Research Journal of Applied Sciences, Engineering and Technology 14(9): 352-360, 2017
DOI:10.19026/rjaset.14.5134
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: January 1, 2017 Accepted: August 14, 2017 Published: September15, 2017

Research Article

Volumetric Medical Images Lossy Compression using Stationary Wavelet Transform and Linde-Buzo-Gray Vector Quantization

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Abstract: The aim of the study is to reduce the size required for storage along with decreasing the bitrate and the bandwidth for the process of sending and receiving the image. It also aims to decrease the time required for the process as much as possible. This study proposes a novel system for efficient lossy volumetric medical image compression using Stationary Wavelet Transform and Linde-Buzo-Gray for Vector Quantization. The system makes use of a combination of Linde-Buzo-Gray vector quantization technique for lossy compression along with Arithmetic coding and Huffman coding for lossless compression. The system proposed uses Stationary Wavelet Transform and then compares the results obtained to Discrete Wavelet Transform, Lifting Wavelet Transform and Discrete Cosine Transform at three decomposition levels. The system also compares the results obtained using transforms with only Arithmetic Coding and Huffman Coding for Lossless Compression.The results show that the system proposed outperforms the others.

Keywords: Arithmetic coding, discrete cosine transform, discrete wavelet transform, Huffman coding, lifting wavelet transform, Linde-Buzo-gray vector quantization, Lossy compression, stationary wavelet transform, volumetric medical images

INTRODUCTION

Image compression is important for a lot of applications that involve storing, transferring and retrieving data of these with regard to multimedia, documents, video conferencing and medical imaging. Images which are not compressed need massive amounts of storage space and transmission bandwidth. The purpose of the image compression is to decrease the redundancy in the image file for efficient image storage and data transmission. It leads to decreasing the file size and permitting a lot of images to be stored for specific amounts of disk and/or memory space by Mozammel Hoque Chowdhury and Khatun (2012). Lossy compression is commonly used to compress multimedia data such as audio, video and images, especially in applications such as streaming media and internet telephony and the lossless compression is required for text and data files, such as bank records and text articles. It is useful in some cases to make a master lossless file which is to be used to produce new compressed files. For example, a 10 kilobyte lossy copy can be made for a small image on a web page and a multi-megabyte file can be used at full size to produce a full-page advertisement in a glossy magazine.

There are two types of image compression: lossy and lossless techniques. The lossy compression decreases a file constantly by moving away overflowing information. Lossy methods are especially suitable for natural images such as photographs in applications where a minor loss of accuracy is acceptable to achieve a substantial reduction in bit rate. Major performance concerns of a lossy compression are the compression ratio, Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and the speed of encoding and decoding by Navneet *et al*. (2014). More generally, some forms of lossy compression can be thought of as an application of transform coding. Transform coding algorithm usually start by partitioning the original image into sub images (blocks) of small size (usually 8×8). For each block the transform coefficients are calculated, effectively converting the original 8×8 array of pixel values into an array of coefficients closer to the top-left corner usually

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contains most of the information needed to quantize and encode the image with little perceptual distortion.

The resulting coefficients are then quantized and the output of the quantized issued by a symbol encoding technique to produce the output bit stream representing the encoded image by Samra (2012). The transformation coefficients are calculated using different discrete transforms such as discrete cosine transform, discrete wavelet transform, discrete lifting wavelet transform by Kaur and Lalit (2012) and stationary wavelet transforms by Nema *et al*. (2012). The vector quantization is a classical quantization technique for signal processing and image compression, which allows the modeling of probability density functions by the distribution of prototype vectors. The main use of Vector Quantization (VQ) is for data compression by Mukesh *et al*. (2013) and Vlajic and Card (2001). It works by dividing a large set of values (vectors) into groups having approximately the same number of points closest to them. Each group is represented by its centroid value, as in the Linde-Buzo-Gray algorithm by Amin and Amrutbhai (2014). The density matching property for vector quantization is powerful, especially in the case for identifying the density of large and high dimensioned data. Since data points are represented by their index to the closest centroid, commonly occurring data have less error and rare data have higher error. Hence VQ is suitable for lossy data compression. It can also be used for lossy data correction and density estimation. The methodology of vector quantization is based on the competitive learning paradigm; hence it is closely related to the self-organizing map model. Vector Quantization (VQ) is used for lossy data compression, lossy data correction and density estimation by Amin and Amrutbhai (2014). The extremely fast growth of data that needs to be stored and transferred has given rise to the demands of better transmission and storage techniques. Lossless data compressions categorized into two types are: models & code and dictionary models. Various lossless data compression algorithms have been proposed and used. Huffman Coding, Arithmetic Coding, Shannon Fano Algorithm, Run Length Encoding Algorithm are some of the techniques in use by Maan (2013) and by Kumar *et al*. (2015). In the case of multimedia data, the perceptual coding transforms the raw data to a domainthat more accurately reflects the information content.

In this study, a novel scheme for lossy compression of the volumetric medical images is suggested based on Stationary Wavelet Transform and a combination of the Linde-Buzo-Gray Vector Quantization that results low computational complexity with no sacrifice in image quality and Arithmetic coding and Huffman coding for lossless compression. The execution of the suggested algorithm has been compared with some other common transforms such as Lifting Wavelet Transform by Al-Rababah and Al-Marghirani (2016), Discrete Wavelet Transform by Gopi and Rama Shri (2013) and Hadi (2014) and Discrete Cosine Transform for lossy compression and by Hadi (2014) and Prabhu *et al*. (2013) and Stationary Wavelet Transform for lossless compression by Anusuya *et al*. (2014).

MATERIALS AND METHODS

This study was conducted on 2016 and in the Department of Information Technology, Institute of Graduate Studies and Researches, Alexandria University, Egypt.

Stationary wavelet transform: The Stationary Wavelet Transform (SWT) is a recent type of wavelet transform family that is similar to the Discrete Wavelet Transform (DWT). It is designed to overcome the lack of translation-invariance in the Discrete Wavelet Transform by suppressing the process of down-sampling and up-sampling in the DWT. This means that SWT is translation-invariant and is designed by upsampling only the filter coefficients by a factor of $2^{(j-1)}$ in the j^{th} level of the algorithm. SWT follows an inherently redundant scheme as each of its output levels contains the same number of samples as the input. For a decomposition of N levels there is a redundancy of N in the wavelet coefficients. The two dimension WT decomposition scheme is illustrated in Fig. 1 by Nema *et al*. (2012). These sub-band images would have the same size as that of the original image because no down-sampling is performed during the wavelet transform process.

Linde-Buzo-gray vector quantization: Vector Quantization (VQ) is a lossy data compression method based on the principle of block coding. The Vector Quantization technique is made to develop a dictionary of fixed-size vectors, called code vectors. A vector is usually a block of pixel values. A given image is separated into non-overlapping blocks called image vectors. Then each is determined in the dictionary. The dictionary index is used as the encoder of the original image vector. VQ is the most powerful quantization technique used for the image compression. The image Vector Quantization includes four stages: vector formation, training group selection, codebook generation and quantization by Mittal and Lamba (2013) and Amin and Amrutbhai (2014).

Generalized Lloyd Algorithm (GLA) is also called the Linde-Buzo-Gray (LBG) Algorithm. It used a mapping function to partition training vectors in N clusters. The mapping function is defined as $R_k \rightarrow CB$. Let $X = (x_1, x_2, \ldots x_k)$ is a training vector and d (X, Y) be the Euclidean Distance between any two vectors. The iteration of GLA for a codebook generation is given as follows:

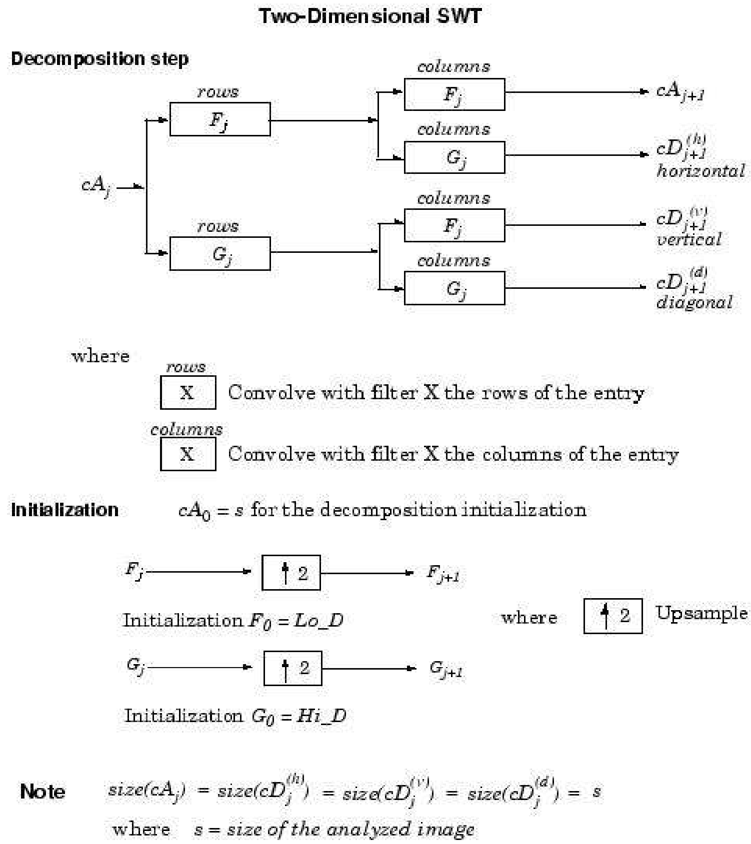

Fig. 1: Stationary wavelet transform of an image

Step 1: Randomly generate an initial codebook CB_0.
Step 2: I = 0.
Step 3: Perform the following process for each training vector.

Compute the Euclidean distances between the training vector and the code words in CB_i. The Euclidean distance is defined as in Eq. (1):

$$d(X,C) = \sqrt{\sum_{t=0}^{k}(x_t - c_t)^2} \quad (1)$$

Search the nearest code word among CB_i.
Step 4: Partition the codebook into N cells.
Step 5: Compute the centroid of each cell to get the new codebook CB_{i+1}.
Step 6: Compute the ratio deformation for CB_{i+1}. If it is changed by a small enough amount since the last iteration, the codebook may converge and the procedure stops. Otherwise, I = I + 1 and go to Step 3.

LBG algorithm has the local optimization problem and the utility of each code word in the codebook is low. The local optimization problem means that the codebook guarantees local minimum deformation, but not global minimum deformation by Mittal and Lamba (2013) and Amin and Amrutbhai (2014).

LBG Algorithmic steps:

Step 1: Divide the input image into non overlapping blocks and transform each block into vectors.
Step 2: Randomly generate an initial codebook CB0
Step 3: Initialize I = 0.
Step 4: Perform the following process for each training vector.

- Compute the Euclidean distance between all the training vectors belonging to this cluster and the code words in CBI by Eq. (1).
- Compute the centroid (code vector) for the clusters got in the above step.

Step 5: Increment I by one and repeat the step 4 for each code vector.
Step 6: Repeat the Step 3 to Step 5 till codebook of the desired size is got.

The proposed lossy compression approach applied SWT and LBG Vector Quantization techniques in order to compress input images through four phases; namely preprocessing, image transformation, Zigzag scan and lossy/lossless compression. Figure 2 shows the main steps of the system proposed. It shows how a matrix arrangement gives the best compression ratio and least

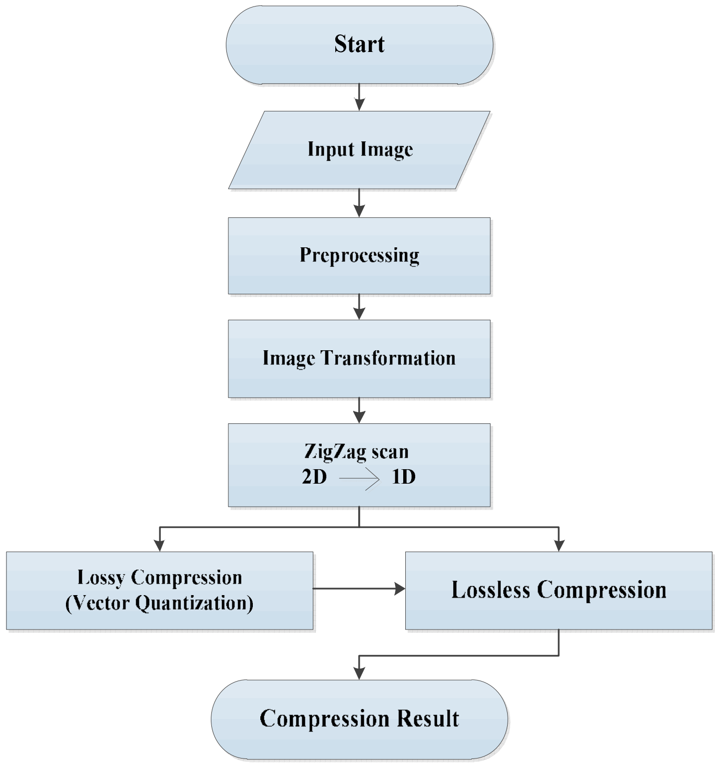

Fig. 2: Flowchart of the proposed system

loss of the characteristics of the image through a wavelet transform with lossy compression techniques. The steps for the proposed system are as follows:

- **Preprocessing:** The preprocessing phase takes images as input, so that the proposed approach resizes images of different sizes to the size of 8×8 pixels then converts from RGB to grayscale.
- **Image transformation:** The image transformation phase receives the resized grayscale image and produces a transformed image. This phase uses four types of the transforms which are: DCT, DWT, LWT and SWT at three decomposition levels.
- **Zigzag scan:** The Zigzag scan phase takes the transformed image from a 2D matrix input and reproduces it in a 1D matrix, so that the frequency (horizontal + vertical) increases in this order and the coefficient variance decreases in this order.
- Lossy Compression by Linde-Buzo-Gray Vector Quantization
- Lossy compression technique provides higher compression ratio than lossless compression.

Lossless compression: Lossless image compression schemes exploit redundancies without incurring any loss of data. Lossless image compression is therefore exactly reversible. The lossless compression schemes are the Arithmetic Coding and Huffman Coding by Kumar *et al*. (2015).

Finally, measure the Compression Ratio (CR) which is the ratio of size of the compressed database system with the original size of the uncompressed database systems. CR also known as "compression power" is a computer-science term used to quantify the reduction in data-representation size produced by a data compression algorithm. Compression ratio is defined as follows by Mozammel Hoque Chowdhury and Khatun (2012) as in Eq. (2):

$$CR= \frac{\text{size of original image data}}{\text{size of compressed image data}} \tag{2}$$

And measure also the Peak Signal-to-Noise Ratio (PSNR) that is defined as the following formula by Mozammel Hoque Chowdhury and Khatun (2012) as in Eq. (3):

$$PSNR = 10\log10\ (2552/MSE)\ dB \tag{3}$$

RESULTS AND DISCUSSION

This study introduced a novel lossy compression on the 8-bit volumetric medical image data set using a combination of LBG vector quantization and lossless coding such as Arithmetic Coding and Huffman Coding using stationary wavelet transform at three decomposition levels and with the wavelet filter that is the db1 filter. Then these results are compared with other types of transforms which are DCT and DWT and

LWT. The performance metrics used are the Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR) and the time needs to do the compression that is called the running time. The description of the data sets used in our experiments is shown by Gaudeau and Moureaux (2009).

A volumetric medical image is a three-dimensional (3D) image dataset which can be considered as a sequence of two-dimensional (2D) images (or slices). A direct way to perform compression on it is straight forwardly apply a two-dimensional compression algorithm to each slice independently. This section shows the performance of the four discrete transforms which are the DCT, DWT, LWT and SWT and at the three decomposition levels with the wavelet filter that is the db1 filter.

The performance also shows the use of lossless compression using Arithmetic Coding and Huffman Coding with the lossy using Vector Quantization by LBG and without. The performance for the four transforms is shown in Table 1 to 5.

Where the results in Table 1 show the compression ratio, the peak signal-to-noise ratio and the running time for the proposed system using SWT with a combination of the LBG Vector Quantization and the lossless coding techniques such as Arithmetic Coding and Huffman Coding. The results in this table show that the performance of the running time and the compression ratio using Arithmetic Coding better than using Huffman Coding at the same peak signal-to-noise ratio for the three decomposition levels.

The results in Table 2 show that the compression ratio, the peak signal-to-noise ratio and the running time using SWT by Anusuya *et al*. (2014) without the LBG Vector Quantization and using the lossless coding techniques such as Arithmetic Coding and Huffman Coding. The results in this table show that the performance of the running time and the compression ratio using Arithmetic Coding better than using Huffman Coding at the same peak signal-to-noise ratio for the three decomposition levels.

From Table 1 and 2 the results show the compression ratio with the combination in the proposed system in Table 1 better than without combination of LBG and lossless coding in Table 2.

The results in Table 3 show also the compression ratio, the peak signal-to-noise ratio and the running time using DWT by Gopi and Rama Shri (2013) and by Hadi (2014) with a combination of the LBG Vector Quantization and the lossless coding techniques such as Arithmetic Coding and Huffman Coding and without the combination. The results in this table show that the performance of the compression ratio using a combination of the LBG Vector Quantization and the lossless coding techniques better than without the combination at the three decomposition levels and the results in Table 1 is better than these results.

The results in Table 4 show also the compression ratio, the peak signal-to-noise ratio and the running time using LWT by Al-Rababah and Al-Marghirani

Table 1: Stationary wavelet transform, vector quantization (lbg), arithmetic and huffman coding

SWT		SWT Zigzag LBG and Arithmetic			SWT Zigzag LBG and Huffman		
Image	Level	C.Ratio	PSNR	Time (Sec)	C.Ratio	PSNR	Time (Sec)
Carotid	1	5.0818	17.1566	0.018	4.3481	17.1566	0.0467
	2	5.0818	17.1566	0.0099	4.3481	17.1566	0.0039
	3	5.0818	17.1566	0.034	4.3481	17.1566	0.0556
Liver_t1	1	5.8995	17.328	0.1635	4.8416	17.328	0.0879
	2	5.8995	17.328	0.0212	4.8416	17.328	0.0788
	3	5.8995	17.328	0.1565	4.8416	17.328	0.0777
Liver_t2e1	1	5.0073	15.9569	0.011	4.785	15.9569	0.0489
	2	5.0073	15.9569	0.0121	4.785	15.9569	0.1009
	3	5.0073	15.9569	0.055	4.785	15.9569	0.0343
Pad_chest	1	4.9708	19.1208	0.011	4.8301	19.1208	0.0578
	2	4.9708	19.1208	0.0331	4.8301	19.1208	0.0344
	3	4.9708	19.1208	0.031	4.8301	19.1208	0.0601
Aperts	1	4.9349	17.619	0.0111	4.2226	17.619	0.0517
	2	4.9349	17.619	0.0556	4.2226	17.619	0.0565
	3	4.9349	17.619	0.3901	4.2226	17.619	0.0989
Sag_head	1	4.8878	17.5288	0.0103	4.7517	17.5288	0.0439
	2	4.8878	17.5288	0.0243	4.7517	17.5288	0.0634
	3	4.8878	17.5288	0.0104	4.7517	17.5288	0.0359
Skull	1	5.0693	16.7471	0.0141	4.853	16.7471	0.047
	2	5.0693	16.7471	0.0051	4.853	16.7471	0.0444
	3	5.0693	16.7471	0.0043	4.853	16.7471	0.07
Wrist	1	5.2783	17.2772	0.0098	3.7996	17.2772	0.0543
	2	5.2783	17.2772	0.0099	3.7996	17.2772	0.0466
	3	5.2783	17.2772	0.01	3.7996	17.2772	0.066
Average	1	5.1412	17.3418	0.0311	4.5539	17.3418	0.0547
	2	5.1412	17.3418	0.0214	4.5539	17.3418	0.0536
	3	5.1412	17.3418	0.0864	4.5539	17.3418	0.0623

Table 2: Stationary wavelet transform, arithmetic and huffman coding

SWT		SWT Zigzag Arithmetic		SWT Zigzag Huffman	
Image	Level	C.Ratio	Time(Sec)	C.Ratio	Time(Sec)
Carotid	1	3.69	0.0681	2.4734	0.88
	2	3.69	0.0491	2.4734	0.8879
	3	3.69	0.0881	2.4734	0.69
Liver_t1	1	4.171	0.0713	2.629	0.0469
	2	4.171	0.0689	2.629	0.665
	3	4.171	0.0663	2.629	0.0565
Liver_t2e1	1	3.519	0.8817	2.519	0.8673
	2	3.519	0.0817	2.519	0.6672
	3	3.519	0.0317	2.519	0.734
Pad_chest	1	4.5612	0.029	2.2806	0.8721
	2	4.5612	0.229	2.2806	0.7421
	3	4.5612	0.0891	2.2806	0.933
Aperts	1	3.9922	0.0493	2.2579	0.9088
	2	3.9922	0.0674	2.2579	0.9923
	3	3.9922	0.0786	2.2579	0.881
Sag_head	1	3.828	0.0316	2.278	0.8996
	2	3.828	0.0666	2.278	0.3346
	3	3.828	0.0113	2.278	0.824
Skull	1	4.1541	0.0892	2.6771	0.8789
	2	4.1541	0.0267	2.6771	0.9984
	3	4.1541	0.0969	2.6771	0.8843
Wrist	1	4.1124	0.03	2.0983	0.8678
	2	4.1124	0.37	2.0983	0.8666
	3	4.1124	0.0119	2.0983	0.2008
Average	1	4.0034	0.1562	2.4016	0.77767
	2	4.0034	0.1199	2.4016	0.7692
	3	4.0034	0.0592	2.4016	0.6504

Table 3: Discrete wavelet transform, vector quantization (lbg), arithmetic and huffman coding

DWT		DWT Zigzag Arithmetic		DWT Zigzag LBG & Arithmetic		
Image	Level	C.Ratio	Time (Sec)	C.Ratio	PSNR	Time (Sec)
Carotid	1	1.0513	0.068	1.2641	18.4991	0.0676
	2	1.1716	0.0509	1.2832	18.3813	0.0125
	3	1.1403	0.1351	1.2929	18.3848	0.0098
Liver_t1	1	1.2161	0.6479	1.6195	18.2978	0.0153
	2	1.199	0.0462	1.3368	18.3244	0.0218
	3	1.3161	0.0638	1.7161	18.3443	0.0178
Liver_t2e1	1	1.1082	0.0987	1.3161	18.0236	0.0093
	2	1.2278	0.2769	2.415	17.9054	0.0339
	3	1.2397	0.0374	1.3473	18.1348	0.0128
Pad_chest	1	1.2047	0.0459	2.2654	26.8882	0.0115
	2	1.2278	0.0339	2.6654	26.8882	0.0121
	3	1.2579	0.0389	2.1244	27.3571	0.0179
Aperts	1	1.047	0.0363	1.8754	18.5491	0.0105
	2	1.2132	0.0395	1.9962	18.7252	0.0181
	3	1.0711	0.043	1.9176	18.6427	0.0095
Sag_head	1	1.0801	0.0339	2.415	22.2526	0.0089
	2	1.1851	0.0396	2.1157	22.4535	0.0086
	3	1.2018	0.0454	2.1422	22.3508	0.0113
Skull	1	1.2278	0.0562	1.3689	17.9054	0.015
	2	1.2736	0.0491	1.3229	17.9649	0.016
	3	1.3195	0.0561	1.3509	18.0213	0.0101
Wrist	1	1.0756	0.2769	2.0645	27.2766	0.0121
	2	1.2549	0.0601	2.0398	27.8388	0.0094
	3	1.1252	0.0381	1.9393	27.7193	0.0139
Average	1	1.12635	0.15797	1.7736	20.9615	0.0187
	2	1.219125	0.07452	1.8968	21.0602	0.01655
	3	1.20895	0.05722	1.7288	21.1193	0.01288
DWT		DWT Zigzag Huffman		DWT Zigzag LBG & Huffman		
Image	Level	C.Ratio	Time (Sec)	C.Ratio	PSNR	Time (Sec)
Carotid	1	1.0192	0.1765	1.0847	18.4991	0.0477
	2	1.0241	0.0743	1.96	18.3813	0.0435
	3	1.0904	0.071	1.047	18.3848	0.0589
Liver_t1	1	1.087	0.1771	1.1082	18.2978	0.0488
	2	1.1034	0.0765	1.1179	18.3244	0.0465
	3	1.0377	0.0995	1.1327	18.3443	0.0696

Table 3: Continue

DWT Image	Level	DWT Zigzag Huffman C.Ratio	DWT Zigzag Huffman Time (Sec)	DWT Zigzag LBG & Huffman C.Ratio	DWT Zigzag LBG & Huffman PSNR	DWT Zigzag LBG & Huffman Time (Sec)
Liver_t2e1	1	1.0642	0.0632	1.094	18.0236	0.0709
	2	1.0663	0.064	1.8476	17.9054	0.0815
	3	1.0225	0.0759	1.087	18.1348	0.0486
Pad_chest	1	1.0663	0.0671	1.9078	26.8882	0.0446
	2	1.0663	0.064	1.8648	26.8882	0.0436
	3	1.0619	0.0647	1.9078	27.3571	0.063
Aperts	1	1.0476	0.0676	1.5014	18.5491	0.0653
	2	1.0819	0.0731	1.5678	18.7252	0.0506
	3	1.0332	0.0739	1.8378	18.6427	0.0572
Sag_head	1	1.0634	0.0973	1.8476	22.2526	0.0579
	2	1.0858	0.0619	1.9078	22.4535	0.0476
	3	1.7901	0.0694	1.9898	22.3508	0.0598
Skull	1	1.0824	0.064	1.1277	17.9054	0.0436
	2	1.0406	0.0688	1.1403	17.9649	0.05
	3	1.0096	0.0909	1.1403	18.0213	0.0486
Wrist	1	1.0216	0.0815	1.8648	27.2766	0.0457
	2	1.105	0.0821	1.9078	27.8388	0.0443
	3	1.742	0.0857	1.8888	27.7193	0.0577
Average	1	1.0564	0.09928	1.4420	20.9615	0.0530
	2	1.0716	0.07058	1.6642	21.06021	0.0509
	3	1.2234	0.0788	1.5039	21.11938	0.0579

Table 4: Lifting wavelet transform, vector quantization (lbg), arithmetic and huffman coding

LWT Image	Level	LWT Zigzag Arithmetic C.Ratio	LWT Zigzag Arithmetic Time (Sec)	LWT Zigzag LBG & Arithmetic C.Ratio	LWT Zigzag LBG & Arithmetic PSNR	LWT Zigzag LBG & Arithmetic Time (Sec)
Carotid	1	1.3636	0.1433	1.6842	15.1588	0.0116
	2	1.1636	0.1076	1.641	14.1798	0.0107
	3	1.1428	0.1301	1.641	16.4423	0.0104
Liver_t1	1	1.3743	0.4263	1.641	17.5346	0.0141
	2	1.2636	0.0486	1.6842	14.1617	0.0118
	3	1.1228	0.0448	1.6623	19.5076	0.0074
Liver_t2e1	1	1.4327	0.0313	1.6955	16.0485	0.0069
	2	1.1962	0.078	1.641	14.2502	0.007
	3	1.1931	0.0601	1.4564	19.5367	0.0104
Pad_chest	1	1.3428	0.0292	1.9833	15.8712	0.011
	2	1.1327	0.0338	1.7066	16.3622	0.0071
	3	1.2075	0.0414	1.7066	17.6318	0.0103
Aperts	1	1.1636	0.0298	1.7066	15.3466	0.0107
	2	1.1962	0.0492	1.641	13.3961	0.014
	3	1.3195	0.0343	1.6202	17.3437	0.0124
Sag_head	1	1.4428	0.0636	1.7777	15.9653	0.0072
	2	1.1327	0.1024	1.7297	17.3593	0.0077
	3	1.1444	0.1645	1.641	20.5763	0.0077
Skull	1	1.1428	0.052	1.641	17.9075	0.0105
	2	1.28	0.0766	1.6623	13.3142	0.0102
	3	1.1228	0.0938	1.6842	19.4484	0.008
Wrist	1	1.2075	0.0276	1.6842	15.7742	0.0071
	2	1.2075	0.0529	1.7066	16.2986	0.0104
	3	1.2075	0.0276	1.6842	15.7742	0.0071
Average	1	1.3087	0.1003	1.7266	16.2008	0.0098
	2	1.1965	0.0686	1.6765	14.9152	0.0098
	3	1.1784	0.0782	1.6315	18.4662	0.0095

LWT Image	Level	LWT Zigzag Huffman C.Rati	LWT Zigzag Huffman Time (Sec)	LWT Zigzag LBG & Huffman C.Ratio	LWT Zigzag LBG & Huffman PSNR	LWT Zigzag LBG & Huffman Time (Sec)
Carotid	1	1.2929	0.0482	1.3934	15.1588	0.0155
	2	1.1451	0.0718	1.4712	14.1798	0.0157
	3	1.1228	0.0399	1.4222	16.4423	0.0165
Liver_t1	1	1.1763	0.0445	1.4065	17.5346	0.0216
	2	1.1851	0.0449	1.4456	14.1617	0.0149
	3	1.1531	0.0455	1.4222	19.5076	0.0177
Liver_t2e1	1	1.3333	0.0696	1.4545	16.0485	0.0143
	2	1.1246	0.0601	1.4712	14.2502	0.0159
	3	1.1743	0.109	1.3763	19.5367	0.0161
Pad_chest	1	1.2549	0.1238	1.3763	15.8712	0.0263
	2	1.1021	0.0779	1.4545	16.3622	0.0258
	3	1.0756	0.0419	1.4545	17.6318	0.0177

Table 4: Continue

LWT		LWT Zigzag Huffman		LWT Zigzag LBG & Huffman		
Image	Level	C.Rati	Time (Sec)	C.Ratio	PSNR	Time (Sec)
Aperts	1	1.3195	0.07	1.4545	15.3466	0.0261
	2	1.0756	0.0672	1.4712	13.3961	0.0142
	3	1.0406	0.0509	1.4712	17.3437	0.0201
Sag_head	1	1.3913	0.0344	1.5555	15.9653	0.0261
	2	1.1851	0.038	1.4382	17.3593	0.0186
	3	1.1228	0.043	1.4712	20.5763	0.0266
Skull	1	1.1113	0.037	1.5382	17.9075	0.0222
	2	1.1333	0.0749	1.4222	13.3142	0.0146
	3	1.1851	0.066	1.4484	19.4484	0.0175
Wrist	1	1.1195	0.0436	1.5566	15.7742	0.0182
	2	1.1531	0.0697	1.4545	16.2986	0.0196
	3	1.1195	0.0436	1.5566	15.7742	0.0182
Average	1	1.2498	0.0588	1.4669	16.2008	0.0212
	2	1.138	0.0630	1.4535	14.9152	0.0174
	3	1.1271	0.0542	1.4594	18.4662	0.0188

Table 5: Discrete cosine transform, vector quantization (lbg), arithmetic and huffman coding

DCT	DCT Zigzag Arithmatic		DCT & LBG Zigzag Arithmatic		
Image	C. Ratio	Time (Sec)	C. Ratio	PSNR	Time (Sec)
Carotid	1.0711	0.1167	1.28	18.7433	0.0212
Liver_t1	1.1962	1.1862	1.5375	18.3015	0.0208
Liver_t2e1	1.2132	0.03	1.3333	18.8851	0.0135
Pad_chest	1.3368	0.0484	2.3703	30.3357	0.0105
Aperts	1.2278	0.0325	1.8962	19.6048	0.0139
Sag_head	1.1203	0.0285	2.0078	21.6627	0.0142
Skull	1.1743	0.0434	1.467	21.1481	0.0144
Wrist	1.2864	0.0345	2.4265	27.2516	0.0089
Average	1.2032625	0.190025	1.789825	21.9916	0.014675
DCT	DCT Zigzag Huffman		DCT & LBG Zigzag Huffman		
Image	C. Ratio	Time(Sec)	C. Ratio	PSNR	Time (Sec)
Carotid	1.0427	0.0712	1.06	18.7433	0.0445
Liver_t1	1.099	0.0845	1.2513	18.3015	0.0484
Liver_t2e1	1.0046	0.0753	1.113	18.8851	0.048
Pad_chest	1.0039	0.0773	1.8533	30.3357	0.0437
Aperts	1.0275	0.1019	1.3078	19.6048	0.0469
Sag_head	1.0178	0.1008	1.8767	21.6627	0.0424
Skull	1.0743	0.0591	1.6578	21.1481	0.0447
Wrist	1.059	0.0576	1.8533	27.2516	0.0718
Average	1.0411	0.0784625	1.49665	21.9916	0.0488

(2016) with a combination of the LBG Vector Quantization and the lossless coding techniques such as Arithmetic Coding and Huffman Coding and without the combination. The results in this table show that the performance of the compression ratio using a combination of the LBG Vector Quantization and the lossless coding techniques better than without the combination at the three decomposition levels and the results in Table 1 is also better than these results.

The results in Table 5 show also the compression ratio, the peak signal-to-noise ratio and the running time using DCT by Hadi (2014) and Prabhu *et al.* (2013) with a combination of the LBG Vector Quantization and the lossless coding techniques such as Arithmetic Coding and Huffman Coding and without the combination. The results in this table show that the performance of the compression ratio using a combination of the LBG Vector Quantization and the lossless coding techniques better than without the combination and the results in table Iis also better than these results.

The results in Table 3 using LWT outperform the results in Table 3 using DWT and the results in Table 3 using DWT outperform the results in Table 5 using DCT. Then the results in Table 1 outperform the results in Table 2 to 5 using DCT.

So, the proposed system outperforms the other previous methods in Table 2 to 5.

CONCLUSION

This study proposes a system that works on medical images compression by using a combination of lossy compression through LBG Vector Quantization and lossless compression through Arithmetic Coding. It also used Huffman Coding for comparison and different transforms which are DCT and three types of wavelet transforms which are SWT, DWT and LWT at three levels.

The results show that the performance depends on the type of the transform, whether LBG was used or not, the number of decomposition levels and the type of the lossless coding whether it was Huffman Coding or Arithmetic Coding.

The lossy compression approach used SWT and a combination of the LBG Vector Quantization and the lossless coding outperforms the other wavelet transforms such as the DWT and the LWT and the other transform which is DCT. The arithmetic coding gives the best compression ratio with less time possible.

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