35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Compression of the CT Images Using Classified Energy and Pattern Blocks*

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Abstract— **In this work, a new biomedical image compression method is proposed based on the classified energy and pattern blocks (CEPB). CEPB based compression method is specifically applied on the Computed Tomography (CT) images and the evaluation results are presented. Essentially, the CEPB is uniquely designed and structured codebook which is located on the both the transmitter and receiver part of a communication system in order to implement encoding and decoding processes. The encoding parameters are block scaling coefficient (BSC) and the index numbers of energy (IE) and pattern blocks (IP) determined for each block of the input images based on the CEPB. The evaluation results show that the newly proposed method provides considerable image compression ratios and image quality.**

I. INTRODUCTION

Transferring medical data or image from one place to the other place is called as telemedicine and it is very crucial especially for diagnostic purpose. Since 1960, telemedicine plays a vital role in the other areas such as medical education, practice of medical care, diagnosis, consultation and treatment and transfer of medical data. Telemedicine techniques also include sending medical images and other patient information to another specialist, discussing diagnosis, treatment and archiving data for future purpose. Especially, with the recent technological developments in electronics and computing area, the spatial and temporal/bit depth resolution of the medical devices has increased remarkably. The results in processing huge amount of 2D and or 3D medical data for recording, archiving and diagnosing purposes without losing the clinical information that has crucial importance for the human health. That's why the aim of the medical image compression is not only to decrease the data volume but also to achieve low bit rate in the digital representation of the images without losing the clinical information [1-2].

Image compression algorithms take into account the spatial, temporal or spectral redundancies among the neighboring pixel regions in the images. These algorithms are classified into the two groups as lossless and lossy in broad sense. In lossless image compression, compressed and decompressed images are identical bit per bit. Despite of having perfect reconstruction schemes, main disadvantage of the lossless algorithms are to obtain very limited compression rates. Arithmetic Coding, Run Length Coding, Huffman Coding techniques are well known ones. In the lossy compression methods exact recovering of the original image data is not possible once it has been compressed. One of the main advantages of the lossy compression methods is to reach very low bit rates or higher compression ratios depending on the quality levels and the image content [3-5].

CT image compression algorithms with different schemes have been developed especially since 1990s. These algorithms are generally based on the Discrete Cosine Transform, Wavelet Transform, Principal Component Analysis [6-10]. In [11-12], a novel method referred to as SYMPES (systematic procedure for predefined envelope and signature sequences) was introduced and implemented on the representation of the 1-D signals such as speech signals. The performance analysis and the comparative results of the SYMPES with respect to the other conventional speech compression algorithms were also presented in the other work [12]. The method was also implemented in the compression of the biomedical signals such as ECG [13] and EEG [14] signals. In [15] an improved and more efficient ECG compression method was presented, which relies on the variable-length classified signature and envelope vector sets (VL-CSEVS) and wavelet transform. In [16], a new block-based image compression scheme was proposed based on generation of fixed block sets called Classified Energy Blocks (CEBs) and Classified Pattern Blocks (CPBs). All these unique block sets were associated under the framework called Classified Energy and Pattern Blocks (CEPBs).

In this work, the CEPBs are uniquely designed for the CT images and the compression performance of the newly proposed method is evaluated.

II. PROPOSED METHOD

A. *Construction of the CEPB Codebook*

The input image $I_m(m,n)$ is first divided into non-overlapping image blocks, $B_{r,c}$ of size $i \times j$, where the image block size is $i = j = 8$. The pixel location of the k^{th} row and l^{th} column of the block, $B_{r,c}$ is represented by $P_{B_{r,c}k,l}$, where the pixel indices are $k = 1$ to i and $l = 1$ to j. In this case, the total number of blocks in the $I_m(m,n)$ will be equal to $N_B = (M \times N)/(i \times j)$. The indices r and c of the $B_{r,c}$ are in the range of 1 to M/i and N/j, respectively. All the image blocks $B_{r,c}$ from left to the right direction are reshaped as column vectors and constructed a new matrix denoted as B_{I_m}.

In the construction of the two block sets (CEPB), a certain number of image files are determined as a training set from the whole image database. Each image file in the training set are divided into the 8×8 ($i = j = 8$) image blocks and then each image block is reshaped as a column vector called image block vector which has $i \times j$ pixels. All the image files have the same number of pixels and equal number of image blocks N_B. After the blocking process, the image matrix can be written as follows.

$$I_m = \begin{bmatrix} B_{1,1} & B_{1,2} & \cdots & B_{1,(N/j)} \\ B_{2,1} & B_{2,2} & \cdots & B_{2,(N/j)} \\ \vdots & \vdots & \ddots & \vdots \\ B_{(M/i),1} & B_{(M/i),2} & \cdots & B_{(M/i),(N/j)} \end{bmatrix} \quad (1)$$

*Research supported by ISTANBUL University (Project Number: 16806).

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The matrix I_m is transformed to a new matrix, B_{I_m} which its column vectors are the image blocks of the matrix, I_m.

$$B_{Im} = [B_{1,1} \quad \cdots \quad B_{1,(N/j)} \quad B_{2,1} \quad \cdots \quad B_{(M/i),(N/j)}] \tag{2}$$

The columns of the matrix B_{I_m} is called as image block vector (IBV) and the length of the IBV is represented by $L_{IBV} = i \times j$. As it is explained above, in the method that we proposed the $IBVs$ of an image can be represented by a mathematical model that consists of the multiplication of the three quantities; scaling factor, classified pattern and energy blocks. In our method it is proposed that any i^{th} IBV of length L_{IBV} can be approximated as $IBV_i = G_i P_{IP} E_{IE}$, $i = 1, \ldots, N_B$ where the scaling coefficient, G_i of the IBV is a real constant, $IP \in \{1,2,\ldots,N_{IP}\}$, $IE \in \{1,2,\ldots,N_{IE}\}$ are the index number of the CPB and index number of the CEB where N_{IP} and N_{IE} are the total number of the CPB and CEB indices, respectively. IP, IE, N_{IP}, and N_{IE} are all integers. The CEB in the vector form is represented as $E_{IE}^T = [e_{IE1} \quad e_{IE2} \quad \cdots \quad e_{IEL_{IBV}}]$ and it is generated utilizing the luminance information of the images and it contains basically the energy characteristics ofIBV_i under consideration in broad sense. Furthermore, it will be shown that the quantity $G_i E_{IE}$ carries almost maximum energy of IBV_i in the least mean square (LMS) sense. In this multiplication expression the contribution of the G_i is to scale the luminance level of the IBV_i.

$$P_{IP} = diag[P_{IP1} \quad P_{IP2} \quad P_{IP3} \quad \cdots \quad P_{IPL_{IBV}}] \tag{3}$$

P_{IP} acts as a pattern term on the quantity, $G_i E_{IE}$ which also reflects the distinctive properties of the image block data under consideration. It is well known that, each IBV can be spanned in a vector space formed by the orthonormal vectors$\{\phi_{ik}\}$. Let the real orthonormal vectors be the columns of a transposed transformation matrix (Φ_i^T),

$$\Phi_i^T = [\phi_{i1} \quad \phi_{i2} \quad \cdots \quad \phi_{iL_{IBV}}] \tag{4}$$

$$IBV_i = \Phi_i^T G_i \tag{5}$$

$$G_i^T = [g_{i1} \quad g_{i2} \quad \cdots \quad g_{iL_{IBV}}] \tag{6}$$

From the property of $\Phi_i^T = \Phi_i^{-1}$, the equations $\Phi_i IBV_I = \Phi_i \Phi_i^{-1} G_i$ and $G_i = \Phi_i IBV_I$ can be obtained respectively. IBV_i can be written as a weighted sum of these orthonormal vectors as follows.

$$IBV_i = \sum_{k=1}^{L_{IBV}} g_k \phi_{ik} \quad , \quad k = 1,2,\ldots,L_{IBV} \tag{7}$$

From the equation above, the coefficients of the $IBVs$ can be obtained as

$$g_k = \phi_{ik}^T IBV_i \quad , \quad k = 1,2,\ldots,L_{IBV} \tag{8}$$

Let $IBV_{it} = \sum_{k=1}^{t} g_k \phi_{ik}$ be the truncated version of IBV_i such that $1 \le t \le L_{IBV}$. It is noted that, if $t = L_{IBV}$ then IBV_i will be equal to IBV_{it}. In this case, the approximation error (ε_t) is given by

$$\varepsilon_t = IBV_i - IBV_{it} = \sum_{k=t+1}^{L_{IBV}} g_k \phi_{ik} \tag{9}$$

In this equation, ϕ_{ik} are determined by minimizing the expected value of the error vector with respect to ϕ_{ik} in the LMS sense. The above mentioned LMS process results in the following eigenvalue problem [17].

$$R_i \phi_{ik} = \lambda_k \phi_{ik} \tag{10}$$

R_i is the correlation matrix. It is real, symmetric with respect to its diagonal elements, positive-semi definite, and toeplitz matrix. Obviously, λ_{ik} and ϕ_{ik} are the eigenvalues and eigenvectors of the eigenvalue problem under consideration. It is well known that the eigenvalues of R_i are also real, distinct, and non-negative. Moreover, the eigenvectors ϕ_{ik} of the R_i are all orthonormal. Let eigenvalues be sorted in descending order such that ($\lambda_{1i} \ge \lambda_{2i} \ge \lambda_{3i} \ge \cdots \ge \lambda_{L_{IBV}i}$) with corresponding eigenvectors. The total energy of the IBV_i is then given by $IBV_i^T IBV_i$.

$$IBV_i^T IBV_i = \sum_{k=1}^{L_{IBV}} g_k^2 = \sum_{k=1}^{L_{IBV}} \lambda_{ik} \tag{11}$$

(11) may be truncated by taking the first p principal components, which have the highest energy of the IBV_i such that,

$$IBV_i \cong \sum_{k=1}^{p} g_k \phi_{ik} \tag{12}$$

The simplest form of (12) can be obtained by setting $p = 1$. The eigenvector ϕ_{ik} is called energy vector. That is to say, the energy vector, which has the highest energy in the LMS sense, may approximate each image block belonging to the IBV_i. Thus,

$$IBV_i \cong g_1 \phi_{i1} \tag{13}$$

In this case, one can vary the L_{IBV} as a parameter in such way that almost all the energy is captured within the first term of (12) and the rest becomes negligible. That is why ϕ_{i1} is called the energy vector since it contains most of the useful information of the original IBV under consideration. Once (13) is obtained, it can be converted to an equality by means of a pattern term P_i which is a diagonal matrix for each IBV. Thus, IBV_i is computed as

$$IBV_i = G_i P_i \phi_{i1} \tag{14}$$

In (14), diagonal entries p_{ir} of the matrix P_i are determined in terms of the entries of ϕ_{i1r} of the energy vector ϕ_{i1} and the entries (pixels) IBV_{ir} of the IBV_i by simple division. Hence,

$$P_{ir} = IBV_{ir} / G_i \phi_{i1r} \quad , \qquad r = 1,2,\ldots,L_{IBV} \tag{15}$$

In essence, the quantities p_{ir} of (15) somewhat absorb the energy of the terms eliminated by truncation of (12).

In this research, several tens of thousands of $IBVs$ were investigated and several thousands of energy and pattern blocks were generated. It was observed that the energy and the pattern blocks exhibit repetitive similarities. In this case, one can eliminate the similar energy and pattern blocks and thus, constitute the so called classified energy and classified pattern block sets with one of a kind, or unique blocks. For the elimination process Pearson correlation coefficient (PCC) [18] is utilized. PCC is designated by ρ_{YZ} and given as,

$$\rho_{YZ} = \frac{\sum_{i=0}^{L}(y_i z_i) - \left[\sum_{i=0}^{L} y_i \sum_{i=0}^{L} z_i\right]/L}{\sqrt{\left[\sum_{i=0}^{L} y_i^2 - \left(\sum_{i=0}^{L} y_i\right)^2/L\right]\left[\sum_{i=0}^{L} z_i^2 - \left(\sum_{i=0}^{L} z_i\right)^2/L\right]}} \tag{16}$$

In (16), $Y = [y_1 \quad y_2 \quad \cdots \quad y_L]$ and $Z = [z_1 \quad z_2 \quad \cdots \quad z_L]$ are two sequences subject to comparison where L is the length of the sequences. It is assumed that the two sequences are almost identical if $0.9 \le \rho_{YZ} \le 1$. Hence, similar energy and pattern blocks are eliminated accordingly.

Finally, the energy blocks which have unique shapes are combined under the set called classified energy block CEB=$\{E_{n_{ie}};\ n_{ie} = 1,2,\ldots,N_{IE}\}$ set. The integer N_{IE} designates the total number of elements in this set. Similarly, reduced pattern blocks are combined under the set called classified pattern block CPB=$\{P_{n_{ip}};\ n_{ip} = 1,2,\ldots,N_{IP}\}$ set. The N_{IP} designates the total number of unique pattern sequences in CPB set.

B. Reconstruction Process:

The input images are reconstructed block by block using the best representative parameters which are called block scaling coefficient (BSC), classified energy block index (IE) and classified pattern block index (IP) based on the mathematical model as presented in the following algorithm.

Inputs:

- The encoding parameters G_i, IP and IE which best represent the corresponding image block vector IBV_i of the input.
- $L_{IBV} = i \times j$
- The CEPB (CEB=$\{E_{IE};\ IE = 1,2,\dots,N_{IE}\}$ and CPB=$\{P_{IE};\ IP = 1,2,\dots,N_{IP}\}$) located in the receiver part.

Computational Steps

- Step 1: After receiving the encoding parameters G_i, IP and IE of the IBV_i from the transmitter, the corresponding IE^{th} classified energy and IP^{th} classified pattern blocks are pulled from the CEPB.
- Step 2: Approximated image block vector IBV_{Ai} is constructed using the mathematical model $IBV_{Ai} = G_i P_{IP} E_{IE}$ proposed.
- Step 3: The previous steps are repeated for each IBV to generate approximated version ($\hat{B}_{Im}$) of the B_{Im}.

$$\hat{B}_{Im} = [\hat{B}_{1,1} \quad \cdots \quad \hat{B}_{1,(N/j)} \quad \hat{B}_{2,1} \quad \cdots \quad \hat{B}_{(M/i),(N/j)}] \tag{17}$$

- Step 4: $\hat{B}_{Im}$ is reshaped to obtain the reconstructed version of the original image data as follows,

$$\hat{I}_m = \begin{bmatrix} \hat{B}_{1,1} & \hat{B}_{1,2} & \cdots & \hat{B}_{1,(N/j)} \\ \hat{B}_{2,1} & \hat{B}_{2,2} & \cdots & \hat{B}_{2,(N/j)} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{B}_{(M/i),1} & \hat{B}_{(M/i),2} & \cdots & \hat{B}_{(M/i),(N/j)} \end{bmatrix} \tag{18}$$

III. SIMULATION RESULTS

A. Evaluation Metrics

The reconstructed image quality is measured by the ratio between the signal's maximum power and the power of the signal's noise called peak to signal noise ratio (PSNR). The higher PSNR means that better quality of the reconstructed image. The PSNR is defined as

$$\text{PSNR} = 20log_{10}\left[\frac{2^m - 1}{\sqrt{\text{MSE}}}\right] \tag{19}$$

where,

$$\text{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I_m(m,n) - \hat{I}_m(m,n)\right]^2 \tag{20}$$

In (19), m denotes the bit-depth of the original image, MSE is the mean square error and the PSNR is given in decibel units (dB). In (20), $I_m(m,n)$ and $\hat{I}_m(m,n)$ are the reconstructed and the original images, respectively. $M \times N$ is the dimension of the images.

The compression ratio (CR) is defined as the ratio between the number of the bits required to represent the original and reconstructed image blocks.

$$\text{CR} = \frac{b_{original}}{b_{reconstructed}} \tag{21}$$

It is emphasized that the CR depends on the bit-depth of the original image. Therefore, the bit-per-pixel (bpp) ratio which is independent from the bit-depth of the original image is employed to evaluate the compression performance of the image compression algorithm. The bpp ratio is defined as

$$\text{bpp} = \frac{b_{pixel}}{\text{CR}} \tag{22}$$

where the b_{pixel} denotes the number of bits required to represent the pixels in the original image.

B. Experimental Results

In this experimental research work, we use the CT image database obtained from the Istanbul University Oncology Institute in order to evaluate the performance of the proposed method. The database contains 30 CT images which are randomly selected different patient records. Each CT images in the database are stored in DICOM format as 12-bits grayscale image with a resolution of 512×512 pixels. 15 randomly selected CT image files from the database are used for training or constructing the CEPB. The rest of the CT images in the database are used as the test database.

In this experiment, several CEPBs with different size are constructed by using the proposed method. Bit allocation scheme for the encoding parameters of the proposed method is given in the Table I. In the Table I, b_{G_i}, b_{IE}, b_{IP}, and b_{total} are the number of bits required to represent the BSC, the number of the CEBs, the number of the CPBs, and the reconstructed IBV.

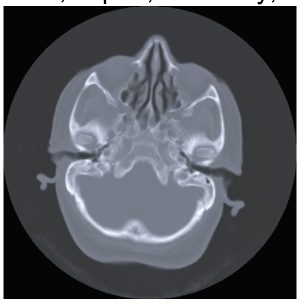
The performance of the proposed compression algorithm with respect to PSNR, CR, and bpp is evaluated for each test image files. The average PSNR values for different compression ratios are presented in Table II. As it can be seen from Table II, the proposed compression algorithm achieves the average CRs from 38.40:1 to 48.00:1 with average PSNR varies between 33.34dB and 35.57dB. Furthermore, the average encoding and decoding times of the proposed compression algorithm are 3.56 and 13.52 sec., respectively. Two original CT images randomly chosen from test database and their reconstructed versions for different compression ratios are illustrated in Fig. 1 to reveal the visual quality of the CT images which are reconstructed by using the proposed compression algorithm.

TABLE I. BIT ALLOCATION TABLE

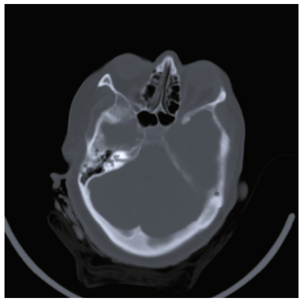
CEPB Size		Encoding Parameters				Compression Ratio	
N_{IE}	N_{IP}	b_{G_i}	b_{IE}	b_{IP}	b_{total}	CR	bpp
32	1024	5	5	10	20	38.40	0.31
32	512	5	5	9	19	40.42	0.30
32	256	5	5	8	18	42.67	0.28
16	1024	5	4	10	19	40.42	0.30
16	512	5	4	9	18	42.67	0.28
16	256	5	4	8	17	45.18	0.27
8	1024	5	3	10	18	42.67	0.28
8	512	5	3	9	17	45.18	0.27
8	256	5	3	8	16	48.00	0.25

TABLE II. THE PERFORMANCE OF THE PROPOSED METHOD

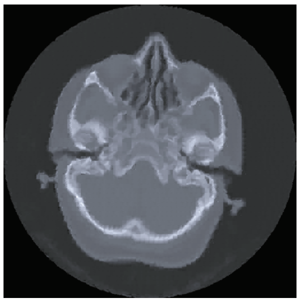
N_{IE}	N_{IP}	CR	bpp	Encoding Time(sec)	Decoding Time(sec)	Average PSNR(dB)
32	1024	38.40	0.31	3.67	16.41	35.57
32	512	40.42	0.30	3.51	13.74	35.25
32	256	42.67	0.28	3.49	11.70	34.58
16	1024	40.42	0.30	3.60	15.69	34.83
16	512	42.67	0.28	3.59	12.40	34.49
16	256	45.18	0.27	3.49	11.68	33.91
8	1024	42.67	0.28	3.60	15.35	34.41
8	512	45.18	0.27	3.51	12.96	33.87
8	256	48.00	0.25	3.59	11.73	33.34



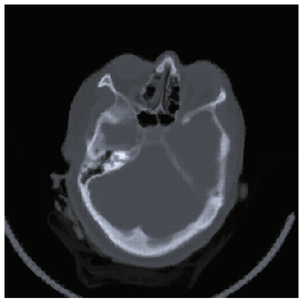
(a) Original CT Image



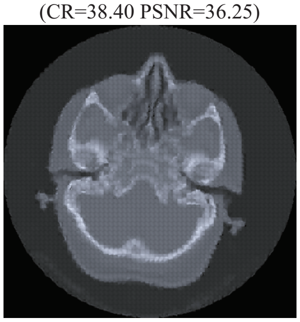
(b) Original CT Image



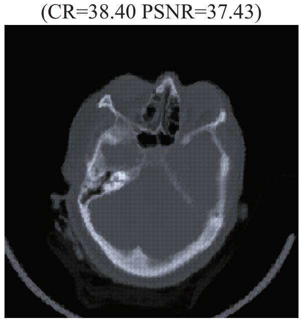
(c) Reconstructed CT Image (CR=38.40 PSNR=36.25)



(d) Reconstructed CT Image (CR=38.40 PSNR=37.43)



(e) Reconstructed CT Image (CR=48.00 PSNR=33.03)



(f) Reconstructed CT Image (CR=48.00 PSNR=36.22)

Figure 1. Original and reconstructed CT images for different CRs

TABLE III. THE COMPARISON OF THE COMPRESSION PERFORMANCE OF THE PROPOSED METHOD WITH THE OTHER METHODS

bpp	PSNR (dB)			
	JPEG [9]	JPEG2000 [9]	SPIHT [10]	Proposed Method
0.3	26	27	37.55	35.57

The proposed compression algorithm is compared to the well-known image compression algorithms JPEG [9], JPEG2000 [9], and SPIHT [10] in terms of the CR, bpp, and PSNR. As it can be seen from the Table III, the PSNR value of the proposed compression algorithm is better than those of the JPEG and JPEG2000 at the given bit rate. On the other hand, the proposed method achieves the similar PSNR value with the SPIHT algorithm at 0.3 bpp.

IV. CONCLUSION

The main contribution of this research work is to introduce, for the first time, the classified energy and pattern blocks (CEPBs) for CT images and propose a new and more efficient CT image compression algorithm based on the CEPBs which are uniquely designed for CT images. In the proposed algorithm, first the CEB and CPB sets are constructed and CT images can be reconstructed block by block using a BSC and the index numbers of the classified energy and pattern blocks placed in the CEB and CPB. At the end of a series of the experimental works, the evaluation results show that the proposed method provides high compression ratios such as 38.40:1, 48.00:1 while preserving the image quality at 33.34-35.57dB level on the average.

In our future works, we will be focused on better designed CEB and CPB in order to increase the level of the PSNR while reducing the number of bits required representing the CT image blocks.

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