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MEDICAL IMAGE COMPRESSION TECHNIQUE FOR TELEMEDICINE APPLICATIONS

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ABSTRACT
In the Internet of medical things (IoMT) and big data era, medical image compression is crucial in today's world. Importantly, compression of large sized medical images is required for everyday tasks, including, storage space utilization and transmission bandwidth of healthcare systems and internet transmissions. However, in this paper, Modified Run Length Encoding (MRLE) is applied as a lossless compression and fast technique to compress medical images. RLE is applied to further increase the compression factor. The goal of using RLE is to enhance the compression factor without adding any distortion to the resultant decompressed image. Since, in healthcare systems and medicine applications, it is necessary to obtain high quality of the decompressed image. Moreover, MRLE is used to enhance the original RLE algorithm. The Block-Block scanning technique will be applied. Thus, this technique produces high efficiency compared with previous RLE techniques. The medical image is divided into equivalent blocks, where, the pixels inside each block are either scanned vertically or horizontally and all blocks together are also scanned vertically or horizontally. In the produced vector, the similar run of the same pixels' value will merge to reduce the size of the output vector. Importantly, the results of the proposed algorithm are shown to be comparable in quality and performance with other existing medical image compression methods.

Keywords: big data problem, compression factor, medical image, run length encoding (RLE).

INTRODUCTION
Nowadays, digital medical images [1] have gained a vital role in healthcare systems [2]. Save and transmit the big size medical images are challenging for hospital management systems (HMS) [3]. However, high resolution and big size medical images got by different modalities [4] (such as, x-rays, computed tomography (CT), mammography, magnetic resonance imaging (MRI), ultrasound (US), positron emission tomography (PET), and single photon emission computed tomography (SPECT)) require higher storage space and media bandwidth [4-6]. Many algorithms have been proposed in the field of medical image compression [7]. The main goal of all of them is to reduce the size of the medical image, in order to increase the storing capacity, processing efficiency, and transmission capabilities [8].

Importantly, there are two main algorithms: compression algorithm and decompression algorithm [9]. The output of the compression algorithm is the compressed image which is smaller in size compared to the original image [10]. The decompression algorithm reconstructs the original image from the compressed image. All image compression algorithms aim to achievehigh compression ratio (CR) and high-quality compression [11]. However, medical images have an important diagnostic information, so that, the compression/decompression algorithms must be lossless in order to keep all entire pixel data [12].

Image compression/decompression block diagram for medical images is shown in Figure-1.

The efficiency of the compression algorithms [13] can be measured, by using different criterions. The most common criteria are the compression ratio (CR), mean square error (MSE) and the peak signal to noise ratio (PSNR) [14, 15]. The CR is calculated by the ratio between the original image and compressed size. MSE and PSNR indicate the noise between original image and decompressed image. CR, MSE, PSNR are given by equation (1), (2), and (3) respectively.

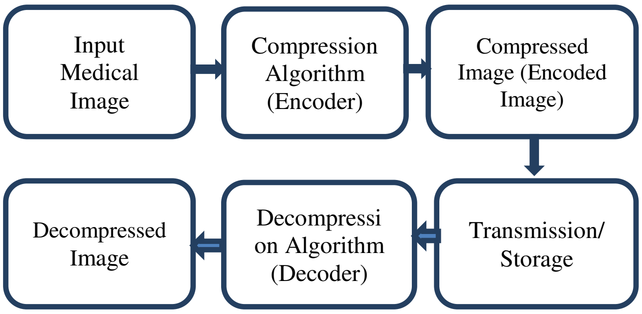

Figure-1. Medical image compression/decompression procedure.

$$\mathrm{CR} = \frac{\mathrm{S(original)}}{\mathrm{S(compressed)}} \quad (1)$$

where, S(original) and S(compressed) are the sizes of the original and compressed images, respectively.

$$\mathrm{MSE} = \left(\frac{\sum(\mathrm{Pi}-\mathrm{Qi})^2}{(\mathrm{N}*\mathrm{M})}\right) \quad (2)$$

where: P_i is the pixel value form the decompressed image, Q_i is the pixel value form the original image, and (N, M) are the number of rows and columns, respectively.

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$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{\frac{1}{N*M}\sum_i(Pi-Qi)^2}\right) \quad (3)$$

Even though, reducing the size of medical images with keeping diagnostic information [16] gives the opportunity to storemore images on thehospital database [17]. In addition, images transmission will be faster and easier for medical and health applications [18]. Basically, lossless image compression techniques [19] (also called reversible techniques)are used in medical images [20]. Importantly, the quality of the decompressed image is the most important factor [21]. The main goal is to obtain a high correlation factor between the original and decompressed images. Therefore, the decompressed image will preserve all data details about the original image [22]. Recently, many lossless algorithms for medical image compression [23] have been proposed. In [24], delimiter based compression technique for telemedicine images is proposed. Moreover, binary values of image data is obtained at the encoded stage. Continuous repetition is sought. At the decoded stage, the decoded original image is obtained by repeating each pixel value depending on the repetitions. In [25], a hybrid method by combining geometry-adaptive partitioning and quadtree partitioning is discussed. This combined technique is applied in order to achieve irregular segmentation and region-based prediction. predictive coding using gradient edge detector (GED) method is proposed in [26]. Huffman coding compression method is proposed in [27]. Moreover, Huffman coding is applied to compress digital Imaging and Communication in Medicine (DICOM) image files in hospitals using optimal prefix code strategy. However, sensitivity to the noise is the main problem of applying this method. As redundancy removal approach, Lempel-Ziv-Welch (LZW) coding method is proposed in [28, 29]. JPEG-LS lossless compression algorithm is applied in [30]. JPEG-LS is used to achieve lower complexity and better compression ratio compared with standard lossless JPEG. Moreover, in order to decrease the noise, adopt a block-based image compression technique is employed. In order to achieve high compression rate and to reduce the computational cost, arithmetic coder method is proposed in [31]. In [32], a hybrid prediction modelnamed LPC-DWT-Huffman (LPCDH) is applied to obtain a high compression rate.

Furthermore, RLE algorithm [33-36] is extensively used in medical image compression. Vector quantization and RLE approach is proposed in [37]. Discrete wavelet transform (DWT) coding and discrete cosine transform (DCT) with RLE is applied to compress CT-Scan, X-Ray, and MRI in [38]. Moreover, volumetric run-length approach is proposed in [39]. Hilbert space-filling curve method with RLE is proposed in [40]. Haar wavelet and RLE approach is employed in [41]. In [42], chain code compression method based on move-to-front transform and an adaptive RLE is proposed.

In this paper, MRLE is used to enhance the original RLE algorithm. The Block-Block scanning technique will be applied. Thus, this technique produces high efficiency compared with previous RLE techniques. The medical image is divided into equivalent blocks, where, the pixels inside each block are either scanned vertically or horizontally and all blocks together are also scanned vertically or horizontally. In the produced vector, the similar run of the same pixels' value will merge to reduce the size of the output vector.

METHODOLOGY

The Run-Length Encoding (RLE) algorithm is a lossless data compression technique, where it is used to reduce the number of redundant bits [43]. The main goal of RLE algorithms is to find the redundant data sequence from the input data and reduce it to the shorter sequence. The main advantage for using the lossless RLE algorithm is to compress data without any effect on the output data [44]. RLE is considered a fast algorithm; when compared with other complex compression algorithms. The term "Run" means redundant data. Thus, the redundant data is implemented or encoded using two terms [45]. The first one is the number of redundant data while the second term is the data itself; Figure-2 shows the flowchart of the RLE algorithm.

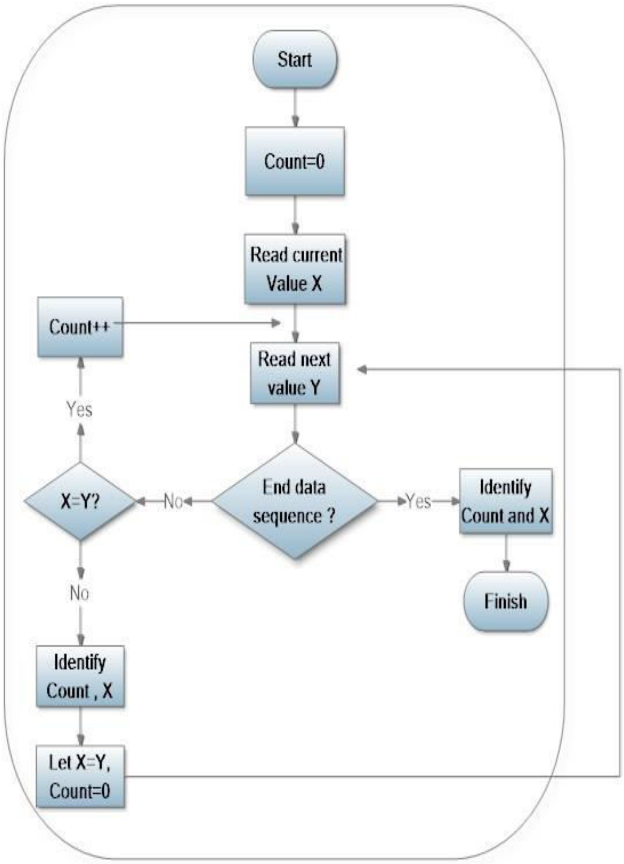

Figure-2. Flowchart of RLE algorithm.

As example of applying RLE in data compression the following character data sequence:

FFFFAAAAAAAARRRRRTTOOOOOOBBBBBBBB

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needs 33 bytes to be stored in memory (each character requires one byte), but when applying the RLE algorithm the sequence becomes:

4F8A5R2T6O8B

The RLE algorithm is used as a lossless medical image compression. Figure-3 shows the RLE compression/decompression procedure.

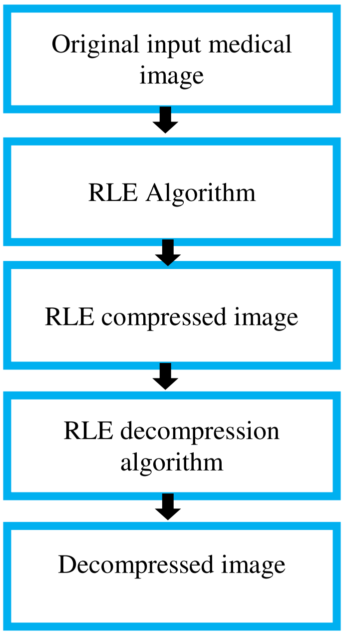

Figure-3. RLE compression/decompression procedure.

The RLE algorithm for image compression is similar to that of data compression. The original medical image is scanned to find the run of similar pixels as shown in Figure-4.

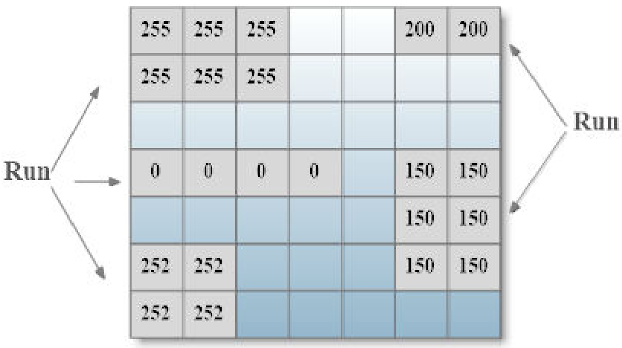

Figure-4. Runs scanning in the medical image.

In order to make use of this repetition and redundancy, RLE algorithm is used to further compress the medical image. The original medical image is scanned to find the run of similar pixels. Three types of scanning are applied: horizontally, vertically, and Zig-Zag.

As an example of scanning techniques, Figure-5 shows the horizontal scanning technique.

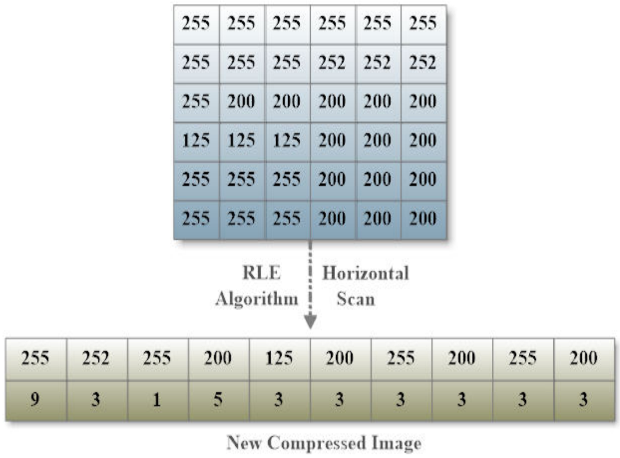

Figure-5. RLE output vector using horizontal scan.

In order to improve the efficiency of RLE algorithm, modified RLE (MRLE) is proposed in this paper. The Block-Block scanning technique is proposed. The main aim of applying this improved technique is to produce higher compression efficiency (high compression rat and low computation time). The Block-Block scanning is shown in Figure-6. Firstly, the image is divided into sub images (blocks). Secondly, the pixels inside each block are also scanned vertically, horizontally, or zig-zag. Finaly, blocks together are also scanned vertically, horizontally, or zig-zag. In this paper, blocks are scanned vertically and pixels inside the block are scanned horizontally. Moreover, different block sizes are examined. The results (after applying scanning step) are stored as an output vector. This vector contains the pixel values and runs. However, the similar runs value are merged again to reduce the size of the vector [46].

To reconstruct/decompress the image, a reverse decompression algorithm is applied. The vector resulted from the RLE algorithm will be used to reconstruct all blocks of the image.

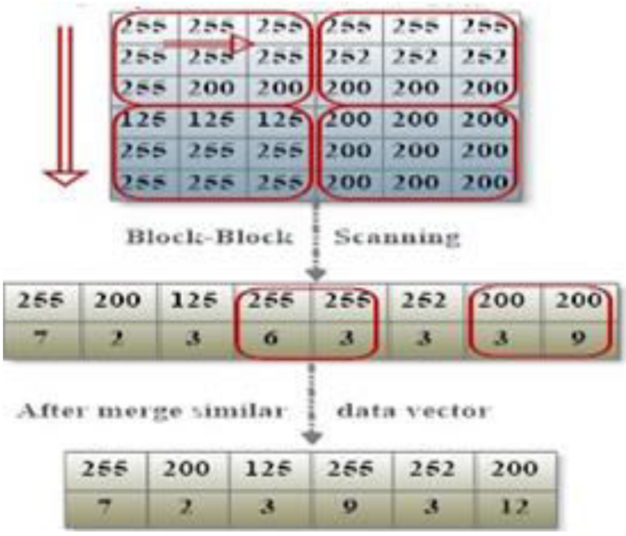

Figure-6. Block-Block proposed scanning technique.

RESULTS AND DISCUSSIONS

In this section, the experimental result obtained by applying the proposed compression algorithm is presented. The proposed algorithm has been implemented and tested using MATLAB software. Several medical images (https://pixabay.com/) have been tested, as shown in Figure-7.

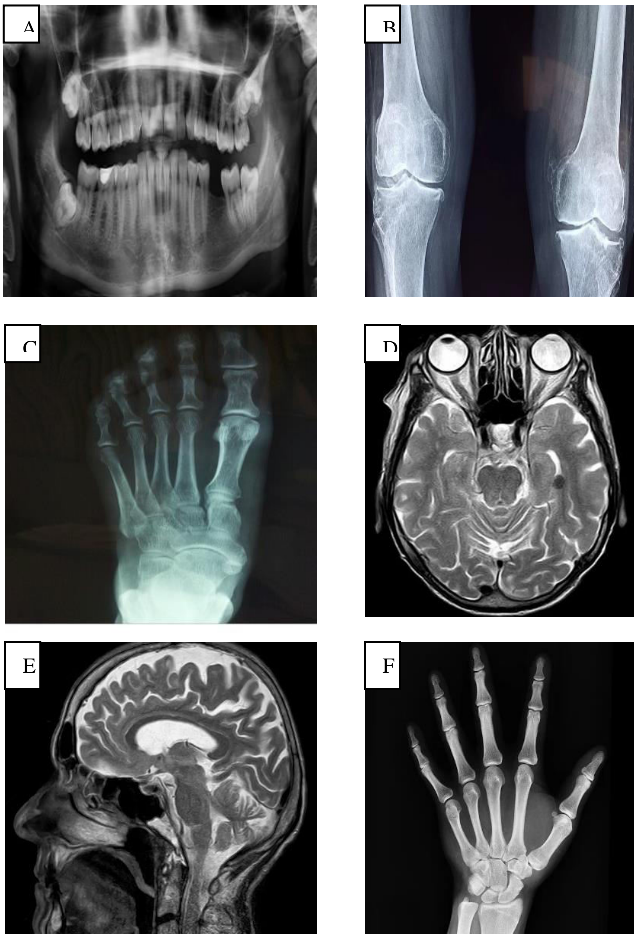

Figure-7. Test images; A) Mouth, B) Knee, C) Foot, D) Brain, E) Head, and F) Hand.

Table-1 shows the results of RLE compression algorithm.

Table-1. RLE compression ratio results.

The image	CR
Mouth	1.7056
Knee	2.9817
Foot	2.1043
Brain	1.9032
Head	1.8659
Hand	3.5907

The results obtained after applying MRLE with 3*3, 5*5, 7*7, 9*9, and 12*12block sizes are shown in Tables 2, 3, 4, 5, and 6 respectively.

Table-2. MRLE compression ratio results with 3*3 block size.

The image	CR
Mouth	2.5901
Knee	2.7956
Foot	2.9829
Brain	2.0032
Head	1.8906
Hand	3.6715

Table-3. MRLE compression ratio results with 5*5 block size.

The image	CR
Mouth	2.2096
Knee	2.5907
Foot	2.9981
Brain	2.0984
Head	1.7453
Hand	3.4780

Table-4. MRLE compression ratio results with 7*7 block size.

The image	CR
Mouth	2.7631
Knee	2.8053
Foot	3.0842
Brain	2.1098
Head	1.9523
Hand	3.8452

Table-5. MRLE compression ratio results with 9*9 block size.

The image	CR
Mouth	2.1562
Knee	2.2955
Foot	2.8613
Brain	2.0083
Head	1.2074
Hand	3.1731

Table-6. MRLE compression ratio results with 12*12 block size.

The image	CR
Mouth	1.5098
Knee	2.0081
Foot	1.9862
Brain	1.8096
Head	1.6890
Hand	2.7109

As shown in the results, MRLE gives a high compression ratio when the medical image contains long runs. However, the highest compression rate was for the block with size 7*7.

In order to show the effectiveness of the proposed algorithm, we compared it with several algorithms. Table-7 shows the compression rateCR for different compression algorithms applied on the medical images [47]. As shown in the results, the proposed algorithm outperforms other algorithms by big margin.

Table-7. Comparison with other compression techniques.

The technique	CR
Proposed method	2.8
Set Partitioning in Hierarchical Trees (SPIHT)	2.7
JPEG2000	2.2
Context based adaptive lossless image codec (CALIC)	2.1
Smart storage management (SSM)	2
Wavelet-based medical image compression with adaptive prediction (WCAP)	1.95

CONCLUSIONS

In this paper, a fast and lossless compression algorithm of digital medical images is proposed. The proposed algorithm introduced a Modified Run-Length Encoding (MRLE). The main focus of this algorithm was to obtain a higher compression factor while decreasing the distortion of the decompressed image.

The experimental results showed the efficiency of the proposed algorithm in term of compression factor. The MRLE provides high compression factor and yet preserve high correlation values. To improve the compression factor. The results of the proposed algorithm outperfroms other algorithms in the area of medical image compression.In the future, the proposed medical image compression algorithm can be extended and applied for the RGB medical images.

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