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Research paper

A refined modified read compression technique for efficient sharing of multimedia data

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Abstract

Compression technique expedites in solving many of the research problems for storage and sharing of multimedia data over the wireless channel. Many applications such as UIDAI (Unique Identification Authority of India) and Digi Locker adopts cloud platform. The digital data such as fingerprint, iris, driving license, school certificates are scanned, encrypted and stored in cloud platform. These applications require lossless compression. Modified Huffman (MH) encoding is the most preferred technique to achieve lossless compression. However, the existing MH encoding technique suffers due to numerous codewords of large bit lengths thus effecting performance. Modified READ (MR) and Machine learning techniques are used by the state-of-art technique compression algorithms to achieve better compression. However, they incur computation overhead. To improve the compression ratio and reduce the processing time, a Refined Modified READ (RMR) encoding scheme is presented, the encoding is done using Refined Huffman (RH) by encoding the pixels diagonally instead of encoding the pixels horizontally. Then the subsequent lines are encoded using RMR in parallel fashion and in both directions, which helps in reducing the computation time. Experimental outcome shows that RMR achieves significant improvement in compression ratio over its predecessor and as well as many of the state-of-art technique compression algorithms like Lempel-Ziv-Welch (LZW), Joint Bi-level Image Group 2 (JBIG2) and Neural network-based compression technique Levenberg–Marquardt (LM) back propagation algorithm.

Keywords: *Cloud Computing; Compression Technique; Huffman Code; Modified READ; Neural Network*.

1. Introduction

Rapid growth of smart devices has led to increased storage and sharing of multimedia data over wireless channel. This evolution is due to the wide availability of applications, range of services, cheap availability of smart devices and increased adaptation of multimedia data to technological growth for editing and managing multimedia data. Some of the applications that use multimedia data is to provide services such as distance learning program, medical imaging, remote sensing and entertainment organization. To store digital multimedia data in a pel-by-pel (Picture Element) format, huge amount of storage space and bandwidth is required. For example, an image of size 640*480 pixels requires storage space of about 1 megabyte. Despite the growth of technology of transmission and storage, the demand versus availability of storage devices and bandwidth consumed is still an issue.

Evolution of cloud computing has led to rapid changes in the way user access the data. Many applications have adopted cloud platform for storing and managing digital data. For example, UIDAI (Unique Identification Authority of India) and Digi Locker recently there has been an increased usage and adoption for various application purposes. The digital data such as fingerprint, iris, driving license, school certificates etc. are scanned, encrypted and stored in cloud platform [1]. Encrypting digitally scanned data further increases the size of data; thus, induce higher storage cost and bandwidth requirements. Therefore, minimizing the size of image is utmost desired. For example, an A4 size image of size (2480*3508) pixels with a resolution of 300 dpi (dots per inch) requires about 1.1 MB (Megabytes) of storage space in binary representation. One way to address storage issue is by adopting image compression technique.

Image compression can be classified into two types, lossy and lossless compression techniques [2]. Lossy scheme provides better compression over lossless techniques. However, some relevant information is neglected during the encoding process. As a result, lossy technique may not be applicable for applications where data information loss is not acceptable (tolerated), for example medical imaging, compressive sensing, Aadhar verification, etc. Hence lossless compression technique is considered in this work.

Digital images are majorly composed of spectral and spatial redundancies due to pixel-to-pixel relationship. Most compression takes benefits of these redundancies to minimize the bits needed to represent an image. The objective of any compression scheme is to minimize the number of bits, without affecting the pictorial quality of the reconstructed digital data. In [3] conducted experiments to evaluate the performance of both lossy and lossless compressions for medical data and minimize the bandwidth, storage and transmission cost. However, the model induces high computational overhead, which is addressed in [4] by adopting HEVC encoding. However, [4] supports lossless compression up to coding unit level [5] and requires parallel computing platform [6]. A fixed length coding [7] does not guarantee minimizing the total size of the file/data. Since some characters in image occurs more predominantly than others, but still it requires the same amount of bits as predominantly occurring characters. Therefore, prefix-free codes for compression can be an effective solution.

In [8], presented an Variable-Length Codes (VLCs) and [9] presented an hybrid compression algorithm, both [8] and [9] have adopted Huffman code [10] to reduce total bit length and support efficient lossless compression over the wireless channel. To further improve compression ratio [11] presented modified Huffman (MH) and Modified READ (MR), lossless compression techniques. In [12] presented neural network-based compression technique was presented, the model is designed using multi-layer neural network. The neural network takes foreground and background feature class as an input for training and reconstruction phases, the pixel addresses are feed to the network as inputs and the network output is obtained. It has attained significant performance improvement over its predecessor [11] in terms of compression ratio. However, the model needs to be retrained for every new object resulting in NP-Hard problems. As a result, it incurs computational complexity.

To overcome the above issues and research challenges, this research work adopts a prefix-free code technique [13] by modifying state-of-art Huffman code technique. To further, improve compression efficiency and processing time a Refined Modified READ (RMR) scheme is also presented. RMR reduces the number of bits required for encoding and also reduces the computation time and memory requirement. The RMR incorporates a fewer number of codewords for encoding/decoding. Reduction in number of codewords and their corresponding size of codewords enable proposed refined technique to exhibit better performance, which is proved and presented in this paper. The proposed model is a lossless compression technique with better compression ratio and maintains good quality of the reconstructed images.

The Contribution of research work is as follows:
A key contribution of our work is, here we present a refined modified READ (RMR). The existing MR is a 2-D technique, uses MH (1-D) and the subsequent lines are encoded horizontally by comparing current line with previous scan lines of the image. The RMR is a combination of RH and diagonal encoding. The scanning lines are read diagonally and encoding is done diagonally using refined Huffman [13], and then the subsequent lines are encoded diagonally in parallel fashion, which will aid in reducing computation time. To the best of our knowledge, no prior work has considered diagonal encoding. RMR achieves significant improvement in compression ratio over its predecessor [11] [12]. The RMR achieves significant performance improvement in terms of computation time and memory usage over its state-of-art techniques [11-12] and [13].

The rest of the paper is organized as follows. In section II Literature survey is presented, in section III the proposed Refined Modified READ is presented. In penultimate section, experimental study is carried out. The conclusion and future work is described in the last section.

2. Literature survey

There have been several methodologies that have been proposed in recent times in order to improve the performance of compression of bi-level and halftone images which are surveyed below.

In the last few decades, the field of data compression arithmetic and Huffman coding methods are proved as most efficient entropy encoders. Both encoding methods are different from each other. One is symbol wise coding and other is continuous coding. Optimality of the encoding technique depends on how best the encoder reduces redundancies present in the data. The probability of source symbols is an essential information for any statistical coder. However, these methods are very time-consuming. Instead of arithmetic coding, a simple and non-probabilistic method for bi-level compression is suggested in [15] namely CSI-1 and CSI- 2. A standard context model in association with interpolative encoding provides high compression rate than JBIG and JBIG2 standard coding and the processing time required is very less. This process provides better compression rate. The experimental results using CSI-1 and CSI-2 are compared with existing techniques like JBIG and JBIG2. Using CSI-1 technique the compression gain attained is comparable, but compression speed is reduced to half when compared with JBIG and JBIG2 coders. However, processing time is much longer for CSI-2 than JBIG2 coders.

In [16], FPGA implementation of a binary image compression technique is presented. Here, a study is presented to compare various techniques for different image sets. All the techniques are compared with each other in terms of compression efficiency, time and ratio. The compression algorithm is implemented with FPGA workflow. This paper helps in the selection of best compression technique, six types of compression algorithms are discussed namely, Pack bits, Lempel- Ziv-Welch (LZW), LZ77, Zip (Deflate), JBIG2 and CCITT Group 3 & 4. Among all of these algorithms CCITT G4 algorithm is the best algorithm. However, the computational complexity is very high. Extensive research survey carried out shows that there is a need to develop an efficient compression technique to support the future application needs such as UIDAI and Digi Locker. These applications require lossless and efficient compression technique that minimizes storage space and processing time. To support all such research requirements, we present a RMR compression technique in the next section.

In [17], Visual Sensor Nodes (VSN) obtains images from different areas of interest in the field and performs processing on images and the results are transmitted using embedded wireless transceivers. These VSN's together form a wireless Sensor Network. However, VSN introduces a high amount of redundancy and the compression efficiency is dependent on the algorithm. The proposed algorithm detects ROI (Region of Interest) for lossless coding standard which includes various shapes, locations and different objects and thus compression rate obtained is increased. Three different compression techniques, namely JBIG2, CCITT Group 4 and Gzip are used as coding standards for discussion. The compression performance is best in CCITT technique with low computational complexity. This paper focuses on the enhancement of compression efficiency for binary images. However, CCITT Group 4 introduces large size compressed file compared to other JBIG2 and Gzip coders.

In [18], a parallel lossless low-complexity compression algorithm is presented for both small and large distributed systems with minimum computational cost. To increase the speed of operation, GPU parallel configuration is used. Image is subdivided into 256 blocks and a compression method using monochromatic substitution for binary images is presented. The partitioned blocks are processed in parallel and the experimental results are carried for 4, 16 and 32 number of parallel processors and the results show high speed performance compared to that of sequential processing.

In [19], a novel Universal image compression technique is presented to compress textual information. The compression technique involves two steps. Firstly, Universal fixed to variable codebook, and secondly a Row and Column elimination coding scheme is proposed. In recent years the volume of text information over internet has drastically increased. More than 40% of data volume is in text form over the internet such as chatting, blogging, email and digital libraries, etc. Many techniques are adopted for encoding text information like Huffman, arithmetic coding, Ziv-Lempel family and Burrow-Wheeler Transform. The proposed technique shows an improvement in compression efficiency of 87% over the above-mentioned techniques, and in particular, compared with JBIG2 to compress specific language textual information for Arabic, Persian and Hebrew textual images.

3. Proposed refined modified read (RMR) compression algorithm

Here, we present an efficient compression technique for digitally scanned images, which is stored on public cloud platform. The proposed work is presented in Section-'b'. The existing modified read (MR) algorithm is a combination of both MH (1-D) and horizontal scanning. It finds similarities between the successive lines which is explained in section-'a' and section-'b' to get a complete idea of the proposed work.

3.1. Modified READ relative element address designates

MR is also called as Modified Relative Element address designated (READ). MR is a 2-D technique. MR exploits the correlation among successive lines. The successive lines of a high-resolution image are composed of very high percentile of single transition pixels. Considering this case, instead of scanning the lines as in MH (Modified Huffman), line by line, MR takes in reference line and then encodes each scan line that follows, by exploiting the similarities. It can be stated that MR is more complex than MH. Since MR encoding uses both MH and MR coding techniques. The reference line is encoded using MH and following lines are encoded using MR encoding until next reference line occurs. The selection of next reference line depends on the parameter K. The parameter K defines the resolution of the compression technique. The parameter K depicts the quantum of lines that uses 2-D occurrences, which is $K - 1$ lines. However, every K^{th} reference line is encoded using MH which uses 1-D technique. The modified read structure is shown in Fig 1. For k=4, first line will be MH encoded and next 3 lines are encoded using MR and repeated for next lines in a similar fashion.

MH	MR	MR	MR	MH	MR	MR	MR

Fig 1: Modified Read Structure

Modified READ (Relative Element Address Designates) Coding:
The resolution of an image defines the value of 'K'. Since, two adjacent scan lines of a bi-level image are highly correlated, the corresponding run lengths of black and white pixels are too highly correlated. Thus, the run lengths of a scan line can be coded with respect to the run lengths of the previous scan line. In READ coding, before encoding a run length it first establishes five reference pixels on present and previous scan line, which are represented as a_0, a_1, a_2, b_1 and b_2 respectively. The defintion of picture elements and coding modes are discussed below in Fig. 3a and Fig. 3b.

Refinement of MR for two-dimensional coding:
The compression efficiency obtained by 1-D coding is very limited. Since, it does not take into account vertical correlation, i.e., correlation among adjacent scan lines. An efficient way to exploit vertical correlation is to process the pixels line by line as in 1-D coding, and use the previous scan line pixel information to encode sequence of pixels in the current line. The flow diagram of proposed refined MR for two dimensional coding is shown in Fig. 2 and the method for proposed diagonal scanning is shown in Fig. 4.

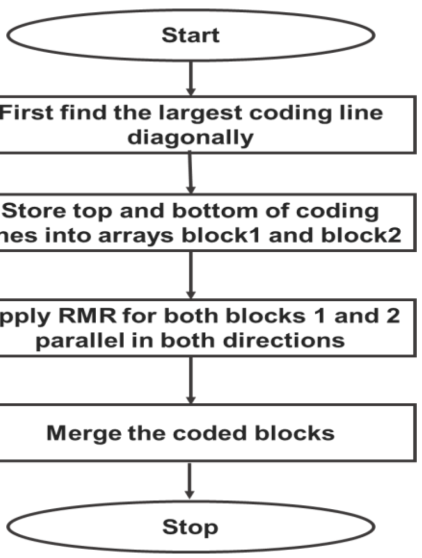

Fig. 2: Flow Diagram of Proposed Diagonal Encoding.

First find the largest coding line diagonally, then subdivide the image into two parts diagonally and store into two arrays. Then, apply RMR technique for both subdivisions in diagonal fashion and continue encoding the successive lines in parallel till the top and bottom corners of the image is reached or no more lines for encoding is left. It can be observed from Fig4., that the scan lines lengths reduce as we move diagonally till we reach the top and bottom corners of the image.

Definition of picture elements: Referring to Fig. 3a and 3b. The initial picture elements and the changing picture elements are defined as follows:
a_0 is the starting picture element on the coding line, which becomes the reference picture element, a_1 is the changing picture element on the coding line, right next to a_0. a_2 is the changing picture element on coding line, right next to a_1, b_1 is the first changing picture element, whose color is opposite to a_0, which occurs on the reference line after the picture element toward right of a_0. b_2 is the first changing picture element toward right of b_1 on the reference line.

For our case study, the scan line to be encoded with respect to reference line, then the changing pixels are to be encoded, the identification of changing pixels are shown in Fig. 3a and 3b. The encoder (Transmitter) and decoder (Receiver) have prior information of positions of a_0, b_1 and b_2. However, the information of position of a_1 and a_2 are known only to the transmitter.

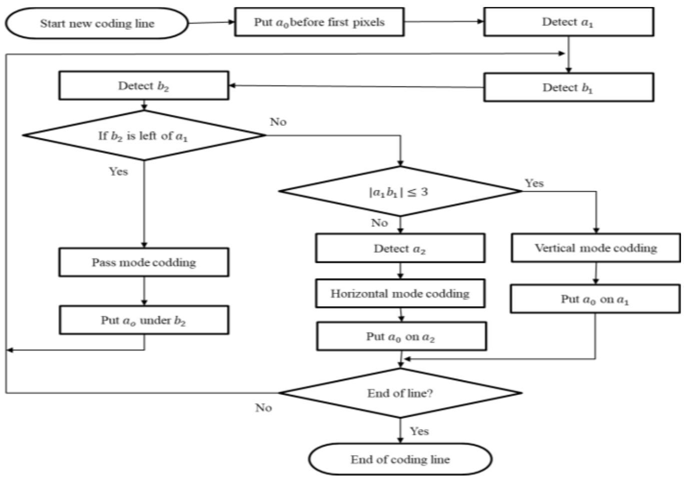

Fig. 3a: Flow Diagram of Two-Dimensional MR Encoding.

Coding Modes: Based on the relative position of these pixels, the selection of modes can be defined. If the run lengths on present and reference lines are similar, then the distance between a_0 and b_1 would probably be very less when compared with the distance between a_0 and a_1. Therefore, the present run length is identified by encoding the distance between (a_1, b_2) and this mode is called vertical coding mode. However, when the distance between a_1 and b_1 is large i.e., there is no identical run lengths on the reference line), then it is ideal to use 1-D run length coding, and this type of encoding mode is called as horizontal coding mode. Last mode of coding is called as pass mode. This mode is performed when $a_0 \le b1 < b2 < a_1$ occurs. For this scenario, we simply move to the next pixel to be encoded identified as $\bar{a}_0$ which is the pixel on present line that is exactly under b_2. Before transmitting the run lengths, the codeword specifies the mode being used is transmitted. Details of the mode codewords used is detailed in [11].

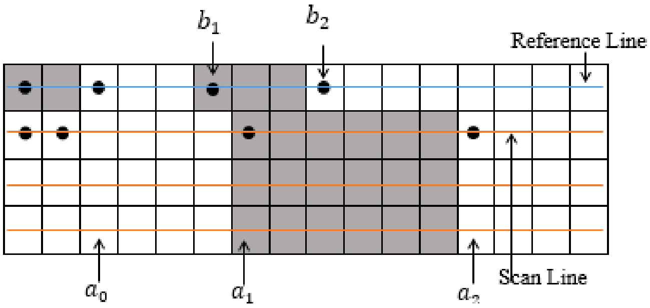

Fig. 3b: Existing Modified READ: Two Rows of an Image, The Transition Pixels Are Marked with A Dot.

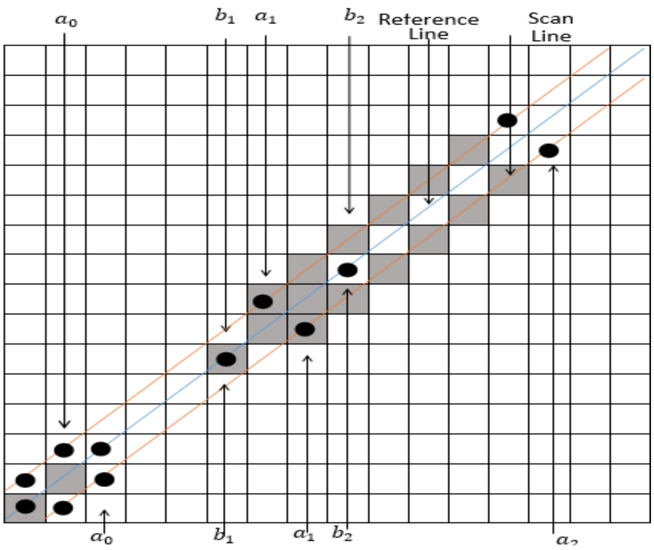

Fig. 4: Two Rows of an Image, the Transition Pixels Are Marked with A Dot.

The drawback of existing MH compression technique is the memory requirement. Since the numbers of codewords are around 183 and maximum length of codeword is 13. As a result compression ratio is low [11] and also incurs computation overhead. Minimizing number of code words and their corresponding lengths, without effecting data loss is the major objective of Refined Huffman (RH) which is discussed in [12]. The Refined Huffman (RH) minimizes the number of codewords and their lengths which has been proved to be efficient and achieved better compression ratio. Refined Huffman code words are segmented into three segments. First segment comprises of multiples of 144 up to 1728 and contains a total of 24 codes (12 each for black and white). Second segment comprises of multiples of 13 up to 143 and contains a total of 22 codes (11 each for black and white). The last segment has the remaining 24 terminating codes (12 each for white and black). Additional details of proposed code words are available in [13]. All segments put together have a total of 71 code words and the maximum length of any codeword in a segment is observed to be 7 bits. The proposed code words are uniquely decoded and they satisfy Kraft McMillan inequality condition. The memory consumption is reduced, and the encoding and decoding time is also reduced. The proposed codeword run length (RL) is computed and is represented as $\mathrm{RL} = 144 * s_1 + 13 * s_2 + t$, where t is terminating code, s_1 makeup code, s_2 is makeup code. From Fig. 3b and Fig. 4, it can be seen that in existing MR the size of scan line remains same whereas in proposed RMR, the size of the scan lines decreases with every successive scan. Thus, it reduces the number of comparisons which finally results in improving compression ratio. Encoding is carried out in both directions in parallel fashion, thus improving the performance of computing time and as well as compression ratio. In the next section, experimental results are discussed to prove our claim is presented.

4. Simulation results and analysis

In this section, the performance of proposed compression technique is evaluated by considering three different databases. The experiment is carried out on windows 10 operating system, Intel I-7 core processor, 8GB RAM and 2 GB dedicated GPU (Graphic Processing Unit). The algorithms of proposed and existing models [11-12] are implemented in VC++, MATLAB and C# 6.0 programming language using Microsoft Visual Studio Dot Net Framework 4.0. The simulation is carried out using MATLAB 2016b framework. Three case studies are considered.

Firstly, the experiment is conducted for bi-level images obtained from [14]. First eight CCITT images are considered for experimental analysis. Secondly, the experiment is conducted for halftone images obtained from [14]. Eight halftone images are considered for experiment analysis. Lastly, the experiment is conducted for bi-level images obtained from [12]. Four images are considered for experimental analysis.

The performance evaluation of proposed model over existing model is carried out in terms of Compression Ratio (CR), Encoding Time (ET), Decoding Time (DT) and Memory Utilized (MU) for both bi-level and half tone images and as well images considered in [12].

4.1. Case study for bi-level images obtained from [14]

For the first case study, the bi-level images are obtained from [14], the first 8 images are considered for evaluation. All images have dimension (W*H) of 1728*2339 and resolution of 200 dpi. The results obtained are tabulated in Table 1 and 2. It can be observed that the proposed RMR model achieves better compression ratio than existing MR model. The image 4 has the least compression ratio and image 2 has the highest compression ratio for both proposed RMR and existing MR model. An average compression ratio performance improvement of 15.015% is achieved by proposed RMR model over existing MR approaches.

Experiments are conducted to evaluate the performance in terms of memory usage and computation time for both proposed RMR and existing MR approaches which are tabulated in Table 1 and 2. The proposed RMR model utilizes less memory when compared to existing MR model. An average reduction of 1.18% memory is achieved by proposed over existing model. The computation time of both proposed RMR and existing MR approach is evaluated in terms of encoding time, decoding time and total execution time which are shown in Table 2. An average encoding time of 0.0558 seconds and 0.0934 seconds is consumed by proposed RMR and existing MR approaches respectively. An average reduction of 40.25% encoding time is achieved by proposed RMR model over existing MR approaches.

An average decoding time of 0.00256 seconds and 0.003 seconds is achieved by proposed RMR and existing MR approaches respectively. An average decoding time reduction of 15.2% is achieved by proposed RMR model over existing MR approaches. An average total computing time of 0.058 seconds and 0.096 seconds is achieved by proposed RMR and existing MR approach respectively. An average computing time reduction of 39.45% is achieved by proposed RMR model over existing MR approaches. The overall outcome shows that the proposed RMR achieves significant performance improvement over existing MR approach in terms of compression ratio, encoding, decoding time, total computing time and memory utilization.

Table 1: Performance Evaluation of Compression Ratio and Memory Utilization

Images	Compression Ratio		Memory Utilized(bits)	
Bi-level	Proposed RMR	Existing MR	Proposed RMR	Existing MR
1	35.35729532	30.03415804	591179776	616727424
2	39.16811594	33.2638466	592756736	601155200

3	20.22665144	17.19556627	499122176	500957184
4	12.0343575	10.23548876	492670976	498905088
5	19.24279558	16.36008539	490438656	494039040
6	25.8335765	21.95638603	493129728	494421632
7	12.23799423	10.40852151	487288832	489730048
8	21.03449123	17.88180805	491614208	492056576
AVG	23.14190972	19.66698258	517275136	523499024

Table 2: Performance Evaluation of Encoding, Decoding and Total Computation Time in seconds

Images	Encoding Time		Decoding Time		Total Time	
Bi-level	Proposed RMR	Existing MR	Proposed RMR	Existing MR	Proposed RMR	Existing MR
1	0.02876	0.03499	0.00278	0.00296	0.03154	0.03795
2	0.04712	0.06901	0.00260	0.00354	0.04972	0.07254
3	0.04392	0.07794	0.00245	0.00291	0.04637	0.08085
4	0.09718	0.11514	0.00259	0.00284	0.09977	0.11798
5	0.02640	0.05664	0.00240	0.00290	0.02880	0.05955
6	0.05004	0.06439	0.00248	0.00272	0.05252	0.06711
7	0.09730	0.12510	0.00296	0.00280	0.10026	0.12789
8	0.05604	0.20456	0.00231	0.00338	0.05835	0.20794
AVG	0.05585	0.09347	0.00257	0.00301	0.05842	0.09648

4.2. Case study for halftone images obtained from [14]

For the second case study, halftone images are obtained from [14], and 8 images are considered for evaluation. The results obtained are tabulated in Table 3 and 4. It can be observed from tables that the proposed RMR model achieves better compression ratio than existing MR model. The image4 has the least compression ratio and image1 has the highest compression ratio for both proposed RMR and existing MR model. An average compression ratio performance improvement of 15.11% is achieved by proposed RMR model over existing MR approaches.

Experiments are conducted to evaluate the performance in terms of memory usage and computation time for both proposed RMR and existing MR approaches which are tabulated in Table 3 and 4. The proposed RMR model utilizes reduced memory when compared to existing MR model. An average reduction of 0.98% memory is achieved by proposed RMR over existing model. The computation time of both proposed RMR and existing MR approach is evaluated in terms of encoding time, decoding time and total execution time which are shown in Table IV. An average encoding time of 0.09 seconds and 0.112 seconds is achieved by proposed RMR and existing MR approaches respectively. An average reduction of 20.05% encoding time is achieved by proposed RMR model over existing MR approach.

An average decoding time of 0.01 seconds and 0.012 seconds is achieved by proposed RMR and existing MR approaches respectively. An average decoding time reduction of 16.48% is achieved by proposed RMR model over existing MR approach. An average total computing time of 0.1 seconds and 0.124 seconds is achieved by proposed RMR and existing MR approaches respectively. An average computing time reduction of 19.7% is achieved by proposed RMR model over existing MR approach. The overall outcome shows that the proposed RMR achieves significant performance improvement over existing RMR approach in terms of compression ratio, encoding, decoding time, total computing time and memory utilization.

Table 3: Performance Evaluation of Compression Ratio and Memory Utilization

Images	Compression Ratio		Memory Utilized	
Half-tone	Proposed RMR	Existing MR	Proposed RMR	Existing MR
1	6.151288756	5.221817029	451944448	466796544
2	1.297421089	1.102695384	448376832	449847296
3	3.934178744	3.334612924	447590400	441397248
4	1.200810985	1.020679931	459350016	459083776
5	4.153649984	3.519719071	459915264	459087872
6	1.967144919	1.672211597	447614976	447137472
7	3.653805774	3.098720089	453795840	453406720
8	5.035970573	4.285578889	458747904	459945088
AVG	3.424283853	2.907004364	453416960	454587752

Table 4: Performance Evaluation of Encoding, Decoding and Total Computation Time

Images	Encoding Time		Decoding Time		Total Time	
Half-tone	Proposed RMR	Existing MR	Proposed RMR	Existing MR	Proposed RMR	Existing MR
1	0.01706	0.10266	0.00288	0.00976	0.01994	0.11242
2	0.03100	0.03654	0.00280	0.00334	0.03380	0.03988
3	0.01431	0.01411	0.05999	0.05418	0.07431	0.06829
4	0.03236	0.04154	0.00286	0.01439	0.03522	0.05593
5	0.01113	0.01323	0.00280	0.00466	0.01392	0.01789
6	0.03738	0.04848	0.00278	0.00330	0.04016	0.05178
7	0.01162	0.01395	0.00303	0.00346	0.01465	0.01741
8	0.56594	0.63107	0.00354	0.00353	0.56948	0.63459
AVG	0.09010	0.11270	0.01009	0.01208	0.10018	0.12477

a) Case study for bi-level images obtained from [12]:

For the last case study, the bi-level images are obtained from [12], the images considered for evaluation are shown in Fig. 5. All images have dimension (W*H) of 256*256 and resolution of 72 dpi. The results obtained are tabulated in Table 5. It is seen from table that the proposed RMR model achieves better compression ratio than state-of-art models. An average compression ratio performance improvement of 26.94% is achieved by proposed RMR model over existing approaches and as well as proposed work of [12] using neural networks.

Table 5: Compression Ratios Performance

Bi-level	CCITT G4	JBIG2	ES [12]	Proposed RMR
1	3	11.2	7.5	10.48
2	3.3	10.2	7.4	11.8
3	3.6	10.2	8.1	11.7
4	4.8	9.9	11.4	13.1
AVG	3.675	10.375	8.6	11.77

Original Image **Reconstructed Image**

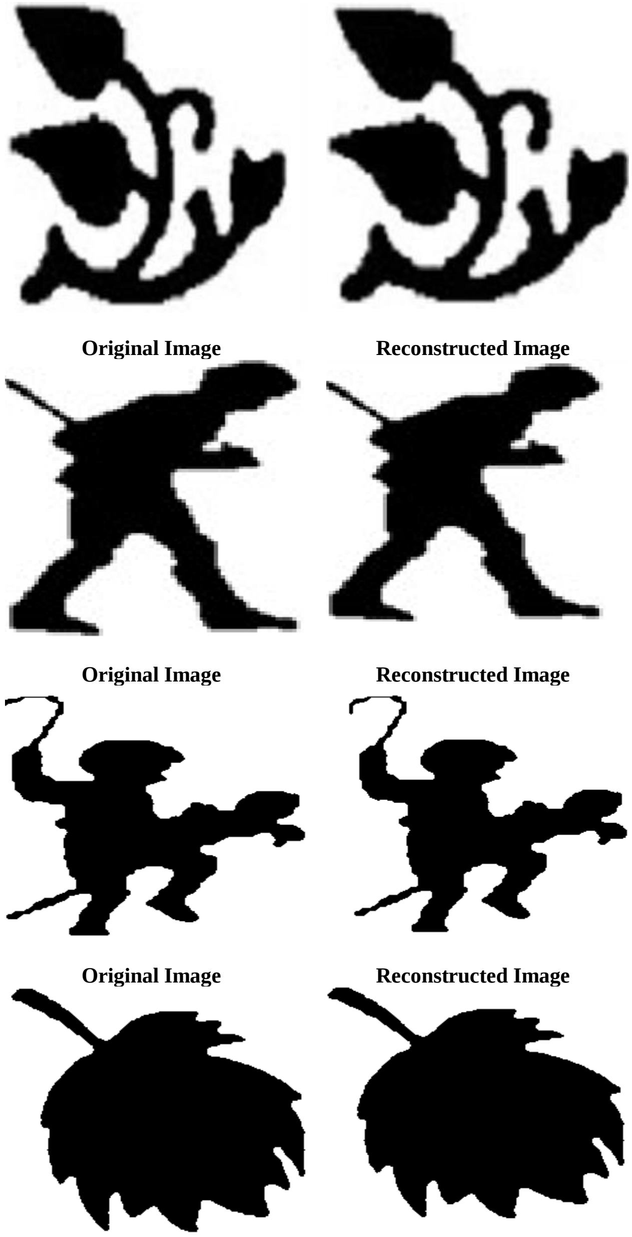

Fig. 5: Experiment Result of Proposed RMR Evaluated on Bi-Level Images [12].

5. Conclusion

The growth of internet and cheap availability of smart phones has led to increase resource sharing of multimedia data. The cost per storage bit is coming down due to growth of cloud platforms. This led to increased adoption of cloud platform by various organizations for various applications in use. For example, UIDAI, Digi Locker, etc. These applications require lossless compression. To improve compression ratio and reduce processing time a Refined Modified READ (RMR) scheme is presented in this work. The encoding is done diagonally using refined Huffman (RH) and then the subsequent lines are encoded using RMR in parallel fashion, which has resulted in reducing computation time. Experiments are conducted considering different datasets. Experimental outcome shows RMR achieves significant compression ratio over its predecessor. An average improvement of 15.015% is achieved by proposed RMR over Existing MR in terms of compression ratio for bi-level images.

The RMR achieves significant performance improvement in terms of encoding time, decoding time, and total computation time and memory usage over its stat-of-art technique. An average improvement of 40.25%, 15.2% and 39.45% and 1.18% is achieved with proposed RMR over existing MR respectively for bi-level images. An average improvement of 15.11% is achieved by proposed RMR over Existing MR in term of compression ratio for halftone images. The RMR achieves significant performance improvement in term encoding time, decoding time, and total computation time and memory usage over its stat-of-art technique. An average improvement of 20.05%, 16.48% and 19.7% and 0.98% is achieved with proposed RMR over existing MR respectively. For another case, we had compared with neural network-based compression technique. An average compression ratio improvement of 26.94% is achieved by proposed RMR over Neural network-based compression technique. The overall result achieved shows the efficiency of proposed model over state-of art techniques. The future work would consider further improving the compression performance and minimize communication overhead.

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