -IIS, IntDCT-II, LDCT-II). A comparative performance in aspect of lossless coding showed that the first order entropy rate of LDCT-II is the best and confirmed that the LDCT-II is the best for lossless coding performance. Therefore, in our approach we opted for this type of lossless DCT (LDCT-II) [23].

For embedded zerotree methods, a zerotree data structure is defined by using the self-similarity of wavelet transform sub-image at different scales. There are two main techniques, EZW and SPIHT.

In the EZW algorithm, two passes are used to code the image: a dominant pass and a subordinate pass. The dominant pass finds pixel values above a certain threshold, and the subordinate pass refines all significant coefficients found in the dominant pass [34].

In the dominant pass, a wavelet coefficient x is said to be insignificant with respect to a given threshold T if: $|x| < T$. In this case, once all wavelet coefficients of the same orientation in the same spatial location are insignificant, a zerotree can be formed, and it is called zerotree root (ZTR). In order to encode a zerotree, three additional symbols are defined: if the coefficient is insignificant but has some significant descendant, it is called isolated zero (IZ). In addition, the coefficients can be either positive or negative significant. As a result, the wavelet coefficients can be efficiently represented as a string of symbols from four symbol alphabet: ZTR, IZ, positive significant (POS), and negative significant (NEG).

In the subordinate pass, a refinement bit is coded for each significant coefficient. A coefficient is significant if it has been coded POS or NEG in a previous bit-plane. Its current refinement bit is simply its corresponding bit in the current bit-plane. The interested reader is suggested to refer to [34,35] for further details on the EZW coding scheme.

The SPIHT algorithm is a refined version of EZW algorithm. It can perform better at higher compression ratios for a wide variety of images [36,37].

The main idea is based on partitioning of wavelet coefficients in three sets: when a threshold value is given, it partitions the coefficients or the sets of coefficients into significant or insignificant coefficients. Significant coefficients are added to the list of significant pixels (LSP), and insignificant coefficients to the list of insignificant pixels (LIP) or the list of insignificant sets (LIS).

During the compression procedure, the sets of coefficients in the LIS are refined and, if coefficients become significant, they are moved from the LIP to the LSP. The LSP is set as an empty list and all the nodes in the highest subband are put into the LIP. The root nodes with descendants are put into the LIS.

Two encoding passes which are the sorting pass and the refinement pass are then performed in the SPIHT coder. During the sorting pass, a significance test is performed on the coefficients according to the order in which they are stored in LIP. Elements in LIP that are found to be significant with respect to the threshold are moved to the LSP. A significance test is then performed on the sets in the LIS. Here, if a set in LIS is found to be significant, the set is removed from the list and is partitioned into four single elements and a new subset. This new subset is added back to LIS and the four elements are then tested and moved to LSP or LIP, depending on whether they are significant or insignificant with respect to the threshold. In the refinement pass, another bit of precision is added to the magnitudes of coefficients in the LSP. Finally, the threshold is halved and SPIHT coding is repeated until the bit budget is exhausted [37].

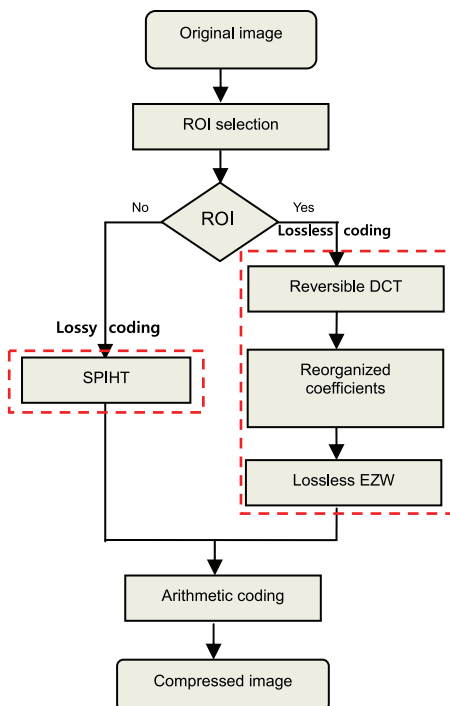


Fig. 1. Proposed compression method.

2.1 The Proposed Compression System

Fig. 1 shows the overall system flow diagram. The proposed system starts with a manual partition of image into two parts namely: ROI and background for selective compression. Once the ROI is extracted, a reversible DCT with lossless embedded technique are used to compress the ROI with higher compression ratio. Also, we have chosen not to discard the background (non-ROI), but rather to highly compress it by SPIHT technique. Finally, an entropy coding based on adaptive arithmetic coder is applied to the final bit stream.

2.1.1 Lossless ROI coding

Rearrangement of RDCT coefficients

In our approach, the ROI is selected manually by a rectangular shape. It is decomposed into non-overlapping 8×8 blocks, which are then transformed with LDCT-II. The LDCT-II coefficients of each block are rearranged into 3-level wavelet pyramid structure. These rearranged coefficients are coded by using embedded zerotree coding based on a modified EZW coder for lossless compression, followed by entropy coding to further compress the result. The detailed descriptions are given in the following subsections.

Consider the ROI part which is composed of $K \times L$ blocks with sizes of $M \times M$, where each block is 2D LDCT-II transformed. Each LDCT-II block of size $M \times M$, including M^2 coefficients is treated as a hierarchical subband structure. Rearranging all blocks of the ROI part in this way, we obtain a 3-scale hierarchical subband structure.

In our approach, for all the DCT blocks and according to their order, we adopt a method to collect the coefficients of the same frequency in order to take full advantage of this relationship between DCT and subband decompositions. For each block of size of 8×8 , we apply the relation illustrated in the following equation:

$$W[(i \% 8) M / 8 + i / 8][(j \% 8) N / 8 + j / 8] = D[i][j] \tag{2}$$

Where:

$D[M][N]$: the matrix of DCT coefficients

$W[M][N]$: the matrix of rearranged coefficients

$I=1,2,\dots,M$ and $J=1,2,\dots,N$

% denotes modulus operator

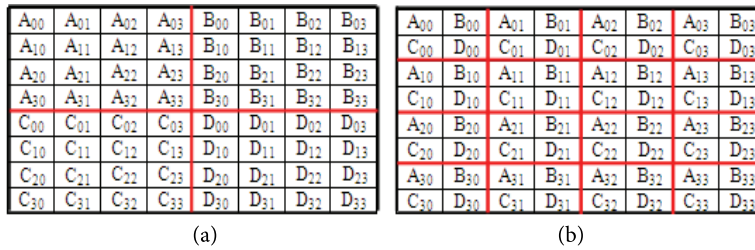


Fig. 2. (a) 4×4 DCT block, (b) reordered DCT coefficients into subband structure.

From Fig. 2, observing the energy distribution among the DCT blocks, the energy compaction is presented in the multi-resolution dimension in so that the largest energy is located at the first subband LL₃ that includes DC coefficients of all 8×8 DCT blocks and the energy declines monotonically in the subbands in lower scale that contains the alternative current (AC) coefficients. Since most of the energy is concentrated in the direct current (DC) coefficients, the quality of the decoded image depends mostly upon DC coefficients then on the AC coefficients. Therefore the rearranged integer DCT having the same structure of multi-resolution wavelet subbands is suitable for the zerotree encoding that allow more efficient coding.

The proposed lossless EZW (LEZW)

We propose a simple coder that yields perfect quality reconstruction at good compression rates. It performs an embedded coding, based on reversible DCT. The lossless embedded zerotree coding of LDCT-II coefficients is based on three steps: 1) determining the significant coefficients across scales by exploiting the self-similarity inherent in reorganized LDCT-II coefficients, 2) successive differences quantizing of LDCT-II coefficients, 3) lossless compressing of the data from the output of the embedded zerotree coder by using an adaptive arithmetic coder [38].

Therefore, we propose some modifications to simplify the conventional EZW algorithm for a lossless coding and improved compression ratio. The modification will change the passes used in the coding algorithm.

In preceding paragraphs, it mentioned that the EZW algorithm used two passes: dominant pass and subordinate pass. The dominant pass looks for the significant coefficients for each bitplane, and the

subordinate then quantizes these found significant coefficients. For lossless compression, the results from two passes must be stored for decoding. Therefore, the resulting compression ratio is a sum of the bit rates from the dominant and subordinate passes. We note that the subordinate pass contributes averagely one-third of the total bit rate.

So, in order to save more of the bit rate (improving compression ratio), we consider removing the subordinate pass. Unlike Shapiro's EZW, the subordinate pass is eliminated by coding residual values obtained per successive differences (i.e., subtracting the subordinate threshold from the coefficients in the subordinate list) to provide an exact representation of the coefficients for each subordinate pass. The coefficient C_{ij} whose absolute value is larger than the current threshold, is recognized as a significant pixel and replaced by a residual value in the image. This is an alternative way to replace the subordinate pass, but still complete the job of quantizing coefficients. The dominant pass can thus be implemented as (LIP; $S_n(Des(i,j))$, significance of descendants):

- 1) Set initial threshold $T=2^{\lceil \log_2(\text{MAX}\{|C_{ij}|\}) \rceil}$
- 2) For each current threshold $T_k \geq 2$ do
 - For each coefficient $C_{ij} \in \text{LIP}$ do
 - If $|C_{ij}| < T_k$ Then
 - Output '0';
 - Remove C_{ij} from LIP;
 - Else
 - Output '1' and Set $D_{ij} = |C_{ij}| - T_k$;
 - Remove C_{ij} from LIP;
 - End If;
 - If ($S_n(Des(i,j)) = 1$) Then
 - Add Children of C_{ij} to LIP;
 - Output '1';
 - Else Output '0';
- 3) Set $T_{k+1} = T_k/2$ and go to step (2)

The LEZW lossless algorithm continues until the last threshold is equal to 2, at which the residual image only contains binary values. We note that, in this lossless coding method, the algorithm forces previously scanned significant coefficients being coded and appended to the dominant list only once during the repeated scanning processes. The final bit stream is stored as a byte stream to shorten its length for adaptive arithmetic coding [38].

2.1.2 Lossy background coding

In order to improve the global compression rates, the background which contains no useful information to establish a medical diagnosis, was highly compressed by using the wavelet zerotree image coding technique (SPIHT) developed by Said and Pearlman [36]. This technique provides a high performance in image compression with low complexity.

3. Experimental Results

We conducted a number of experiments to evaluate the performance of the proposed scheme, on various kinds of medical images including: MRI, X-rays, CT, and ultrasounds images given in Figs. 3–8.

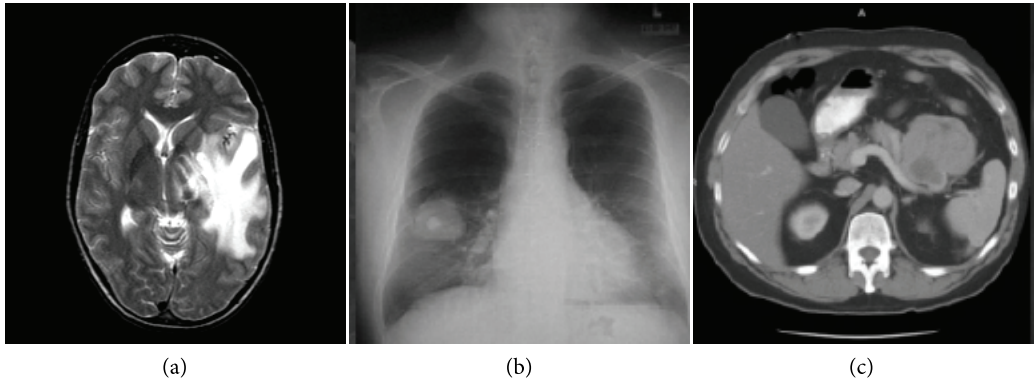


Fig. 3. Original test images with size of 256×256 and 8 bit per pixel: (a): a brain MRI, (b) a lung X-ray, and (c) a pancreas CT image.

We use PSNR (in dB) and correlation coefficient (CoC) as metrics for whole image quality evaluation and bit rate (bit per pixel, bpp) for lossless compression assessment. The mean square error (MSE) is used to calculate the PSNR that is given in the equation 4.

$$MSE = \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (i(x, y) - \hat{i}(x, y))^2 \quad (3)$$

$$PSNR = 10 \log_{10} \frac{255 \times 255}{MSE} \quad (4)$$

With $M \times N$, image size; i , original image; \hat{i} , reconstructed image.

The CoC suggests how closely the reconstructed image is correlated with an original image, on a scale of 0–1:

$$CoC = \frac{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} i(x, y) \times \hat{i}(x, y)}{\sqrt{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} i(x, y)^2} \sqrt{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \hat{i}(x, y)^2}} \quad (5)$$

The coding results were compared with those obtained applying the original SPIHT algorithm and the standards JPEG [39] and JPEG2000 [40] on the whole image. The SPIHT algorithm and JPEG2000 had been utilized with the irreversible 9/7 biorthogonal filters [41].

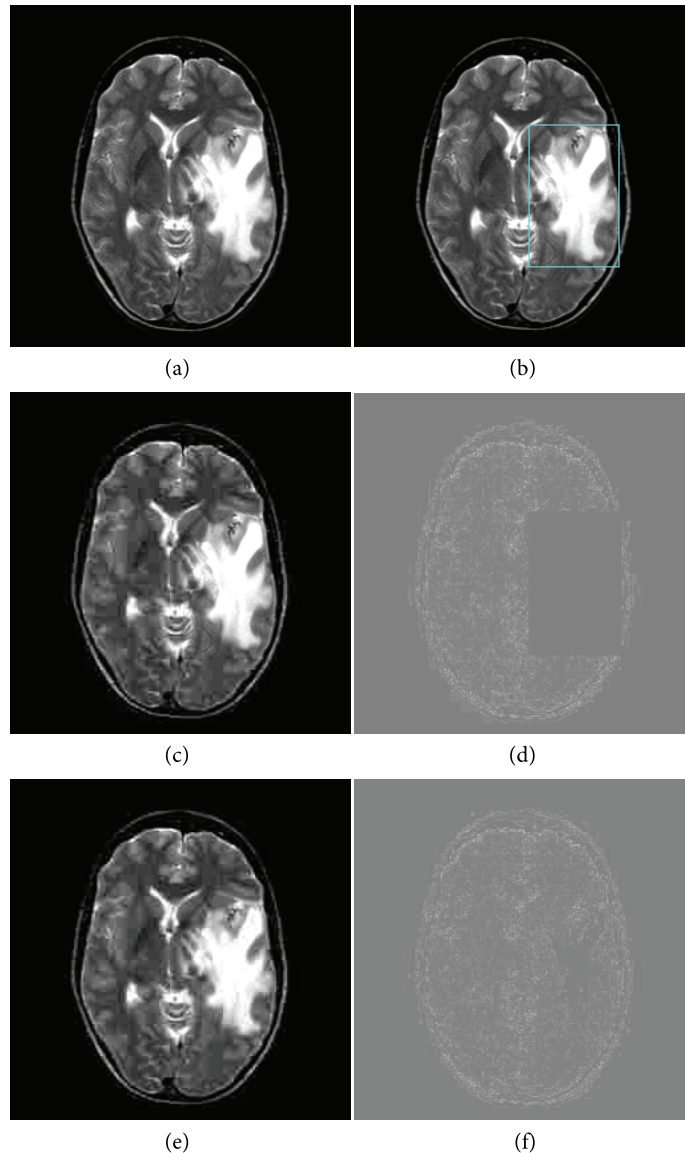


Fig. 4. Visual compression results for brain MRI image at bit rate=0.5 bpp. (a) Original image, (b) ROI selection, (c) ROI encoding—lossless encoding of image background and ROI losslessly coded (PSNR=33.60 dB), (d) image difference between (a) and (c), (e) entire image encoding by SPIHT (PSNR=29.30 dB), and (f) image difference between (a) and (e).

In our scheme, the ROI region is selected by a rectangular shape for each test image, as shown in Figs. 4(b) and 5(b). Thus, information to be transferred to the decoders is its corner coordinates or its origin and radius. The ROI region is coded losslessly by using a reversible integer DCT transform with the modified algorithm LEZW and the background is coded with loss at low bit-rate by SPIHT using 9/7 Daubechies wavelet filter, with 4 levels of decomposition in order to increase the compression ratio. Perceptually the gains are very significant in term of diagnostic information conservation and compression ratio, as illustrated in the following.

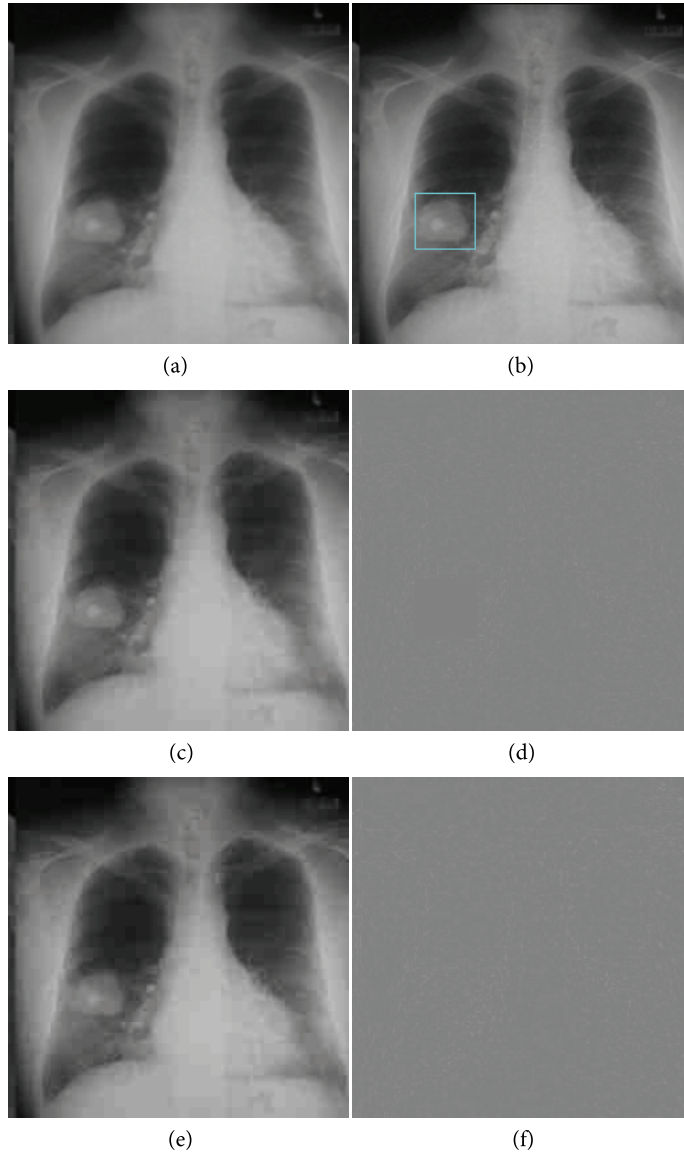


Fig. 5. Visual compression results for lung X-ray image at bit rate=1.0 bpp. (a) Original image, (b) ROI selection, (c) ROI encoding—lossless encoding of image background and ROI losslessly coded (PSNR=36.97 dB), (d) image difference between (a) and (c), (e) entire image encoding by SPIHT (PSNR=30.81 dB), and (f) image difference between (a) and (e).

Figs. 4 and 5 show a comparison results of a brain MRI image and lung X-Ray image, respectively, compressed by proposed method (based ROI) and regular compression method by SPIHT (not based ROI), at the same rates. Figs. 4(b) and 5(b), show the separated parts of the original image, namely the ROI and the background.

In Figs. 4(c) and 5(c), both regions are compressed and merged and formed the compressed images. Figs. 4(e) and 5(e) show the reconstructed images obtained by a regular compression.

Note that the value of PSNR in our method is higher than those obtained by ordinary SPIHT

compression method, this is due to the lossless compression applied to the ROI part, whereas the background is almost useless in diagnosis, therefore it is compressed with higher compression rate.

So we managed to fully preserve the ROI in similar bit rates to the regular compression where distortions are visible in reconstructed image by the SPIHT method as seen in Figs. 4(f) and 5(f), contrary to our proposed method that keeps all the critical information as we can distinguish in Figs. 4(d) and 5(d), where the difference is equal to zero at the ROI portion required by medical care professionals.

Table 1. Comparison of coding results for a brain MRI image

Bit rate (bpp)	PSNR				CoC			
	JPEG	SPIHT	JPEG2000	Proposed	JPEG	SPIHT	JPEG2000	Proposed
0.125	20.12	25.43	28.32	30.50	0.883	0.910	0.925	0.975
0.25	22.05	27.11	30.98	31.20	0.885	0.914	0.928	0.978
0.5	23.85	29.30	32.27	33.60	0.890	0.922	0.933	0.982
1	26.64	30.94	35.71	35.26	0.897	0.925	0.937	0.986

Table 2. Comparison of coding results for a pancreas CT image

Bit rate (bpp)	PSNR				CoC			
	JPEG	SPIHT	JPEG2000	Proposed	JPEG	SPIHT	JPEG2000	Proposed
0.125	21.25	25.40	30.30	31.17	0.884	0.915	0.926	0.977
0.25	22.60	27.07	32.41	33.32	0.888	0.917	0.931	0.981
0.5	24.09	29.30	33.20	34.90	0.893	0.923	0.935	0.984
1	26.64	31.94	35.56	37.25	0.905	0.928	0.938	0.989

Table 3. Comparison of coding results for a lung X-ray

Bit rate (bpp)	PSNR				CoC			
	JPEG	SPIHT	JPEG2000	Proposed	JPEG	SPIHT	JPEG2000	Proposed
0.125	20.20	26.03	29.09	29.60	0.883	0.913	0.923	0.974
0.25	21.50	28.10	31.05	32.68	0.887	0.916	0.927	0.979
0.5	23.07	29.70	34.21	33.02	0.890	0.923	0.933	0.984
1	26.33	30.81	36.08	36.97	0.900	0.930	0.940	0.990

In order to compare our method with other conventional compression methods such as: JPEG [36], SPIHT [36], JPEG2000 [40], Tables 1–3 summarize the coding results in terms of PSNR and CoC, obtained on the three test images presented in Fig. 3, at bit rates ranging from 0.125 to 1.0 bpp. On average, notice the gain of close to 10 dB of our ROI-based coder over JPEG coder. Also, on average, for the three test images, our technique improves, respectively, general SPIHT and JPEG2000 by 5 dB and 1 dB.

In fact, the distortion achieved at 1.0 bpp with SPIHT method, corresponds to a compression rate of 0.125 bpp with proposed approach. Compared to JPEG2000, for the brain MRI image and pancreas CT image, the distortion achieved in 0.5 corresponds to a compression rate of 0.25 bpp with our approach. The JPEG2000 method outperforms our proposed method only in the case of the X-ray image at bit

rate=0.5. This proving clearly the improvement obtained with our ROI based compression technique that guaranties an absolute conservation of the ROI part to make the diagnostic details significantly legible without lowering the compression ratio.

So, in general, our region-based coding method performed substantially better than JPEG, SPIHT, and JPEG2000 (applied to the whole image, with 9/7 irreversible Daubechies filters). The reported CoC of these methods (JPEG, SPIHT and JPEG2000) compared with our method, in Tables 1–3, confirm this conclusion. It is clear that the proposed method yields better CoC value, owing to lossless compression on the ROI part where a perfect reconstruction was obtained.

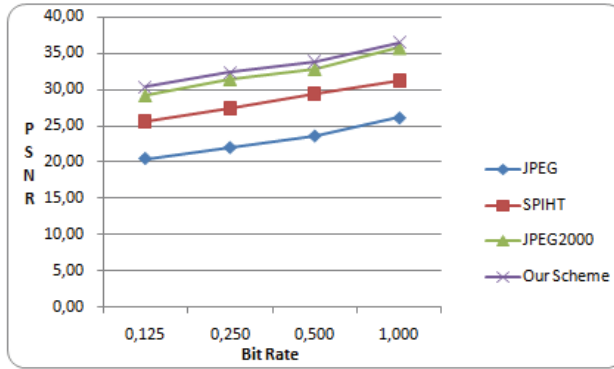


Fig. 6. A comparative evaluation of average PSNR for JPEG, SPIHT, JPEG2000, and our proposed approach.

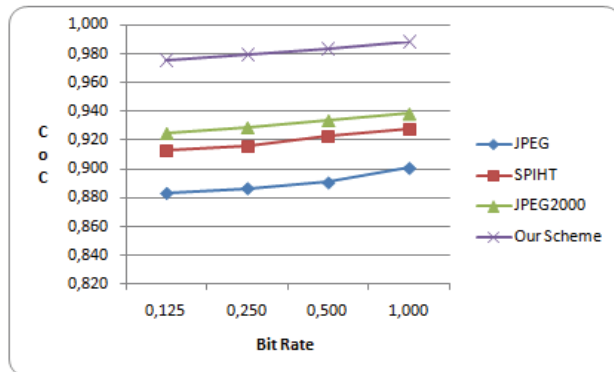


Fig. 7. A comparative evaluation of average CoC for JPEG, SPIHT, JPEG2000, and our proposed approach.

Plots of average PSNR and CoC parameters versus different bit rates are respectively given in Figs. 6 and 7. The climb of PSNR versus rate for our proposed scheme is better compared to JPEG, SPIHT, and JPEG2000 methods.

On the other hand, Fig. 7 plots the CoC measurements that show the high difference in image quality reconstruction performance with the reversible compression on the ROI part, confirming the improvement obtained with our scheme over conventional techniques.

So, we can deduce that our method’s advantage over all three reported methods is more evident as the compression ratio increases since it allows a perfect reconstruction of ROI and slightly degraded background for the entire image at relatively low bit rates.



Fig. 8. Original ultrasound image with size of 512×512.

Table 4. Evaluation of lossless ROI coding on ultrasound image

Lossless method	Bit rate (bpp)
JPEG-LS	3.25
JPEG2000	1.33
Reference [43]	1.44
Proposed	1.36

Moreover, to show the effectiveness of our proposed technique for lossless ROI coding (RDCT+LEZW), we have considered the ultrasound image, sized 512×512 pixels, presented in Fig. 8. Table 4 enumerates bit rate results (bit per pixel, bpp) for lossless coding of ROI part of the ultrasound image. Compared with JPEG-LS [42], and results presented in [43], we can see that the bit rate required by our method for fully reconstruction of ROI is the minimum (1.36 bpp). Yet, lossless JPEG2000 technique with reversible 5/3 wavelet filter [44], provides a very slight bit rate advantage over our approach.

Table 5. Comparison of PSNR (dB) for different ROI based methods

Bit rate (bpp)	EBCOT	MaxShift	Reference [43]	Proposed ROI coder
0.125	24.95	30.08	28.17	31.14
0.25	27.69	33.48	32.58	34.97
0.5	31.52	38.91	38.09	39.58
1	37.77	47.71	37.77	45.07

To more justify our results, we have evaluated the proposed method against the other ROI based methods namely: EBCOT[45], MaxShift [46] and the work presented in [43]. Table 5 lists the PSNR values at different bit rates for the ultrasound image. Compared to the two methods EBCOT and that presented in [43], PSNR values reveal that reconstructed image quality for the proposed method is

much better. These obtained results are very competitive to those obtained by MaxShift method.

The obtained results by our approach show that with the proposed lossless compression technique applied on ROI part, compression results are satisfactory compared to the state-of-art compression methods based ROI.

In addition, applied on MRI brain image, our approach compared to the both based ROI approaches presented respectively in [10,11], is clearly superior in term of PSNR. At a bit rate equal to 1 bpp, with our approach we obtain 45.61 dB of PSNR which is higher to 36.10 dB and 40.91 dB, respectively, obtained by [10,11]. Thus, our approach brings a high compression rate maintaining faultless quality of the ROI while the quality of the background is allowed to have degraded quality, since it is considered to be less important.

4. Conclusion

In this work, to provide solutions for efficient region based image compression, we presented an embedded lossless wavelet-based image coding algorithm based on successive differences, which used only the subordinate pass. Applied on the ROI part, the proposed method is simple in concept and implementation but achieving promising lossless compression efficiency as compared with some reversible methods. Irreversible lifting wavelet transform with SPIHT coder was used for compressing the background.

As we have seen in section of experimental results, the proposed reversible system has not limited efficiency in terms of compression rates and provides a solution to increasingly important conservation of diagnostically relevant information. So, our proposed compression scheme can provide efficient compression for various medical images and offer potential advantages in yielding much higher compression rates, while maintaining the integrity of data in ROI part, combining therefore the advantages from both DCT and wavelet based compression algorithms. The choice of integer transformations is an important aspect of the lossless compression.

Medical images, by their inherent features, are more sensitive to distortion and nonlinear transformation and the definition of ROI varies greatly between different categories. Identifying and extracting the region of interest accurately is very important before coding and compressing the image data for efficient transmission or storage thus further investigation is required to automatically detect the ROI.

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