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Non-Decimated Wavelet Transform and Vector Quantization for Lossy Medical Images Compression

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Abstract: This study presents a new approach for lossy medical image compression using vector quantization. Recently, the digital image has been a reliable replacement for a hard copy of medical images, therefore, an effort has been made to ensure maintaining high-quality images to use for archiving, classification, or automated diagnostics support. Although the medical application contains all sorts of the images like microscopic, X-rays, tomography, and fiber optics imaging by angioplasty, all of this comes at the cost of using digital storage that needs to be regularly backed up and maintained and to help minimize the need for larger storage media, this study is focusing on applying Non-Decimated Wavelet Transform (NDWT) and combined lossy and lossless compression techniques that will allow the images to take much smaller storage space while maintaining the high level of quality for these images. This study is focusing on chest X-ray images compression using a combination of lossy compression techniques using two Vector Quantization (VQ) algorithms such as k-means clustering and Linde, Buzo, and Gray (LBG) algorithm, and three lossless compression techniques such as Arithmetic Coding (AC), Run Length Encoding (RLE) and Huffman Coding (HC) and choose the optimum combination of them. Then, the performance is measured using Compression Ratio (CR), processing time, or called run time, Peak Signal to Noise Ratio (PSNR), and Bit Rate.

Keywords: Medical Image Compression, Non-Decimated Wavelet Transform, Vector Quantization, K-Means Clustering, Linde, Buzo, and Gray Algorithm, Run Length Encoding, Arithmetic Coding, Huffman Coding

Introduction

Compressing an image is a process of minimizing the image into fewer bits than the original representation which means that it would take less space than the original image and the transmission time would decrease. Image compression is divided into two general categories: (a) Lossy compression and (b) Lossless compression in (Chengalvala, 2003). The use of lossless compression is important when the reconstructed signals and the original signals are exactly identical, like the software or the source code compression. However, the compression ratio in lossless compression schemes is not as great as in lossy compression. Lossy compression is used when the reconstructed data wasn't needed to be identical to the original data, but rather "very close". Most of the video, audio, and image compression techniques fall into this category, where in high compression ratio can be accepted by Chengalvala (2003).

Medical images can be processed through computers to aid medical experts in making the right decisions in a short time so more lives can be saved. There are different formats of images based on storage in computers and different types of medical imaging based on various medical applications. Medical imaging is an idea to improve the content of the image taken from different imaging tools like X-ray images, Computed Tomography (CT) images, Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), ultrasound, Single Photon Emission Computed Tomography (SPECT) and other formats by Vimala and Bobi (2015). The image compression model consists of several modules: The transformer, the quantizer, and the encoder. On the other hand, the modules of the decompression model simply perform the inverse of compression modules by Arunalatha *et al*. (2013).

There are two contributions that this study offers. The first contribution is the vector quantization techniques and non-decimated wavelet transforms for lossy compression which has less compressed data than other wavelets transformation. The second contribution is the application of lossless compressors such as Run length encoding, Huffman coding, and Arithmetic coding.

This study provided a novel approach for image compression specifically designed for chest X-rays. In the work, several lossy compression and lossless compression methods were used. The approach first pre-processed the image then the NDWT of the image was used not followed by vector quantization and was used followed by vector quantization with several methods such as Linde, Buzo, and Grey and k-means clustering, then the resulting image was converted through Zigzag scanning and compressed using several coding techniques such as Run length encoding, Huffman coding, Arithmetic coding, Run length encoding Huffman coding combination and Run length encoding Arithmetic coding combination. The results of each combination of techniques which brought us to have fifteen different comparisons are used in this study where ten chest X-ray images were used to provide the best analysis of the methods. The comparisons were dictated by the compression ratio, the run time, PSNR, and the bit rate. The results of the comparison concluded that the best method used was through the use of NDWT, k-means clustering technique, Zigzag scanning, and Run length encoding algorithm.

Image compression using vector quantization is made by Agrawal and Mohan (2022), color image compression is made using vector quantization and hybrid wavelet transform by Kekre *et al*. (2016), image compression using vector quantization is made also by Madhuri *et al*. (2014), image compression using VQ for lossy compression is made by Chatterjee *et al*. (2019), lossy image compression based on prediction error and vector quantization is made by Ayoobkhan *et al*. (2017) and robust medical image compression based on wavelet transform and vector quantization is made by Ammah and Owusu (2019).

Materials and Methods

The proposed system steps are shown in Fig. 1:

- Read the image file from the source where the input image is (RGB) color image and stored in the memory as 3 matrixes, each matrix represents a color channel (red, green, and blue) Fig. 2
- Preprocessing the input image by resize the image to the size 8 × 8 and convert it from RGB to gray scale Fig. 3

Applying Non-Decimated Wavelet Transform (NDWT).

Vector quantization of the image using one of these methods.

- Linde, Buzo, and Gray (LBG algorithm)
- K-means clustering technique
- No processing

The result then is converted to a vector using Zigzag scanning.

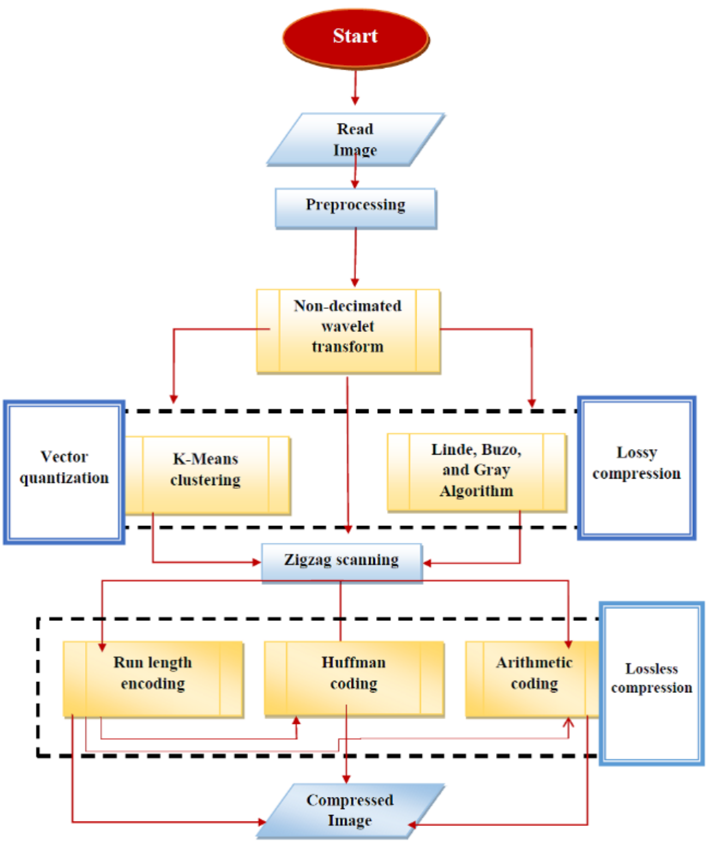

Fig. 1: The main steps for the proposed system

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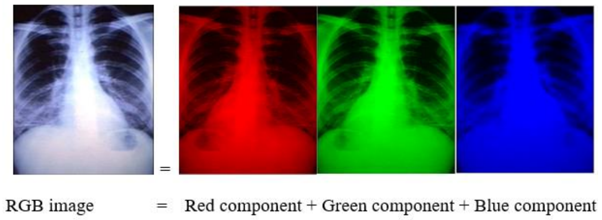

Fig. 2: RGB channels

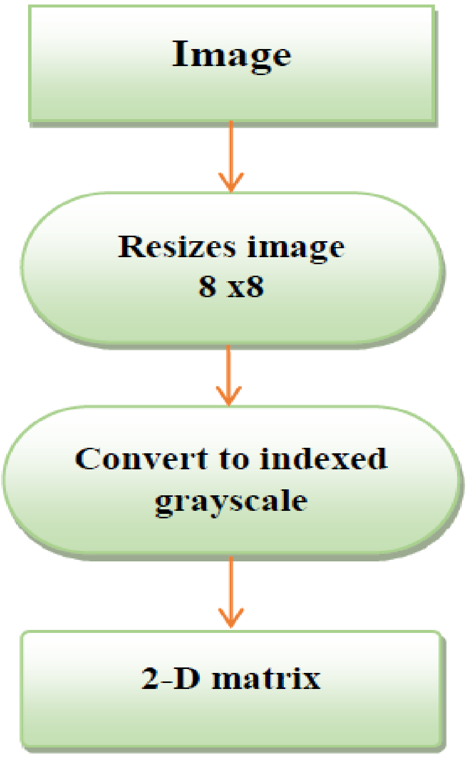

Fig. 3: Image preprocessing (Scherzer, 2010)

The compressed image goes to further lossless compression via one of these methods:

- Run length encoding
- Huffman coding
- Arithmetic coding

Run length encoding Huffman coding combination. Run length encoding Arithmetic coding combination.

The final compressed image goes through several measurements to determine the quality of each proposed technique.

The final step in the proposed methodology is comparing the compression ratio of the proposed method and the run time it took to compress the images with the compression ratio and run time achieved by similar research was done by Patel *et al*. (2013).

Read Image File

This system is designed to be able to read various types of images, however after reading the initial decoding of the image (if needed) it is treated as a full color (RGB) bitmap and stored in the memory as 3 matrixes, each matrix represents a color channel (red, green and blue).

Preprocessing

Preprocessing takes the original image and resizes it accordingly with a measured rate of different sizes too (8×8) and then converts it from RGB to grayscale. In order to make the image easier to work with, the image color components are then transformed into indexed grayscale of 256 indices.

The indexes are calculated using an inverse color map where the inverse color map algorithm quantizes the specified color map into 32 distinct levels per color component. Then, for each pixel in the input image, the closest color in the quantized color map is found.

After the calculation of the new color map, the image is resized to the desired dimensions.

Applying Non-Decimated Wavelet Transform (NDWT)

The Non-Decimated Wavelet Transforms (NDWT) W using the filter bank (h, g) of a 1-D signal c0 that represents an input image after preprocessing-leads to the set $W = \{w_1, w_2,\ldots, w_j, c_j\}$ where w_j are the wavelet coefficients at scale j and c_j are coefficients at coarsest resolution. The passage from one resolution to the next one is obtained using the "à trous" algorithm by Starck *et al.* (2007).

The output of this procedure is now ready to go through the compression steps.

Vector Quantization

In the step of vector quantization, the proposed system studies the effect of lossy image compression using the vector quantization by Mittal and Lamba (2013).

The reason for choosing the vector quantization is due to reduce image size and memory footprint by neglecting some details but also to prepare an image to make further lossless compression even more effective without losing any additional data.

For this purpose, the two different vector quantization techniques are being tested:

- Linde, Buzo, and Gray (LBG algorithm)
- K-means clustering
- And each one work as follows

Linde, Buzo, and Gray (LBG Algorithm)

The LBG algorithm starts with the initialization of the codebook which has random vectors from the training set. The code vectors are generated with the clustering of training set vectors. The centroid of each code vector is calculated and then interchange with this code vector. This process runs until a distortion in the codebook between iterations reaches the predetermined number by Linde *et al*. (1980).

K-Means Clustering

This function is for training the codebook for vector quantization. The data set is split into two clusters, first and mean of each cluster are found that are centroids. The distance of each vector from the centroids is found and each vector is associated with the cluster. The mean of vectors of each cluster replaces the centroid first. If the total distance is not improved substantially, the centroids are each split into two. This goes on until a required number of clusters is reached and the improvements are substantial (Sarode and Mandal, 2013).

Zigzag Scanning

Whether or not a lossy compression is applied to the image, the lossless part of compression will need to 2-D matrix of the image to be transformed into a 1-D vector and it is done by Zigzag scanning (Pennebaker and Mitchell, 1992).

Lossless Compression

Whether the image data has been processed by a lossy compression technique or not, the image data shall go through one or several lossless compression procedures and since lossless compression is totally reversible, several compression techniques can be stacked to try to achieve a better compression ratio such as Run Length Encoding (RLE) (Dhotre and Bagad, 2005), Huffman coding (Reddy *et al*., 2013) and Arithmetic coding by Kumar *et al*. (2015) Kodituwakku and Amarasinghe (2010).

The decompression path is the inverse of the compression path, starting from the compressed image and applying the inverse lossless compression and the inverse non-decimated wavelet transform to get the reconstructed image.

Measurements

For each combination of lossy/lossless compression methods, these factors were measured for each image.

Compression Ratio (CR)

The compression ratio is the ratio of the size of the compressed database system to the original size of the uncompressed database system. *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. The compression ratio is defined as follows by Chowdhury and Khatun (2012) in Eq. (1):

$$CR = \frac{Size\ of\ original\ image\ data}{Size\ of\ compressed\ image\ data} \tag{1}$$

CR = (uncompressed size)/(compressed size)

Bit Rate (bpp)

The bit rate is the number of bits per pixel of the compressed image.

Run Time (Sec)

The run time represents the time period through the procedure and it represents the computational complexity of the model. If it has high computational complexity, it needs a high run time to proceed and if it has low computational complexity, it needs a low run time to proceed.

Peak Signal Noise Ratio (PSNR) in (dB)

The Peak Signal-to-Noise Ratio (PSNR) is defined as the following formula by Chowdhury and Khatun (2012) as in Eq. (2):

$$PSNR = 10 \log 10\left(2552/MSE\right)dB \tag{2}$$

where, *MSE* is the mean square of the difference between the reconstructed image and the uncompressed image and it represents the amount of error in the model.

Results and Discussion

In this study ten images have been used for the testing process, all of them have medical nature (X-ray of the human ribcage) five of these images are grayscale and the other five are RGB color images from the PIERS digital library. The application has been built using "MathWorks MATLAB" software version, 2013, it was running on Microsoft windows 7 ultimate SP1 machine, with these hardware specifications.

Model: Hewlett Packard (HP) pavilion g6 notebook PC. Processor: 4 core, 8 logical threads, Intel core™ i7 3632 QM running at 2.2 GHz. RAM: 6 GB of DDR 3 physical memory. Hard drive: Hitachi 500 GB notebook HDD.

The Measurement Results were as Follows

The results in Table 1, the first part shows the results using the combination of non-decimated wavelet transform and run-length encoding for lossless compression, this part of the table shows that the compression ratio has not been largely affected by changing the image, yet there is a significant processing time difference between images, the second part of this table shows that the combination of NDWT, LBG and RL combination, yielded higher compression ratio and even shorter processing time and the third part of that table shows that the NDWT, k-means, and RL combination is sensitive to image contents, yet it yielded slightly higher compression ratio and much higher processing time than the previous methods, but with a higher Peak signal to noise ratio, meaning the image output quality is better.

The results in Table 2, the first part shows the results using the combination of non-decimated wavelet transform and Huffman coding as a purely lossless compression technique it was expected that it will yield a lower compression ratio as it doesn't scarify with the output image quality, the table shows that this combination has lower compression ratio and runtime that varies significantly with the input image. The second part of this table shows the combination of the non-decimated wavelet transform, LBG, and Huffman coding, and the addition of LBG to the previous experiment in Table 2 didn't have a significant effect on compression ratio, however, the code had a much lower processing time and the PSNR measure shows that the quality of the output image depends greatly on the original contents of the original input image and the third part of that table shows the combination of the non-decimated wavelet transform, k-means, and Huffman coding shows using k-means instead of LBG for lossy compression had a negative effect on both compression ratio and run time, yet it yielded a higher PSNR, which means better image quality.

For the results in Table 3, the first part shows the results using the combination of non-decimated Wavelet Transform and Arithmetic coding as with purely lossless compression, the compression ratio is shown to be low, with relatively high processing time, however; with the introduction of Arithmetic encoding, the run time looks to be much more sensitive to the change of image content with no significant effect on compression ratio. The second part of this table shows the combination of the non-decimated wavelet transform, LBG, and Arithmetic coding, and the addition of LBG lossy compression to the Arithmetic encoding has a positive effect on both compression ratio and run time, also the results show that it made it even more sensitive to the image contents causing high variation in the compression ratio between one test image and another and the third part of that table shows the combination of non-decimated wavelet transform, k-means and Arithmetic coding and the results show that replacing LBG with k-means lossy compression made the compression ratio less sensitive to the image content (but still sensitive), while not changing the overall average compression ratio significantly, yet sacrificing processing time for image quality.

For the results in Table 4, the first part shows the results using the combination of non-decimated wavelet transform, Run-length encoding, and Huffman coding, and the results show that combining the two lossless compression techniques (RLE and HC) didn’t improve the compression ratio, yet it even increased the processing time over the use of only one lossless compression technique. The second part of this table shows the combination of non-decimated Wavelet Transform, LBG, Run Length encoding, and Huffman coding and adding the lossy compression technique (LBG) to the combination of RLE and HC, did have a positive effect on both compression ratio and processing time, but made it slightly more sensitive to the contents of the image. The third part of this table shows the combination of the non-decimated wavelet transform, k-means, Run Length Encoding, and Huffman coding and replacing LBG with k-means had a negative effect on both compression ratio and processing time, but also improved the image quality measure (PSNR).

For the results in Table 5, the first part shows the results using the combination of the non-decimated wavelet transform, Run-length encoding, and Arithmetic coding and using another combination of purely lossless techniques, which had a slightly positive effect on both compression ratio and processing time. The second part of this table shows the combination of the non-decimated wavelet transform, LBG, Run-length Encoding, and Arithmetic coding and adding lossy compression technique (LBG) to the previous combination of lossless compression techniques also had a positive effect on compression ratio and run time, but at cost of much lower bitrate and the average level of PSNR. The third part of this table shows the combination of non-decimated wavelet transform, k-means, Run-length encoding, and Arithmetic coding, and combining all studied compression methods together had a negative effect on compression ratio and processing time, but with better image output quality.

Table 6 shows the average results of all test images to overcome the compression method sensitivity to image contents, and the results of all studied compression techniques could be compared as in that table.

Based on the previous findings, it can be concluded that the best combination of studied lossy/lossless compression technique from a compression ratio point of view is to use a non-decimated wavelet transform followed by k-means vector quantization, followed by the run-length encoding lossless compression technique as shown in the following Fig. 4. The compression ratio was 12.96 that is the advantage of this proposed method. But this proposed method has a higher peak signal-to-noise ratio rather than other methods. The peak signal-to-noise ratio is 11.073 dB and has a run time higher than some other methods and lower than some other methods. The run time is 2.198 sec which is the disadvantage of this proposed method.

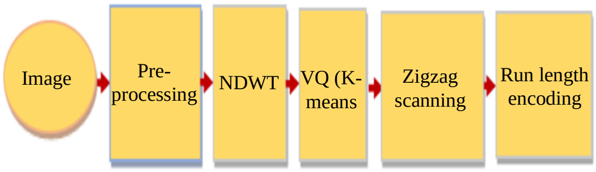

Fig. 4: Optimum compression path

Table 1: RLE lossless compression vs. LBG-RL lossy compression vs. K-means-RL lossy compression

	RLE			LBG-RLE				K-means-RLE			
Image	C.R	Bit rate	Run time (sec)	C.R	Bit rate	Run time (ms)	PSNR	C.R	Bit rate	Run time (sec)	PSNR
Image 1	8.00	1.00	1.2331	10.12	0.790	38.8	9.35	10.45	0.7654	1.450	8.73
Image 2	8.00	1.00	1.8720	10.28	0.777	9.6	9.04	10.45	0.7654	1.780	11.30
Image 3	8.00	1.00	1.9319	12.00	0.666	7.2	10.45	11.78	0.6790	1.990	10.09
Image 4	8.00	1.00	1.9627	12.00	0.666	7.0	8.94	11.57	0.6914	2.940	9.69
Image 5	8.00	1.00	1.6880	10.12	0.790	7.1	6.86	9.52	0.8395	2.490	11.99
Image 6	8.00	1.00	1.2889	10.62	0.753	7.2	10.90	12.96	0.6173	2.350	8.93
Image 7	8.00	1.00	1.4097	10.62	0.753	6.9	11.00	11.17	0.7160	1.940	10.38
Image 8	8.00	1.00	1.3845	10.28	0.777	7.5	10.85	10.98	0.7284	1.910	13.26
Image 9	8.10	0.98	2.1706	10.12	0.790	7.4	12.18	8.30	0.9630	2.530	15.55
Image 10	8.00	1.00	2.6700	11.17	0.716	6.4	8.37	10.80	0.7407	2.560	10.76
Average	8.01	0.99	1.7600	10.73	0.748	10.5	9.78	10.80	0.7500	2.198	11.07

Table 2: Huffman coding lossless compression vs. LBG-HC lossy compression vs. K-means-Huffman Lossy compression

	HC			LBG-HC				K-means-HC			
Image	C.R	Bit rate	Run time (sec)	C.R	Bit rate	Run time (sec)	PSNR	C.R	Bit rate	Run time (sec)	PSNR
Image 1	1.18	6.78	1.64	1.27	6.30	0.09	9.63	1.12	7.12	2.15	8.74
Image 2	1.19	6.70	1.50	1.49	5.36	0.05	7.87	1.17	6.81	1.74	11.30
Image 3	1.20	6.69	2.75	1.35	5.93	0.07	10.67	1.19	6.73	1.94	10.10
Image 4	1.19	6.70	2.02	1.25	6.38	0.09	9.90	1.16	6.89	2.63	9.70
Image 5	1.19	6.70	2.74	1.72	4.64	0.03	6.43	1.18	6.75	1.86	12.00
Image 6	1.20	6.69	1.71	1.30	6.15	0.06	10.79	1.22	6.57	1.84	8.94
Image 7	1.19	6.72	2.26	1.27	6.30	0.10	10.75	1.19	6.74	2.56	10.39
Image 8	1.22	6.54	1.74	1.27	6.30	0.11	11.23	1.20	6.65	2.62	13.27
Image 9	1.18	6.75	2.46	1.29	6.22	0.07	12.61	0.97	8.22	5.68	15.55
Image 10	1.18	6.75	3.56	1.34	5.99	0.12	8.78	1.18	6.75	3.05	10.76
Average	1.19	6.70	2.24	1.36	5.96	0.08	9.87	1.16	6.92	2.61	11.07

Table 3: Arithmetic lossless compression vs. LBG-Arithmetic lossy compression vs. K-means-Arithmetic lossy compression

	AC			LBG-AC				K-means-AC			
Image	C.R	Bit rate	Run time (sec)	C.R	Bit rate	Run time (ms)	PSNR	C.R	Bit rate	Run time (sec)	PSNR
Image 1	1.19	6.70	2.04	2.03	3.94	10.80	9.63	2.77	2.89	1.91	8.74
Image 2	1.20	6.65	1.39	4.87	1.64	7.60	7.87	3.39	2.36	3.05	11.30
Image 3	1.25	6.40	1.92	2.68	2.99	8.30	10.67	3.56	2.25	1.46	10.10
Image 4	1.22	6.54	2.51	1.95	4.11	8.90	9.90	3.18	2.52	2.67	9.70
Image 5	1.21	6.60	2.21	11.57	0.69	6.90	6.43	3.45	2.32	2.13	12.00
Image 6	1.23	6.51	1.48	2.72	2.94	8.10	10.79	3.86	2.07	2.98	8.94
Image 7	1.21	6.63	1.96	1.95	4.10	8.50	10.75	3.24	2.47	1.88	10.39
Image 8	1.66	4.83	2.66	2.02	3.96	9.30	11.23	5.36	1.49	1.92	13.27
Image 9	1.45	5.52	4.79	2.45	3.26	8.10	12.61	1.93	4.15	3.89	15.55
Image 10	1.20	6.64	3.11	2.82	2.84	8.00	8.78	3.72	2.15	3.55	10.76
Average	1.28	6.30	2.41	3.51	3.05	8.45	9.87	3.45	2.47	2.54	11.07

Table 4: Run length and Huffman lossless compression vs. LBG-run length & Huffman lossy compression vs. K-means-RLE and HC lossy compression

	RLE and HC			LBG-RLE and HC				K-means-RLE and HC			
Image	C.R	Bit rate	Run time (sec)	C.R	Bit rate	Run time (ms)	PSNR	C.R	Bit rate	Run time (sec)	PSNR
Image 1	1.18	6.78	2.93	1.73	4.62	50.90	9.35	1.77	4.52	2.08	8.74
Image 2	1.18	6.77	1.79	1.93	4.15	24.20	9.05	1.88	4.26	2.16	11.30
Image 3	1.20	6.69	1.62	2.24	3.57	26.30	10.46	2.17	3.69	2.25	10.10
Image 4	1.19	6.70	2.45	2.23	3.59	27.90	8.94	2.07	3.86	1.50	9.70
Image 5	1.19	6.70	2.38	2.33	3.43	16.90	6.87	1.72	4.65	2.79	12.00
Image 6	1.20	6.69	2.35	1.86	4.30	43.80	10.91	2.45	3.26	2.71	8.94
Image 7	1.19	6.72	2.75	1.85	4.32	70.90	11.00	1.99	4.02	2.86	10.39
Image 8	1.23	6.53	2.99	1.90	4.21	35.50	10.85	2.11	3.79	2.37	13.27
Image 9	1.22	6.57	3.68	1.80	4.46	27.60	12.18	1.33	6.02	2.99	15.55
Image 10	1.18	6.75	3.11	2.13	3.75	23.40	8.38	1.88	4.25	2.94	10.76
Average	1.20	6.69	2.61	2.00	4.04	34.74	9.80	1.94	4.23	2.46	11.07

Table 5: Run length encoding and Arithmetic coding lossless compression vs. LBG-run length and Arithmetic lossy compression vs. K-means-RLE and AC lossy compression

	RLE and AC			LBG-RLE and AC				K-means-RLE and AC			
Image	C.R	Bit rate	Run time (sec)	C.R	Bit rate	Run time (sec)	PSNR	C.R	Bit rate	Run time (sec)	PSNR
Image 1	1.19	6.70	2.35	2.21	3.62	0.01220	9.35	2.33	3.43	2.40	8.74
Image 2	1.18	6.77	1.45	3.24	2.47	0.00870	9.05	2.63	3.04	2.25	11.30
Image 3	1.25	6.40	1.59	3.03	2.64	0.00880	10.46	2.87	2.79	1.66	10.10
Image 4	1.22	6.54	3.02	2.91	2.75	0.00860	8.94	2.62	3.05	2.43	9.70
Image 5	1.21	6.60	2.30	6.06	1.32	0.00780	6.87	2.75	2.91	1.87	12.00
Image 6	1.23	6.51	3.48	2.42	3.31	0.00970	10.91	3.43	2.33	2.23	8.94
Image 7	1.21	6.63	2.31	2.30	3.48	0.00970	11.00	2.72	2.94	1.75	10.39
Image 8	1.65	4.84	2.78	3.15	2.54	0.00890	10.85	3.68	2.17	1.51	13.27
Image 9	1.45	5.52	3.05	2.75	2.91	0.00970	12.18	1.83	4.38	3.35	15.55
Image 10	1.20	6.64	2.86	3.48	2.30	0.00850	8.38	2.66	3.01	3.62	10.76
Average	1.28	6.31	2.52	3.15	2.73	0.00921	9.80	2.75	3.01	2.31	11.07

Table 6: Average results comparison

Compression techniques	Compression Ratio (CR)	Bit rate	Run time (sec)	PSNR (dB)
RLE	8.010	0.99800	1.76000	N/A
LBG-RLE	10.736	0.74800	0.01050	9.799
K-means-RLE	10.800	0.75060	2.19800	11.073
HC	1.193	6.70000	2.23000	N/A
LBG-HC	1.354	5.95000	0.07800	9.865
K-means-HC	1.159	6.92400	2.67000	11.073
AC	1.282	6.30200	2.40800	N/A
LBG-AC	3.506	3.04600	0.00800	9.865
K-means-AC	3.445	2.46600	2.54400	11.073
RLE and HC	1.195	6.69000	2.60500	N/A
LBG-RLE and Huffman	2.000	4.03900	0.03470	9.799
K-means-RLE and Huffman	1.937	4.23300	2.46200	11.07363
RLE and Arithmetic	1.280	6.31481	2.51662	N/A
LBG-RLE and Arithmetic	3.153	2.73457	0.00921	9.79922
K-means-RLE and Arithmetic	2.751	3.00616	2.30625	11.07363

Table 7: Average compression ratio comparison between the proposed method and previous literature

Parameter ----------------------- Comparison	Average compression ratio
Developed method	10.80
Patel *et al*. (2013)	4.54

Table 8: List of abbreviations

AC	Arithmetic coding
bpp	Bit per pixel
CR	Compression Ratio
CT	Computed Tomography
HC	Huffman Coding
LBG	Linde Buzo Gray
MRI	Magnetic Resonance Imaging
MSE	Mean Squared Error
NDWT	Non-Decimated Wavelet Transform
PET	Positron Emission Tomography
PSNR	Peak Signal-to-Noise Ratio
RLE	Run Length Encoding
SPECT	Single Photon Emission Computed Tomography
VQ	Vector Quantization

Patel *et al*. (2013) proposed two methods of compression one through the use of DWT and vector quantization and the other by an extended hybrid DWT-VQ system, the difference between these methods was about 0.75 which was insignificant according to the authors, the results of the proposed compression system was a compression ratio between 2.97 to 6.11 in Patel *et al*. (2013). However, this came at the cost of a long processing time according to the author. This study provides a comparison between the average compression ratios of both methods in Table 7.

As shown in the comparison, the average compression ratio for the five images used by Patel *et al*. (2013) their method presents a less than the average compression ratio that the results of our method provided as the best compression ratio achieved was 4.54 with the best compression ratio of 9.46, while the best compression ratio achieved by the proposed method. The running time that the method proposed takes is far less than the other method Table 8 shows the list of abbreviations.

Conclusion

This study provided a novel approach for image compression specifically designed for chest X-rays. In the work, several lossy compression and lossless compression methods were used. The approach first pre-processed the image then the NDWT of the image was used not followed by vector quantization and was used followed by vector quantization with several methods such as Linde, Buzo, and Grey and k-means clustering, then the resulting image was converted through Zigzag scanning and compressed using several coding techniques such as Run length Encoding, Huffman coding, Arithmetic coding, Run length encoding Huffman coding combination and Run length encoding Arithmetic coding combination. The results of each combination of techniques which brought us to have fifteen different comparisons are used in this study where ten chest X-ray images were used to provide the best analysis of the methods. The comparisons were dictated by the compression ratio, the run time, PSNR, and the bit rate. The results of the comparison concluded that the best method used was through the use of NDWT, k-means clustering technique, Zigzag scanning, and run length encoding algorithm. The results proved to be very promising when it came to the compression ratio and the running time of the experiment. In conclusion, the method proposed, namely using NDWT, k-means clustering, Zigzag scanning, and run length encoding algorithm provided the highest average compression ratio that is 10.800 and the highest average speed in comparison to other methods employed in the work which is 2.198 sec.

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Author's Contributions

Hend A. Elsayed: Participated in all experiments, coordinated the data analysis and contributed to the written of the manuscript, designed the research plan, and organized the study.

Qusay E. Majeed: Participated in all experiments, coordinated the data analysis, and contributed to the written of the manuscript.

Mohammed M. El Sherbiny: Supervision.

Ethics

This article is original and contains unpublished material. There are no ethical issues involved.

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