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Medical Image Compression Using Improved ISOM

Imen Chaabouni
University of Sfax
Sfax Engineering School
BP W, 3038
Sfax, Tunisia
Email: chaabouni.imen@gmail.com

Wiem Fourati
Sciences and Technologies
of Image and Telecommunications
High Institute of Biotechnology,
Sfax, Tunisia
Email: wiem_fourati@yahoo.fr

Med Salim Bouhlel
Sciences and Technologies
of Image and Telecommunications
High Institute of Biotechnology,
Sfax, Tunisia
Email: medsalim.bouhlel@enis.rnu.tn

Abstract*—In recent times, developing hybrid schemes for effective image compression has gained enormous popularity among researchers. This research paper presents a proposed scheme for medical image compression based on improved compression technique: incremental self organizing map (ISOM). The goal is to achieve higher compression ratio by applying different wavelet transform for the input medical image. This method is a combination of discrete wavelet transforms (DWT) decomposition and ISOM image compression. Wavelet transform is applied to entire images, so it produces no blocking artefacts; this is a major advantage of wavelet transform over other transform compression methods. Four families of wavelets are considered: 1) Bi-orthogonal, 2) Daubechies, 3) Coiflet and 4) Symlet. Since the good basis wavelet recommended for DWT compressor may depend on the choice of the test image, we consider the medical image. We then evaluate the performance of the four wavelets families on medical image. A comparative results for several wavelets used in DWT compression techniques are presented using the mean square error (MSE) and compression ratio (CR) as a measure of quality. Finally, we present the comparative result according to MSE versus CR for four families of wavelets, showing that db10 yields a better performance than the other Wavelets in terms of MSE and sym7 in terms of CR.

I. Introduction

Medical image like ultrasound acquired from different modalities comprise huge amounts of data, rendering them impracticable for storage and transmission. Archiving this large amount of image data in the computer memory is very difficult without any compression. An important issue in lossy compression of medical image is the risk of destroying diagnostically relevant information. Current lossy compression standards, such as JPEG [1] and MPEG, are designed for conventional still-image and video display. Transform-based techniques have been proposed for the efficient reduction of the high redundancy usually uncountered in real life images [5]. Unsupervised neural networks can perform nonlinear principal component analysis as a transform-based method in image compression [2]. They outperform linear principal component analysis, and are relatively easy to implement. Another common method to compress images is to code them through Incremental Self Organizing Map technique. ISOM have been used to achieve the process of image compression [3]. They represent an efficient compression scheme based on the fact that consecutive blocks in an image are often similar, and thus coded by similar codewords with ISOM algorithm. Wavelet transform does not reduce the amount of data present in the image. It is simply a different form of representation of the image. Incremental Self Organizing Maps (one form of lossy compression technique) on the other hand can reduce the amount of data in the image. In this work, a combined approach of image compression, based on the wavelet transform [4], [6] and Incremental Self Organizing Maps [3] is presented. This proposed method gives superior results which are in general applicable to any images and tested on gray scale medical image. The rest of the paper is organized as follows: Section II describes the compression technique with Incremental Self Organizing Map (ISOM). Section III describes the introductory concepts on Discrete Wavelet Transform (DWT). Section IV introduces the proposed image compression method. Compression steps of the proposed image compression technique are explained in details in this section. Section V presents the experimental results using the proposed image compression technique and lastly section VI concludes the paper.

A. IMAGE COMPRESSION WITH ISOM

1) Description: The key advantage of SOM is the formation of clusters, which helps to reduce the input space into representative features using a self−organization process. Hence the underlying structure is kept, while the dimensionality of the space is reduced. There are many types of self-organizing networks applicable to a wide area of problems. One of the most basic schemes is competitive learning. The Kohonen network can be seen as an extension to the competitive learning network [7]. Self Organizing Maps are a kind of artificial neural networks which inspire from the learning neural networks. This kind of neural network allows projecting an entry space on a one or two dimensional map called topological map. Its composed of two layers, an entry vector, and a map where all elements are of the same dimension as for the entry.

2) Incremental Self Organizing Map: ISOM is an incremental network having an unsupervised learning scheme. ISOM is a two layer network. The nodes in the first layer represent the coefficients vectors (code words). It is determined after the decomposition of the picture. The winner-takes-all guarantees that there will be only one node activated. While first layer represents input vector, index layer represents the index values of the input vector. The training of Kohonen networks [8], [10], is competitive : when an entry vector x is presented to neural network, all neurons get in completion to determine the winner neuron wi which is the one with the weight vector i closest to the entry vector according to a distance measure (generally the Euclidean distance). Thus the winner neuron get closer to the vector entry by adjusting his weight vectors according to the distance between him and the winner following this rule,

$$\omega_t(k) = \omega_t(k-1) + \eta(x(k-1) - \omega_t(k-1)) \qquad (1)$$

Where k is the iteration index, and η is the gain constant $(0 < \eta \leq 1)$.This process is to be iterated until the convergence of the map (when the distortion of the map between two consecutive iterations is smaller). The number of nodes in the first layer and the indexes of the output nodes are automatically determined during the learning. By the end of the training, the map is ready to be used. Thus when a new entry vector is presented to the map; the distance between this vector and each neuron is calculated to determine the winner which is the closest to the new vector, and hence it will be affected to the class which corresponds to the winner [11].

3) Data compression using SOM: One important feature of SOM is the possibility of achieving high compression ratios with relatively small block size. Another important advantage of SOM image compression is its fast decompression by table lookup technique. SOM is basically a clustering method, grouping similar vectors (blocks) into one class [12]. Our basic approach to image compression consists of several key steps.

Step 1: Extract a square block from the image in an order.
Step 2: Compute the clustering to the block of the image by the methodology of incremental self organizing map.
Step 3: Compute the Euclidean distances between the input vector and the node in the first layer, and find the minimum distance.
Step 4: The competition between the neurons of the card of Kohonen is started. This competition is based on the strategy of "Winner Takes all". If the minimum distance exceeds the threshold ε fixed by the user, the weights will not be modified and increment the index counter by one, otherwise, the weights of the node of the card are updated nearest to the input vector according to equation 1 and the number of classes is the same one.
Step 5: Last step provides us a matrix classes which contains the indices of classes of each block and a matrix weight which represents the weights of the found classes respectively. This phase constitutes the compression phase of the image.
Step 6: Compute decompression phase by rebuilding the compressed image.
The use of incremental self organizing map will provide us two matrixes; one which contain the indices of classes of each block and another matrix which represents the weights of the found classes respectively. This phase constitutes the compression of the image, considering which one has a profit in the face of the image. At the decompression phase, for each index, a lookup process is performed in the input vector to obtain the corresponding weight representative of the original block. The obtained weights are placed, in sequence, at the decompressed file.

1) Load the compressed file.
2) Select, in order, an index i from the indices of classes tables.
3) Using i as an address, access the corresponding vector to obtain the weight and store it in the same order of index i into the decompressed file. These steps are summarized in figure 1.

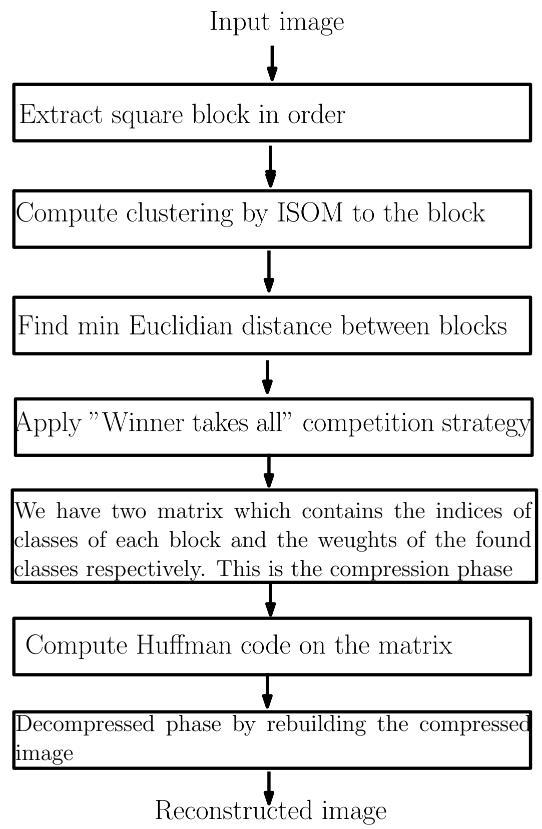

Fig. 1. Algorithm of compression

B. IMAGE PRE-TREATMENT BY WAVELET TRANSFORM

Wavelet analysis is a technique to transform an array of N numbers from their actual numerical values to an array of N wavelet coefficients. Each wavelet coefficient represents the closeness of the fit (or correlation) between the wavelet function at a particular size and a particular location within the data array. By varying the size of the wavelet function (usually in powers-of-two) and shifting the wavelet so that it covers the entire array, one can build up a picture of the overall match between the wavelet function and the data array. Wavelet transform decomposes an image into a set of different resolution sub-images, corresponding to the various frequency bands. Wavelets are a class of functions used to localize a given signal in both space and scaling domains. Wavelets automatically adapt to both the high-frequency and the low frequency components of a signal by different sizes of windows [4], [6]. Wavelets are functions generated from one single function (as shown in the following equation), which is called mother wavelet, by dilations (a) and translations (b).

$$\Psi_{a,b}(x) = |a|^{-\frac{1}{2}}\Psi(\frac{x-b}{a}) \quad (2)$$

Where ψ must satisfy the following conditions.

$$\int_{-\infty}^{+\infty} \psi(x)dx = 0 \quad (3)$$

and

$$\int_{-\infty}^{+\infty} |\psi(x)|^2 dx = 1 \quad (4)$$

Wavelet transform is the representation of any arbitrary signal x(t) as a decomposition of the wavelet basis or write x(t) as an integral over a and b of $\psi_{a,b}$. DWT is implemented using the subband coding method. The whole subband process consists of a filter bank (a series of filters), and filters of different cut-off frequencies, used to analyze the signal at different scales. The procedures starts by passing the signal through a half band high-pass filter and a half band low-pass filter. The filtered signal is then down-sampled. Then the resultant signal is processed in the same way as above. This process will produce sets of wavelet transform coefficients that can be used to reconstruct the signal. However, in each wavelets family, different types of wavelets can be considered, therefore, it is important to study which type of wavelets and which wavelets family provides a better performance for image processing. The main contributions of this paper are as follows.

1) Four wavelets families each with different orders (overall 26 wavelets) are studied and compared with respect to the mean square error MSE and compression ratio CR.

2) In each family, a wavelet which provides the best performance is found, according to the considered image.

3) Among four wavelets families, we show that for a good trade-off between MSE and CR, we should choose the Db10 and Sym7, respectively. In this paper, we emphasize on how we can obtain a better quality and a better compression ratio by selecting a suitable wavelet. For the performance of the DWT coder, the selection of wavelet is important. In the following, we explain how to choose mother wavelets. The choice of wavelet, to be used in compression algorithm, should be adjusted to the information on the image [12], [13] [14], . The properties to choose the mother wavelet are: Compact support, symmetry, orthogonality and regularity [13]. To evaluate the efficiency of DWT, several wavelets has been used with different orders, namely: Bior2.2, Bior3.3, Bior4.4, Bior5.5, Bior6.8, Db2, Db3, Db4, Db5, Db6, Db7, Db8, Db9, Dbl0, Sym2, Sym3, Sym4, Sym5, Sym6, Sym7, Sym8, Coif1, Coif2, Coif3, Coif4, Coif5, which are all compactly supported. Important properties of wavelet functions in image compression applications are compact support (lead to efficient implementation), symmetry (useful in avoiding dephasing in image processing), orthogonality (allow fast algorithm), regularity, and degree of smoothness (related to filter order or filter length). In our experiment, various types of wavelet families are examined: Symmlet Wavelet (SW), Daubechies Wavelet (DW), Coiflet Wavelet (CW), and Biorthogonal Wavelet (BW). Each wavelet family can be parameterized by integer that determines filter order. Biorthogonal wavelets can use filters with similar or dissimilar orders for decomposition and reconstruction.

C. WAVELET AND COMPRESSION

There are many different forms of data compression [16]. This study will concentrate on Wavelet Transforms and Incremental Self Organizing Map. Image data can be represented by coefficients of discrete image transforms. Coefficients that make only small contributions to the information contents can be omitted. However wavelets transform is applied to entire images, rather than subimages, so it produces no blocking artefacts. In this work lossy compression technique ISOM is used. A combined approach of image compression, based on the wavelet transform [15] and ISOM [3] is presented. Our goal is to achieve after image compression, a high quality of reconstruction and a low distortion level. First of all, a DWT algorithm is performed. For the performance of the DWT coder, the selection of wavelet is important. The algorithm for compression of gray scale images is detailed below: The basic steps used were:

1) Calculate the DWT of the original image
2) Apply the inverse discrete wavelet transform (IDWT) for the transformed image
3) Compute the ISOM technique on the first bloc of decomposition wavelet (the approximations)

This explains that the wavelet analysis does not actually compress the image, it simply provides information about this which allows the data to be compressed by ISOM. In 2D, the images are considered to be matrices with N rows and N columns. At every level of decomposition the horizontal data is filtered, and then the approximation and details produced from this are filtered on columns. At every level, four sub-images are obtained; the approximation, the vertical detail, the horizontal detail and the diagonal detail.

D. COMPUTER SIMULATION

To evaluate the quality of image compression technique, we use two classical metrics, namely, objective and subjective evaluations. A commonly used objective metric is Mean Square Error (MSE), MSE is formulated as follows:

$$MSE = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}(x_{i,j} - y_{i,j})^2 \quad (5)$$

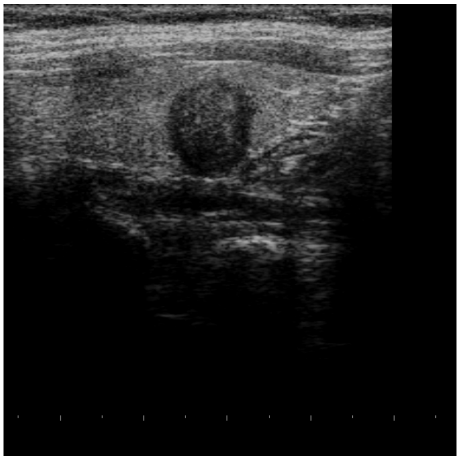

Fig. 2. Ultrasound image of thyroid

and the subjective evaluation is the compression ratio CR which is defined as :

$$\tau = (1 - \frac{T_c}{T_0}) \times 100 \tag{6}$$

Where $x_{i,j}$ and $y_{i,j}$ are the pixel intensities for the original and the reconstructed image and T_c and T_0 are the size of compressed and original file. In this study, different wavelet transform for ISOM compression are comparatively examined for Ultrasound medical image compression. The size of the ultrasound image of thyroid is 512×512. The original medical image is shown in figure 2. In the following, we present numerical results to evaluate and compare the considered compression techniques. We present the summary of the trade-off between EQM and CR results in figure 3 for each wavelet family, separately. We compare the EQM of ultrasound thyroid image compressed by Bi-orthogonal, Daubechies, Symlet and Coiflet wavelets, in figure 3 versus CR.

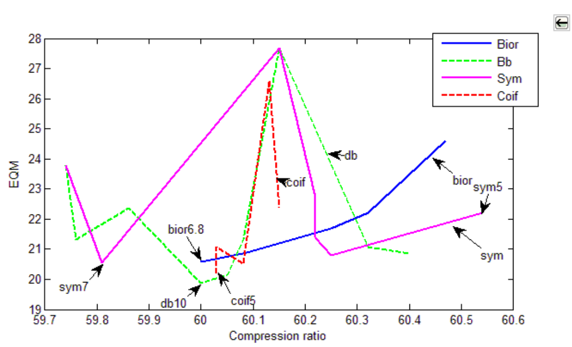

Fig. 3. Image compressed by Biorthogonal wavelets, Daubechies, Symlet, and Coiflet wavelets.

As shown in figure 3, the sym7 yields the best MSE in Symlet family. As indicated also in figure 3, db10 wavelet provides the best trade-off between MSE and CR while the bior 6.8 gives a good compression ratio in Biorthogonal wavelets family. Finally it shows that in Coiflet family, coif5 wavelet present the minimum error MSE.

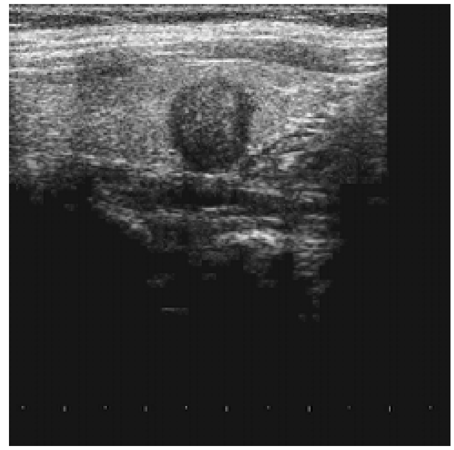

Fig. 4. sym7

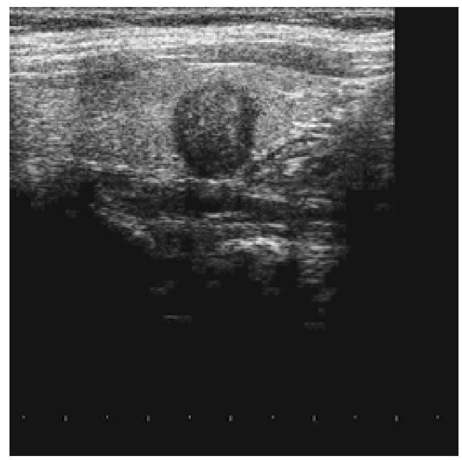

Fig. 5. db10

Figure 4, 5, 6 and 7 presents Thyroid image using the best wavelet in DWT algorithm in each wavelet family, sym7, db10, bior6.8 and coif5.
As shown, all reconstructed images have very high quality and are similar to the original one, but db10 wavelet yields the best tradeoff between MSE and CR.

II. Conclusion

In this paper, we have presented results from a comparative study of four wavelets families used in ISOM based image compression technique. We verify the compromise that exists between the compression ratio and the quality of the rebuilt image. Also, we show that Sym2 and Sym3 wavelets are equivalent to Db2 and Db3, respectively. But in terms of computational complexity, Db2 and Db3 are less complex. Also, for a good trade-off between MSE and CR, we should choose the Bior6.8 or Coif5. However, since Coiflet wavelets are symmetrical, which cause phase shifts in image processing; the Bior6.8 is a better option. In addition, considering only CR as a quality measure, regardless of the MSE, the sym7 wavelets are the best choices.

Fig. 6. bior6.8

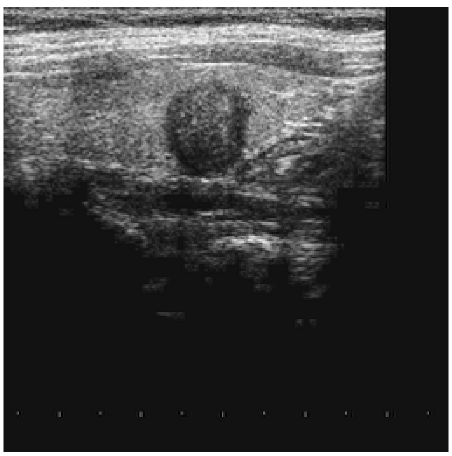

Fig. 7. coif5

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