Pertanika J. Sci. & Technol. 27 (4): 1671 - 1692 (2019)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Resolution Adaptive Threshold Selection for Gradient Edge Predictor in Lossless Biomedical Image Compression

Urvashi[1]*, Meenakshi Sood[2] and Emjee Puthooran[3]

Department of Electronics and Communication Engineering, Jaypee University of Information Technology, Waknaghat, India

ABSTRACT

The high-resolution digital images generated for medical diagnosis produce the extremely large volume of digital data. This necessitates the use of image compression for medical data to be processed, archived and transmitted through a computer network in an efficient way. Due to the criticality in disease diagnostics and legal reasons, biomedical images require lossless compression to prevent permanent loss of image data. Among various approaches to lossless compression of medical images, predictive coding techniques have high coding efficiency and low complexity. Gradient Edge Predictor (GED) used in predictive coding technique for prediction has higher coding efficiency as compared to Median Edge Detector (MED) used in JPEG-LS. GED has lower computational complexity as compared to Gradient Adaptive Predictor (GAP) used in CALIC. GED is a threshold based predictor, however there is no specific method adopted in literature to decide the threshold value for prediction. This paper presents an efficient prediction solution based on predictive coding technique. The main objective of this research work is to develop a Resolution Independent Gradient Edge Predictor (RIGED) technique for choosing an optimal threshold value for GED predictor which will give minimum entropy value irrespective of the type of modality and resolution of the medical images. The empirical experimentation and analysis gave percentage improvement

ARTICLE INFO

Article history:
Received: 3 July 2018
Accepted: 23 April 2019
Published: 21 October 2019

E-mail addresses:
survashi2793@gmail.com (Urvashi)
meenakshi.sood@juit.ac.in (Meenakshi Sood)
emjee.puthooran@juit.ac.in (Emjee Puthooran)
*Corresponding author

ISSN: 0128-7680
e-ISSN: 2231-8526

of the proposed model as 32.4% over MED and percentage difference between high complexity GAP and proposed predictor as 0.68 % in terms of entropy for medical image dataset of different modalities having different resolution.

Keywords: Lossless image compression, medical imaging, predictive coding, predictor, resolution independent gradient edge detection

---

INTRODUCTION

With the advancement of information and communication technology, the amount of digital data produced all over the world is tremendous. This is especially true for biomedical images as typical terabytes of digital image data is generated by a hospital every year (Placidi, 2009). Medical imaging is experiencing a growth in terms of usage and image resolution, specifically in diagnostics systems that entail a large volume of medical images. The higher resolution of medical images results in large amount of digital data which may need to be stored, processed and transmitted in an efficient way (Khatkar & Kumar, 2018). These facts make a demand for effective techniques of image compression. Efficient compression techniques help to reduce bandwidth and storage space requirement. Image compression is a very important aspect of efficient transmission and archiving of medical image data along with the successful real-time application of telemedicine.

Many hospitals have small clinics and satellite centres located in the desolate areas where distance is a critical issue to deliver the health care services. Patient inhabiting in desolate, remote and semi-urban areas find hard time to travelling to the hospitals especially for diagnostic purpose. For the convenience of patients suffering from severe diseases, the big hospitals make use of telemedicine and tele-radiology applications providing health care facilitates from distance in such areas. It allows the physician at the remote centers to take a medical image data of patients (MRI or CT scan) and transmit it to the radiologist in the main hospital placed in the city. Radiologist examines the medical image data of patients and sends back the diagnostic details to the physician. In addition to telemedicine application in medical field, compression techniques are useful in remote sensing applications.

Removal of redundancies present in a medical image results in reduced number of bits to represent the information and achieves compression. The efficiency of the image transmission system is improved by compression techniques that can reduce data size and transmission time. General techniques used for image compression are lossy and lossless. Lossy compression is not generally acceptable to be used in medical field although it results in higher compression ratio, because a permanent loss of biomedical data during compression cannot be tolerated. However, lossless compression algorithms can produce images which are an exact replica of the original images without any loss of diagnostic information. Lossless compression of the image is important and appropriate for medical images because any loss of data could affect the clinical diagnostic process and it may lead to wrong diagnosis (Kaur et al., 2015). Many compression techniques are available in literature viz., transformation coding, entropy encoding and dictionary encoding (Sharma et al., 2017). Among the different techniques, predictive coding performs well for lossless coding in terms of coding efficiency and compression time. The efficiency of predictive coding depends upon the predictors (Avramovicl & Savicl, 2011).

RELATED WORK

Many researchers have worked on applying predictive coding technique for lossless compression of medical images.

2D predictors used in predictive coding technique for reducing interpixel redundancy from the image and is operated in frame by frame basis. JPEG-LS (Joint Photographic Expert Group-Lossless Compression) (ISO/IEC, 1999) and CALIC (Context-Based Adaptive Lossless Image Coding) are 2D benchmark algorithms for prediction based compression. JPEG-LS mainly consists of context modeling, pixel prediction, and prediction error encoding and uses Median Edge Detection (MED) predictor (Avramovic, 2012). CALIC employs Gradient Adaptive Predictor (GAP). The well-known MED predictor is simple but has less coding efficiency than computationally complex GAP (Wu & Memon, 1996). Avramovicl and Savicl (2011) proposed prediction based algorithms on the estimation of local gradients and detection of edges. Standard predictors MED and GAP were analyzed and entropies of predicted medical images were also compared. Baware and Save (2016) presented GAP predictor of prediction scheme that was adaptive to gradients defined in four directions. Errors obtained were grouped on the basis of max plane coding before entropy encoding, which enhanced coding efficiency. This scheme is compared with CALIC and DPCM (Differential Pulse Code Modulation) methods achieve better results in terms of compression ratio, bit rates and lesser computational complexity (Baware & Save, 2016). Avramovic and Reljin (2010) proposed a threshold controlled gradient edge detection (GED) for lossless image compression which combined simplicity of MED predictor and efficiency of GAP. GED predictor achieving bit rates comparable to more complex GAP predictor. It is shown that on the selected set of original medical images, GED predictor shows better results. Shrikhande and Bairagi (2013) introduced many techniques for achieving data compression. It was concluded by author that CALIC algorithm that used GAP predictor achieved better results in terms of entropy values but under higher time (and space) complexity as compared to JPEG-LS that employed MED predictor. Al-Mahmood and Al-Rubaye (2014) presented a lossless image compression technique for compressing medical and natural images by using the combination of adaptive predictive coding and bit plane slicing. In this technique most significant bits used adaptive predictive coding while other used run length coding. This technique achieved higher compression ratio for lossless coding that guaranted full recovery of an image. Fouad proposed a lossless image compression technique integrating an integer wavelet transform with a prediction step (Fouad, 2015). It was a simple median edge detector algorithm used with JPEG-LS technique. Image was first transformed using the predictor and an error image was obtained. The error image was then entropy encoded after being transferred through an integer wavelet transform. Higher compression ratio was achieved by this technique than competing techniques.

Hashemi-Berenjabad and Mojarrad (2016) presented a brief review of medical image compression methods which were applicable in telemedicine, e-health, and teleconsultation. Researchers tried to improve compression techniques in the case of compression ratio and quality of reconstruction images system. Mofreh and Refaat (2016) proposed a new hybrid lossless image compression that depended upon predictive coding, DWT transformation and Huffman coding. Output of predictor is fed to DWT transformation and then Huffman encoding is applied to output of DWT. This hybrid scheme gave better results in terms of bit rate as compare to Huffman and Huffman + DWT. Thombare1 proposed a technique that used a low complexity, lossless, compression algorithm for the compression of 3-D volumetric medical images. 3-dimensional nature of the data was exploited by using 3-D linear prediction (Thombare, 2016). Shanmathi and Maniyath (2017) analyzed commonly used predictors; MED, GAP and GED in term of entropies after prediction. Output of prediction error image was measured for the efficiency of predictor. Analysis showed that GED provided better results as it was simple to implement and also provided efficient results. Context modeling and entropy encoding was also explained by the author. Prediction error was further compressed in lossless manner by using arithmetic coding technique. The lossless compression technique achieved higher PSNR and lower CR values as compared to near lossless image compression method.

Research Gaps

In literature different predictors are described for predictive coding and it is concluded that GED gives better results in terms of entropy at low computational complexity. GED is based on threshold value and for efficient prediction; threshold value should be chosen to provide minimum entropy of residual image. However, in literature, no threshold value is specified for prediction and existing predictor is resolution and modality dependent. Threshold value is different for varying image resolutions and choice of threshold is difficult as there is no specific method reported earlier. But, it is necessary to find an optimal threshold value that provides minimum entropy for varying image modalities and resolutions. The proposed RIGED is designed to provide an optimal threshold value independent of image resolution and modality.

Optimal threshold value is a universal value that does not depend upon the image resolution and modality for prediction in predictive coding technique and also provides minimum entropy value irrespective of image resolution and modality. Dataset used by different authors in literature is small for different modalities of medical images.

Objectives

The main objective of this research work was to develop a technique for choosing an efficient threshold value for GED predictor irrespective of the type of modality adopted and resolution of the medical image. An exhaustive empirical work had been done on various large datasets of different resolutions and of different modalities containing the varying number of slices. Resolution Independent Gradient Edge Predictor (RIGED) was developed in this paper that provided efficient prediction in terms of entropy at optimal threshold for 8-bit depth medical images having varying resolution and modalities.

Entropy symbolizes the number of bits required to encode for compression so the whole of research work is based on a measure of entropy. The novelty of this research paper is to come up with an optimal universal threshold value for prediction and to get the residual image with the lowest entropy. Minor entropy variations at the optimal threshold value for different image modalities and resolutions are taken care of. The optimal threshold value is independent of modality as well as image resolution for every 8-bit image depth.

MATERIALS AND METHODS

Data Set

Medical images datasets were collected from Center for Image Processing Research (CIPR), Massachusetts General Hospital (MGH) , Micro-Dicom , OsiriX sources. All the images were 8-bit depth. They were used for examining predictor efficiency testing and validation of different predictors.

Predictive Based Lossless Image Compression

The amount of information present in an image that does not provide any relevant information is called redundancy (Avramovic, 2012). Spatial and temporal redundancy present in an image should be removed from the image for better compression. Correlation between neighboring pixels in image results in interpixel spatial redundancy. Difference between adjacent pixels can be used to represent an image to reduce the interpixel redundancy. Steps of data processing contained by predictive based lossless image compression are a prediction, context modeling and entropy encoding as shown in Figure1 (Me et al., 2012).

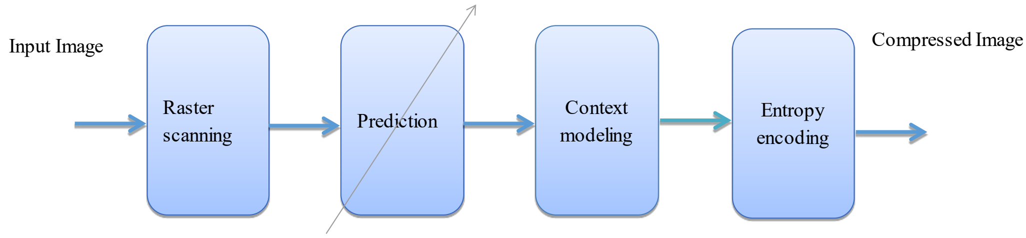

Figure1. General scheme of lossless predictive image compression

Prediction is the essential part of the image compression as it removes most of the redundancy from the image. Prediction of every pixel individually can be done from a context (a group of neighboring pixels) in a raster scan order. Residual image is obtained by subtracting predicted image from an original image. The residual image has lower entropy as compared to the original image. Therefore lesser amount of bits is required to encode it. For the efficiency of compression methods, choice of an optimal predictor is important. Predictor's efficiency is based on the entropy of the prediction error. Lower the entropy better will be the performance of the predictor.

2-D predictors. Spatial redundancy in 2D images can be removed by 2D predictors that exploit the redundancy from the image. 2D predictors can also be used for 3D image compression operating in a frame by frame basis. Here 3D volumetric data was split into 2D images and encoded individually. Common Scheme for labeling of causal neighbors in 2D predictors was shown in equation [1]. Let Xi,j is a current pixel for prediction and XN (North), XW (West), XWW (West-West), XNW (North-West), XNE (North-East), XNN (North-North) and XNNE (North-North-East) are neighboring pixels of Xi, j. Neighboring pixels are denoted as follows:

$$
\begin{aligned}
&XN = X\,[i, j-1],\ XW = X\,[i-1, j],\\
&XNW = X\,[i-1, j-1],\ XNE = X\,[i+1, j-1] \qquad [1]\\
&XNN = X\,[i, j-2],\ XNW = X\,[i-2, j],\\
&XNNE = X\,[i+1, j-2]
\end{aligned}
$$

The various 2D predictors employed are Median Edge Predictor (MED), Gradient Adjusted Predictor (GAP) and Gradient Edge Predictor (GED) which are used in this research work are briefed in the following section.

1. "CIPR." [Online].Available: http://www.cipr.rpi.edu/resource/sequences/sequence01.html.
2. "MGH)." [Online]. Available: http://www.cma.mgh.harvard.edu.ibsr.
3. "Micro-Dicom Dataset." [Online]. Available: http://www.microdicom.com/downloads.html.
4. "OsiriX Dataset." " [Online]. Available: http://pubimage.hcuge.ch:8080/.

Median Edge Detection Predictors (MED). MED predictor was used in JPEG-LS. Three causal pixels were used to select one of the three sub-predictors depending upon whether it was vertical edge or horizontal edge (Weinberger et al., 2000). MED selected the median value among neighboring pixels N, W and W+N-NW.

Gradient Adjusted Predictors (GAP). GAP is based on the gradient estimation which can adapt itself to the intensity gradients of immediate neighbors of predicted pixel. It estimates three types of edges, simple, sharp and a weak edge. To estimate the local gradients and determine the prediction values on some threshold, six causal pixels were used. (Heuristic values of threshold are 8, 32 and 80) (Weinberger et al., 2000) Common scheme for labeling pixels is shown in equation [1].

Gradient Edge Detection (GED). GED predictor is best combination of simplicity and efficiency. Like GAP, it uses local gradient estimation on proper threshold (T) value and chooses between three sub predictors, defined as in MED predictor (Me et al., 2012). It selects one threshold and it can be predefined or user-defined (Avramovicl & Savicl, 2011).

$$\begin{aligned}
&Av = |NW-W| + |NN-N| \\
&Ah = |WW-W| + |NW-N| \\
&\text{if } Av-Ah > T, \qquad Px = W \\
&\text{else if } Av-Ah < -T, \qquad Px = N \\
&\text{else } Px = N+W-NW \\
&\text{where, } T = \text{Threshold value}
\end{aligned} \tag{2}$$

Proposed Model

Resolution Independent Gradient Edge Detection [RIGED]. Existing GED predictor is the finest combination of simplicity and efficiency. It takes advantage from state-of-the-art MED and GAP predictors. However, it is a threshold based predictor and there is no specific method in literature for its threshold value selection.

Threshold selection is important for efficient prediction and efficiency can be increase by reducing the entropy of residual image. Residual image is further entropy encoded for removing coding redundancy. Lower entropy residual requires lower number of bits to encode it. Efficiency of predictor is improved by making it resolution and modality independent. RIGED is the extension of existing threshold based GED predictor which is subjective in nature. Choosing the value of threshold for image prediction is not reported in literature. RIGED removes its demerit by providing an optimal threshold value.

Prediction done at optimal threshold value provides efficient results in terms of entropy. RIGED is less computationally complex and provides better results as that of highly efficient GAP in terms of entropy. RIGED was tested for different image resolution and modalities collected from different standard medical image dataset sources. From the extensive experiments conducted on the medical image datasets of varying modalities and varying resolution, optimal threshold value was selected empirically.

Residual image resulting from RIGED has minimum entropy value resulting in lesser number of bits required for encoding. With proper selection of threshold value for prediction, RIGED is less computationally complex and gives comparable results as that of highly efficient GAP predictor.

$$\left.\begin{array}{c} T = 32\ if\ dataset\ resolution = 256 \times 256 \\ T = 64\ if\ dataset\ resolution = 512 \times 512 \\ T = 44\ \ for\ set\ of\ different\ resolution \\ images\ between\ 256 \times 256\ and\ 512 \times 512 \\ i.e., 256 \times 256 < T < 512 \times 512 \end{array}\right\} \qquad [3]$$

where, T = Threshold value

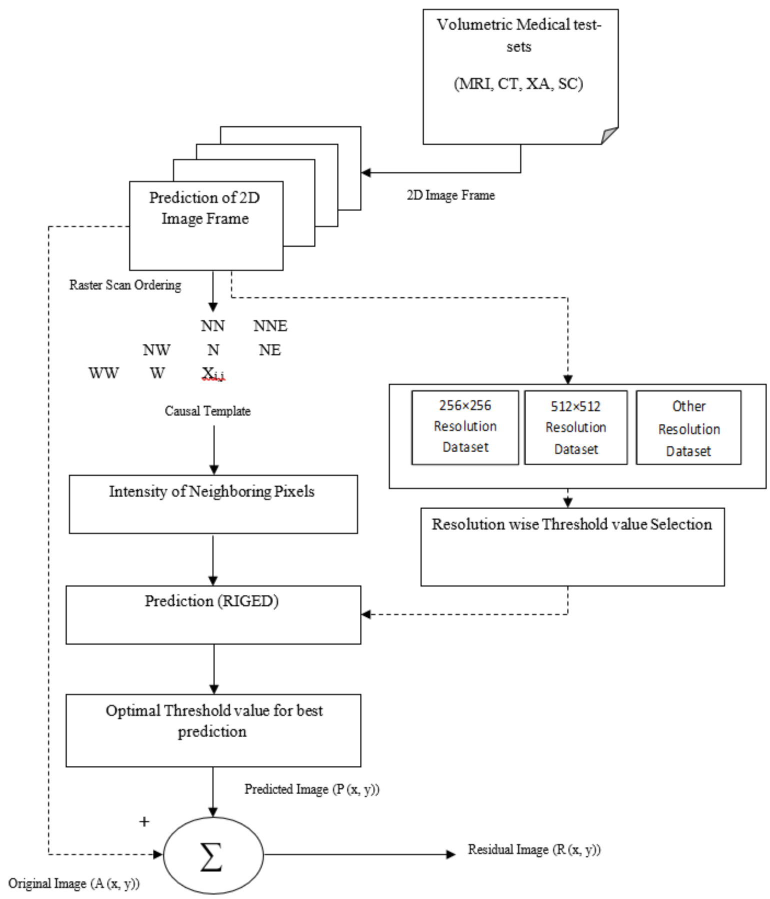

Figure 2. Resolution independent gradient edge detection

A 2D image frame was taken from the volumetric image data set containing number of image frames and the processing of image slices was done on frame-by-frame basis. Neighboring pixels were extracted using causal template of the image and the pixel prediction was done in raster scan order. Pixel prediction was done by RIGED and a common threshold value was used that was optimal for 8 bit depth images. After prediction, residual image or a prediction error image R (x, y) was obtained by subtracting predicted image P (x, y) from original image A (x, y). R (x, y) obtained after predicting at optimal threshold value provided lower entropy that was further entropy encoded. Lower entropy of R (x, y) requires fewer numbers of bits to encode it and provides high compression efficiency. Entire process of the proposed algorithm was repeated for each frame resulting in efficient prediction measured in terms of entropy.

The empirical experimentations involved the number of experiments detailed in this section.

Experiment 1. In this experiment the efficiency of predictor was calculated for medical images of different modalities having resolution 256×256 taken from CIPR and MGH sources. Aim of this experiment was to find the optimal threshold value for prediction of standard size medical images having resolution 256×256. Prediction was done slice by slice basis from 2D predictor and average entropy of residual image was calculated for each modality of 256×256 resolution. The dataset consisted of the following images as shown in Table 1.

Table 1

Dataset detail of R1 (Resolution 256×256)

TAG	Sequence Name	Modality	Image Size	Slices
CIPR-CT-01	CT_Aperts	CT	256×256	97
CIPR-CT-02	CT_carotid	CT	256×256	74
CIPR-CT-03	CT_skull	CT	256×256	203
CIPR-CT-04	CT_wrist	CT	256×256	183
CIPR-MR-01	MR_liver_t1	MR	256×256	77
CIPR-MR-02	MR_liver_t2e1	MR	256×256	58
CIPR-MR-03	MR_ped_chest	MR	256×256	58
CIPR-MR-04	MR_sag_head	MR	256×256	58
MGH-MR-01	657_10	MR (PD)	256×256	18
MGH-MR-02	657_2	MR (T1)	256×256	18
MGH-MR-03	657_11	MR (T2)	256×256	18

Experiment 2. Next set up of experiment involved calculation of entropy with different thresholds of predictor. As image resolutions of 256×256 and 512×512 were standard size for medical images so the objective of this experiment was to find the optimal threshold value that provided the minimum entropy of residual image after prediction. They were tested on various images used in this set of experiment includes MR, CT and XA images. These different image modalities having resolution 512×512 were taken from MIDI and OSRX sources. The dataset consisted of the following images as shown in Table 2.

Table 2
Dataset detail of R2 (Resolution 512×512)

TAG	Sequence Name	Modality	Image Size	Slices
MIDI-MR-01	SAG-T1	MR	512×512	13
MIDI-MR-02	COR-T1	MR	512×512	20
MIDI-MR-03	COR-FSE-T2	MR	512×512	20
MIDI-MR-04	COR-FLAIR	MR	512×512	12
MIDI-MR-05	AX-FSE-T2	MR	512×512	18
MIDI-MR-06	COR-T1-POST-GAD	MR	512×512	15
MIDI-MR-07	SAG-T1-POST-GAD	MR	512×512	15
OSRX_CT_01	BREBIX	CT	512×512	245
OSRX_CT_01	MAGIX	CT	512×512	77
OSRX_MR_01	BRANIX	MR	512×512	22
OSRX_XA__11	GUSERAMBIX	XA	512×512	14
OSRX_XA_01	GUSERAMBIX	XA	512×512	76
PHNT_MR	E1154S7I	MR	512×512	76

Experiment 3. Dataset of medical images having resolution other than 256×256 and 512×512 were also taken from OSRX and tested by predictor with varying values of threshold. To obtain the optimal threshold value for the set of medical images of different resolutions other than 256×256 and 512×512 was the main objective of this experiment. A common threshold value was selected that was optimal for every possible combination of resolution. The dataset consisted images of different resolutions other than 256×256 and 512×512 as shown in Table 3.

Table 3
Dataset detail of R3 (Resolution other than 256×256 and 512×512)

TAG	Sequence Name	Modality	Image Size	Slices
OSRX_CT_02	CEREBRIX	CT	336×336	83
OSRX_SC_01	CEREBRIX	SC	270×320	28
OSRX_SC_02	CEREBRIX	SC	270×320	24
OSRX_SC_04	CEREBRIX	SC	320×384	29

Experiment 4. In this experiment same set of medical images including MR, CT, XA and SC having different resolution and different field of view were tested by state-of-the art MED and GAP predictors. Objective of this experiment was to verify the improvement of proposed RIGED over MED and GAP. RIGED was compared with less computationally complex MED and highly efficient GAP predictor in terms of entropy, computational complexity and execution time.

Performance Metrics

Different predictors for medical images were examined with performance metrics as entropy and computational complexity. Entropy is the main parameter to evaluate the predictor for lossless predictive coding.

Entropies of prediction. Number of bits used to represent the information of an image is described by entropy (Al-Naqeeb & Nordin, 2017). After removing the spatial redundancy from the image by using predictors, entropy is calculated that can be used for the estimation of a final compression ratio (Puthooran et al., 2013). Let X is the random variable of an image, with an alphabet Y= (y_0, y_1…..y_{n-1}) which means it is N-bit image. Entropy of an image is calculated as:

$$H(X) = -\sum_{x \epsilon Y} p(x) \log p(x) \qquad [4]$$

Where, p(x) is probability of a symbol X.

Computational Complexity. A number of operations required for implementation of predictor algorithm compute the computational complexity and time period required for executing the program. Higher the complexity of predictor more will be the running time. A predictor is highly efficient if it provides good results with minimum complexity and runs time.

RESULTS AND DISCUSSION

Comparative Analysis of Different Predictors

In the beginning, a comparative analysis was done for the different techniques. Results of medical images from different predictors MED, GAP and GED as obtained are shown in Figure 3 and Figure 4. It was found that interpixel redundancy was better removed by GAP than MED predictor in terms of entropy of prediction error image. Results of GED predictor were approximately same as that of GAP predictor though it was computationally simpler than GAP predictor. Original image and predicted images that were obtained from MED, GAP and GED predictors with their histograms are depicted in Figure 3 and histograms of residual images are shown in Figure 4.

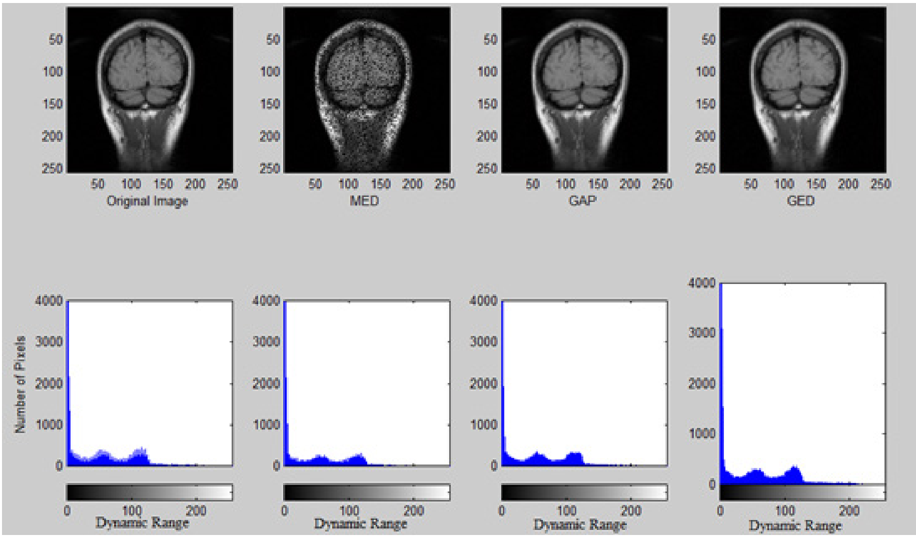

Figure 3. Original MRI-scan image of brain, predicted image obtained from MED, GAP and GED predictors and their histograms

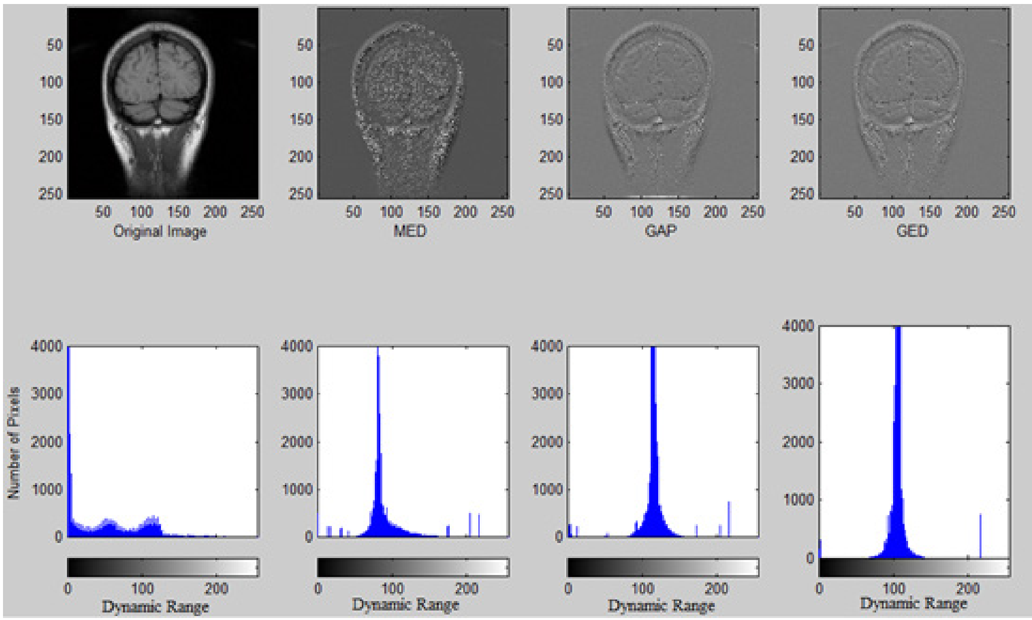

Figure 4. Original MRI-scan image of brain, residual image obtained from MED, GAP and GED predictors and their histograms

Analysis of Entropy Values for Different Resolutions

Structural analysis was carried out for various samples of medical images from all predictors MED, GAP and GED, which provided better assessment with respect to entropy and computational complexity. GED predictor was based upon one threshold value which was selected manually for better results. For images with different resolution, different threshold value had to be chosen for optimal results. Our proposed algorithm RIGED was designed to make this algorithm independent of the modality and resolution. RIGED was tested for different thresholds from 8- 256. After calculating the entropy for a threshold 2k, it was observed that there was significant change in entropy when threshold changed from 8 to 32 whereas threshold ranging from 32 to 80 there was minor variation in the value of entropy. RIGED prediction was also calculated for threshold values 32 to 128 with a difference of 16 (48, 64, 80, 96 and 112). Nomenclature used in this paper was RIGED_8 representing GED predictor with threshold value = 8.

Entropy for R1 dataset for varying threshold values. All the images from different modalities had varying number of slices. Weighted average of entropy for all the slices was calculated. It was found that for set of medical image samples having resolution 256×256 the lowest entropy was obtained at threshold value of 32 i.e., optimum value of threshold was 32 for images of 256×256 resolution. Graphical representation of entropy obtained for R1 set (256×256 resolution) of medical image dataset from GED predictor at varying threshold value is shown in Figure 5. For R1 set of medical images, highest entropy was obtained at the threshold value of 8. On increasing value of threshold, entropy decreased till threshold value of 32 and it started increasing thereafter. There was slight variation in entropy value for threshold values of 32 to 48 and after that significant change was observed for higher values of threshold after 48 as shown in Figure 5.

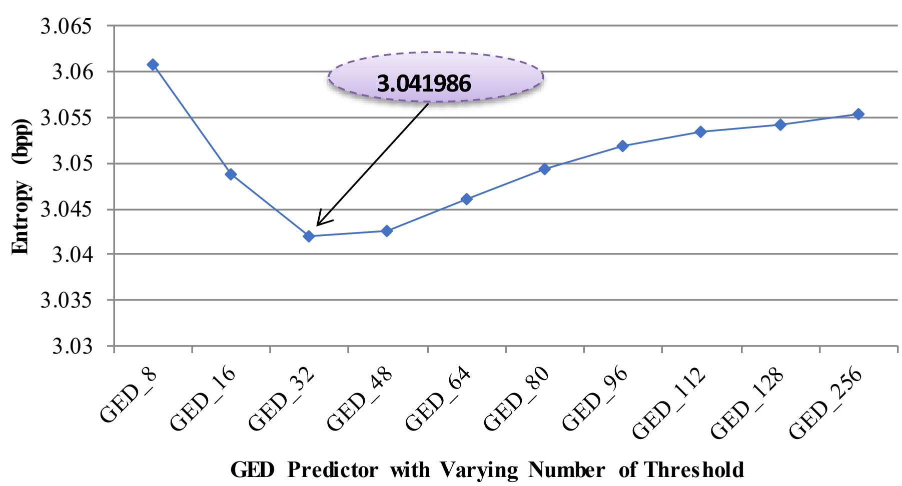

Figure 5. Average value of entropy from GED predictor with varying threshold values for R1 resolution.

Entropy for R2 Dataset for Varying Threshold Values. As stated in experiment 2, the GED predictor was used to determine the optimal threshold value for a set of medical image samples having resolution 512×512. Set of R2 (resolution 512×512) contained different modalities of medical images with number of slices. Entropy was calculated for all slices for different modalities of images and weighted average of entropy for R2 set was obtained. As the resolution increased from 256×256 to 512×512, entropy decreased at varying value of threshold from 32 to 64 and then increased for higher values of threshold of 64, so it was found that minimum value of entropy was obtained at threshold value of 64 for the group R2 of medical image dataset. The results are depicted in Figure 6 showing the minimum entropy at threshold value of 64.

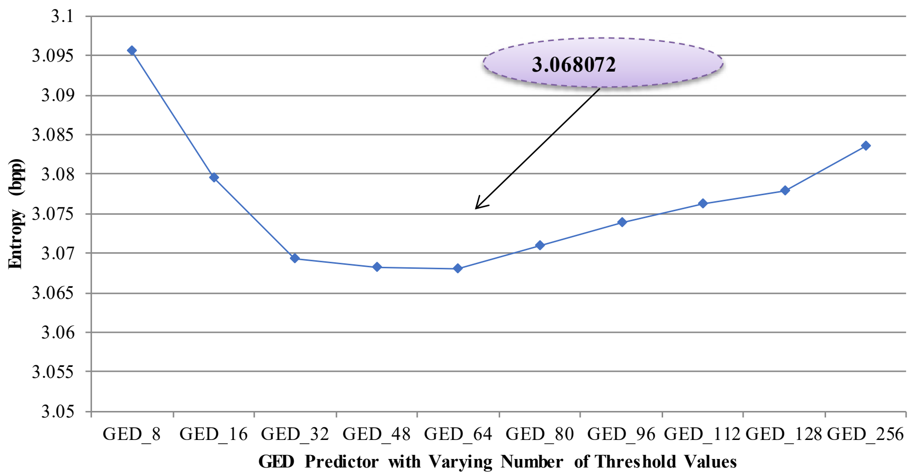

Figure 6. Average value of entropy from GED predictor with varying threshold values for R2 resolution.

Entropy for R3 Dataset for Varying Threshold Values. Some medical images may have different resolution other than 256×256 and 512×512. In experiment 3, proposed algorithm RIGED was applied on such images too. Weighted average of entropy for set of resolution other than 256×256 and 512×512 resolution was calculated. There is significant change in entropy value when threshold varied from 8 to 32 and then slight change in entropy was observed and a minimum of entropy was obtained at threshold value of 48. The result is graphically represented in Figure 7.

Calculation of entropy for all the modality with all the possible resolution for varying threshold values. To come with resolution independent GED, it is mandatory to compare all the modality with all the possible resolutions. Weighted average of entropy for the complete set is calculated and shown in Table 4.

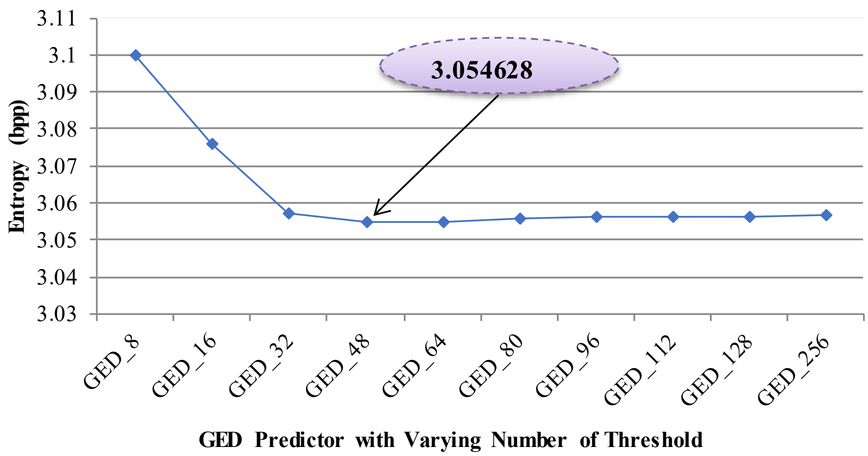

Figure 7. Average value of entropy from GED predictor with varying threshold values for image resolution in between 256×256 and 512×512

Table 4

Entropy values of medical dataset predicted from GED predictors with varying threshold values

Image Dataset Resolutions	No. of Slices	Entropy values before prediction	Entropy values after prediction									
			GED_8	**GED_16**	**GED_32**	**GED_48**	**GED_64**	**GED_80**	**GED_96**	**GED_112**	**GED_128**	**GED_256**
CT (256×256)	557	4.54622	2.69748	2.68278	2.67414	2.67442	2.67865	2.68250	2.68538	2.68732	2.68830	2.68977
CT (512×512)	322	4.67396	2.74261	2.72864	2.72852	2.72810	2.72270	2.728304	2.73388	2.73835	2.74138	2.75137
MRI (256×256)	305	5.31504	3.72402	3.71725	3.71375	3.71473	3.71702	3.71932	3.72096	3.72199	3.72253	3.72302
MRI (512×512)	211	5.27016	3.62855	3.59807	3.57815	3.57126	3.56793	3.56798	3.56806	3.56809	3.56807	3.56817
CT (336×336)	83	2.16590	1.45454	1.40205	1.36309	1.35401	1.35406	1.35409	1.35412	1.35421	1.35427	1.35438
SC (384×320)	29	6.20258	4.61906	4.60863	4.60216	4.60116	4.60413	4.60578	4.60660	4.60696	4.60709	4.60719
SC (320×270)	52	6.41378	5.32638	5.35222	5.36658	5.36136	5.37383	5.37521	5.37602	5.37651	5.37673	5.37709
XA (512×512)	90	5.83941	3.12632	3.12643	3.12950	3.12734	3.12574	3.13127	3.13209	3.13256	3.13300	3.13549
Weighted Average	1649	4.60039	3.08752	3.07197	3.06122	**3.05983**	3.06187	3.06468	3.06733	3.06938	3.07072	3.07483

Finally, a common threshold value was obtained for all the possible cases. Graphical representation of entropy from GED predictor at varying values of the threshold is shown in Figure 8. It was clear that GED with a threshold value of 48 gave a lower value of entropy for a complete set of medical images compared to other threshold values.

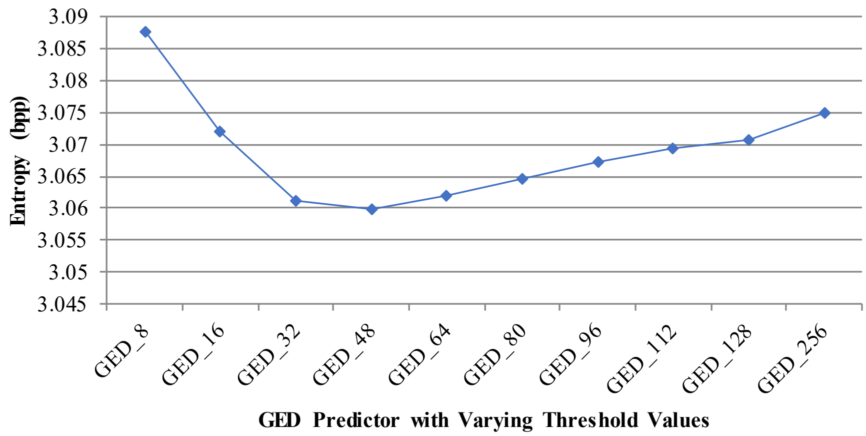

Figure 8. Average value of entropy from GED predictor with varying threshold values for overall dataset including different resolutions and different modalities.

For a complete set of medical images (Table 1, 2, 3), minimum entropy was in between the threshold 32 to 80. Weighted average of minimum entropy was obtained at threshold of 48 for all available dataset. To check the variation near to the optimal value and confirm our findings, entropy value was also calculated for threshold value before and after 48 for exact minima of entropy i.e., for threshold value of 43 to 53 in steps of 1 as represented in Figure 9. It is clear from the figure that entropy obtained at the value of threshold 44 (GED_44) was lower and then it again started increasing with increasing number of threshold value.

Result validation of prediction at optimal threshold values. From above discussion it is clear that lowest value of entropy was obtained for threshold range between threshold values 32 to 64 of GED predictor for complete set of medical images of R1, R2 and R3 resolution. GED with threshold 32 was optimal for 256×256 resolution and threshold of 64 gave optimized results of entropy for 512×512. Threshold of 44 was obtained as optimal for overall database of different modalities of medical images of varying resolution. There was a slight variation in entropy value between these thresholds. Results of medical images from RIGED predictor for all threshold values i.e., 32, 44, 48 and 64 are shown in Figure 10.

Comparison of RIGED with Standard MED and GAP Predictors in Terms of Entropy and Computational Complexity

Entropies of prediction error and computational complexity are two performance parameters used for evaluation of the proposed RIGED predictor. A predictor is efficient if it provides

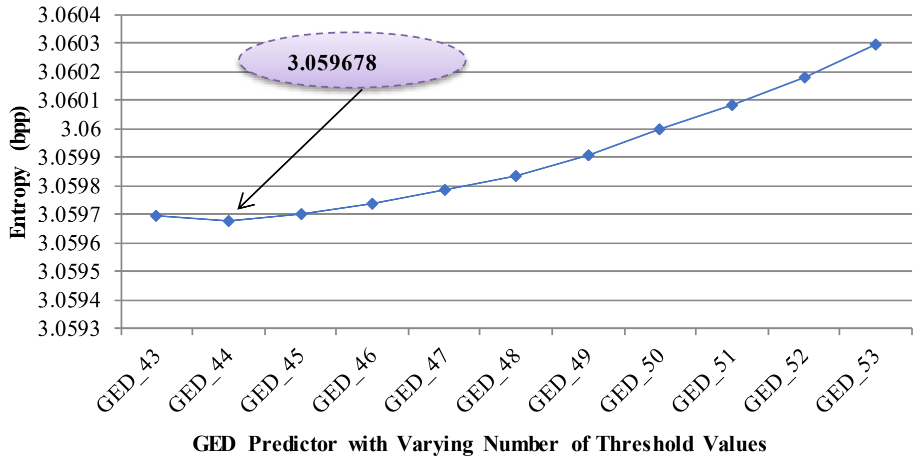

Figure 9. Average value of entropy from GED predictor with varying threshold before and after threshold point 48 for complete set of different modalities of medical images.

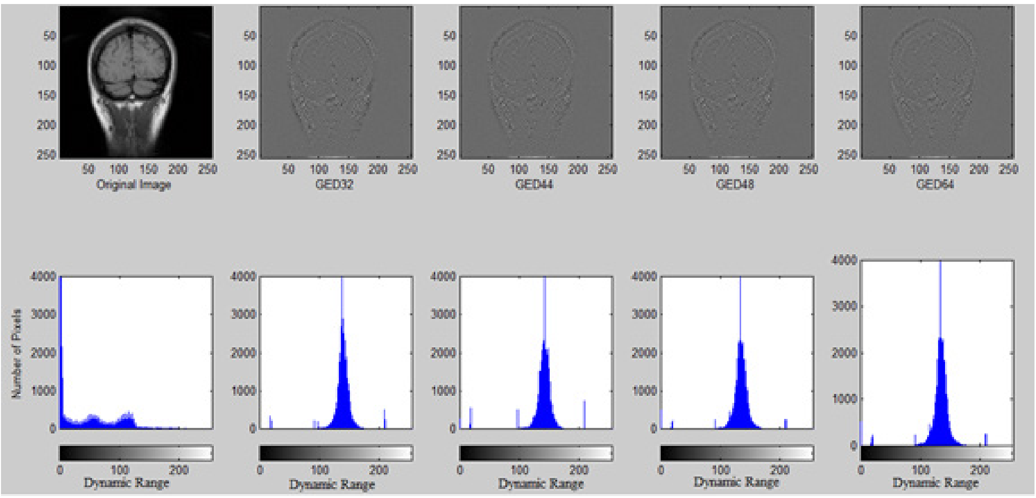

Figure 10. Original MRI-scan image of brain, residual image obtained from RIGED predictor with threshold values 32, 44, 48 and 64 and their histograms.

less entropy value with low computational complexity and run time. The lower the value of entropy obtained, the better is predictor's efficiency (Avramovic, 2012). Proposed algorithm gave better results than MED and comparable results as that of highly efficient standard GAP for same set of database. Comparison of RIGED done with state-of-the-art MED and GAP predictors in terms of entropy is shown in Table 5.

Table 5

Entropy values of medical dataset from different resolution and modality from different predictors and % improvement of RIGED over MED and GAP

Image Dataset Resolution	No. of Slices	Entropy values before prediction	Entropy values after prediction			% Improvement of RIGED	
			MED	**GAP**	**RIGED (Proposed)**	**Over MED**	**Over GAP**
CT (256×256)	557	4.54622	3.75772	2.73264	**2.67414**	40.520	2.187
CT (512×512)	322	4.67396	3.52607	2.76799	**2.72852**	29.229	1.446
MRI (256×256)	305	5.31504	4.69134	**3.54982**	3.71375	26.323	-4.414
MRI (512×512)	211	5.27016	4.84046	3.57121	**3.56793**	35.665	0.091
CT (336×336)	83	2.16590	1.92817	1.48989	**1.35611**	42.183	9.864
SC (384×320)	29	6.20258	5.64326	**4.34587**	4.60161	22.636	-5.557
SC (320×270)	52	6.41378	6.19173	**5.02089**	5.37052	15.291	-6.510
XA (512×512)	90	5.83941	4.18896	**2.8392**	3.12665	33.975	-9.193
Weighted Average	1649	4.60039	4.05145	3.03867	3.05967	32.414	-0.686

It is clear from Table 5 that minimum entropy is achieved by GAP predictor and RIGED has comparable results. Percentage improvement of RIGED over other predictors is also shown in this table and it is revealed that RIGED has a maximum improvement for CT image having resolution 336×336. Average percentage improvement of RIGED for complete sample dataset is 32% over MED and the percentage difference between GAP and RIGED is 0.68 % i.e., performance in terms of entropy for RIGED is 0.68 % less than GAP. RIGED is simple to implement as compared to GAP and also gave comparable results in terms of entropy. But at the overall new threshold value, RIGED performs better for some medical image datasets than highly efficient GAP. In literature entropy of prediction error image from different predictors is calculated only for a small set of medical images that are reported in Table 6. In this research work, weighted average of entropy is calculated for different modality with varying resolution and slices.

As GED is a threshold based and no specific threshold value is provided in literature. Threshold value of 16, 64, and 128 for GED prediction are randomly selected and reported by Avramovic and Savic (2011). These threshold values were tested on some MRI and CT image slices as shown in Table 6.

In this paper, we work on large set of volumetric medical database having varying number of slices, image resolution and modalities. For comparison purpose, reported

GED threshold values are tested on same set of dataset on which RIGED is implemented. Compared results between with RIGED and without RIGED is tabulated in Table 7.

Table 6

Entropy values of medical dataset from different predictors in literature

Images datasets		Image Size	Slices	Entropies after prediction					
				MED	GAP	GED*	GED 16	GED 64	**GED 128**
Avramovic and Savic (2011)	CT1	512×512	38	7.615	7.563	-	7.606	7.495	**7445**
	CT2	512×512	50	5.796	5.727	-	5.779	5.758	**5787**
	CT3	512×512	14	3.998	4.304	-	4.598	4.711	**4786**
	MRI1	640×576	25	4.747	4.851	-	5.072	5.264	**5359**
	MRI2	378×384	15	4.253	4.375	-	4.684	4.876	**4945**
Avramovic (2012)	CT	512×512	1338	4.19	4.39	4.30	-	-	-
	MRI	512×512	528	5.58	5.57	5.76	-	-	-

GED* threshold value is not specified.

GED16 indicates GED with threshold value 16.

GED64 indicates GED with threshold value 64.

GED128 indicates GED with threshold value 128.

Table 7

Comparison of with RIGED and without RIGED in terms of entropy value

Image Resolution	**Without RIGED**			**With RIGED**	**Percentage Improvement of with RIGED over without RIGED**		
	Threshold =16	Threshold =64	Threshold =128		Threshold =16	Threshold =64	**Threshold=128**
256×256	3.0488	3.0460	3.0542	**3.0419**	0.22	0.13	**0.40**
512×512	3.0795	3.0680	3.0779	**3.0680**	0.37	0.00	**0.32**
Other combinations of resolutions	3.0719	3.0618	3.0707	**3.0596**	0.40	0.07	**0.36**
Average Percentage Improvement					**0.33 %**	**0.07 %**	**0.36 %**

Average percentage improvement of with RIGED is around 0.33 % over without RIGED when threshold value is taken as 16. Proposed RIGED performs 0.07 % and 0.36 % better than without RIGED for threshold value of 64 and 128 respectively.

Complexity of RIGED was measured on the basis of arithmetic operations used for predictor's implementation and on the basis of run time of predictor. Total numbers of arithmetic operations involved in implementation of RIGED algorithm were calculated. A minimum of 8 and maximum of 11 operations were required for its implementation. A comparison of computation complexities in GAP, MED and RIGED is tabulated in Table

8. As observed, total number of minimum and maximum operations required for RIGED prediction was less as compared to highly efficient GAP predictor.

Table 8
Computational complexity of GAP and RIGED predictor

Predictors	Operations	Number of Addition/Subtraction	Number of Multiplication/Division	Number of Comparison	Total	Run Time* (µs)
MED	Minimum	-	-	1	1	2.51
	Maximum	2	-	2	4	
GAP	Minimum	11	-	1	12	5.38
	Maximum	18	8	6	32	
RIGED	Minimum	7	-	1	8	4.11
	Maximum	9	-	2	11	

*Tested on AMD A8-7410 APU with AMD Radeon R5 Graphics. 64 bit operating system and x64 based processor. Software: MATLAB 2013.

Time period was measured on the basis of time required for the execution of a predictor. MR-image sample of resolution 256×256 was tested on AMD A8-7410 APU with AMD Radeon R5 Graphics, 64 bit operating system and x64 based processor to measure the execution time (Software: MATLAB 2013). Runtime (execution time) in µs was calculated for all the techniques, and GAP had a high execution time as compare to RIGED predictor as tabulated in the Table 8.

CONCLUSION

Compression based on predictive coding performs well as it has simpler implementation and low computational complexity. 2D predictors GAP and GED predictor with different thresholds are implemented that are used for removing inter-pixel redundancy. It is revealed that prediction based on edge detection called GED is a good solution for prediction. Comparison of GED with GAP predictors is also made in this paper. The entropy of GED is a calculated for different threshold values and it is concluded that for a different resolution of image datasets, GED has optimum results at different thresholds.

The weighted average of entropy achieved by RIGED for different types of the database having varying resolution and it gave optimal threshold value at different image resolution. A common threshold value is selected that is optimal for every possible combination of resolutions and image modalities.

It is concluded that RIGED predictor can achieve comparable results in terms of entropy and it is also simple to implement as compared to GAP. It is revealed from the study that RIGED takes advantage of MED and GAP predictors as it is efficient and also simple to implement. Average percentage improvement of RIGED for complete sample dataset is 32.4% over MED and the percentage difference between GAP and RIGED is 0.68 %.

ACKNOWLEDGEMENT

Authors would like to thank the Jaypee University Waknaghat, Distt. Solan, India for supporting and providing help to this research.

REFERENCES

Al-Mahmood, H., & Al-Rubaye, Z. (2014). Lossless image compression based on predictive coding and bit plane slicing. *International Journal of Computer Applications*, *93*(1), 1-6.

Al-Naqeeb, A. B., & Nordin, M. J. (2017). Robustness watermarking authentication using hybridisation DWT-DCT and DWT-SVD. *Pertanika Journal of Science and Technology*, 25(S), 73-86.

Avramovic, A. (2012). On predictive-based lossless compression of images with higher bit depths. *Telfor Journal*, *4*(2), 122-127.

Avramovicl, A., & Savicl, S. (2011). Lossless predictive compression of medical images. *Serblan Journal of Electrical Engineering*, *8*(1), 27-36.

Avramovic, A., & Reljin, B. (2010, September 15-17). Gradient edge detection predictor for image lossless compression. In *Proceedings of the ELMAR* (pp. 131-134). Zadar, Croatia.

Baware, E. A., & Save, J. (2016). Medical image compression using adaptive prediction and block based entropy coding. *International Journal of Computer Applications*, *153*(9), 28-33.

Fouad, M. M. (2015). A lossless image compression using integer wavelet transform with a simplified median-edge detector algorithm. *International Journal of Engineering and Technology*, *15*(4), 68-73.

Hashemi-Berenjabad, S., & Mojarrad, S. (2016). A review on medical image compression techniques. International *Journal of Emerging Technologies in Engineering Research (IJETER)*, *4*(1), 88-91.

ISO/IEC 14495–1. (1999). *Information technology-lossless and near-lossless compression of continuous tone still images. JPEG-LS source code.* Retrieved August 29, 2019 from http://www.stat.columbia.edu/%7Ejakulin/jpeg-ls/mirror.htm.

Khatkar, K., & Kumar, D. (2018). A new genetic algorithm based technique for biomedical image enhancement. *Pertanika Journal of Science and Technology*, *26*(4), 1725-1750.

Kaur, H., Kaur, R., & Kumar, N., (2015). Review of various techniques for medical image compression. *International Journal of Computer Application*, *123*(4), 25-29.

Me, S. S., Vijayakuymar, V. R., & Anuja, R. (2012). A survey on various compression methods for medical images. *International Journal of Intelligent System and Applications*, *4*(3), 13-19.

Mofreh, A., & Refaat, A. M. (2016). A new lossless medical image compression technique using hybrid prediction model. *Signal Processing: An International Journal (SPIJ)*, *10*(3), 21-30.

Placidi, G. (2009). Adaptive compression algorithm from projections: Application on medical greyscale images. *Computers in Biology and Medicine*, *39*(11), 993-999.

Puthooran, E., Anand, R. S., & Mukherjee, S. (2013). Lossless compression of medical images using a dual level DPCM with context adaptive switching neural network predictor. *International Journal of Computational Intelligence Systems*, *6*(6), 1082-1093.

Sharma, U., Sood, M., & Bhardwaj, C. (2017). Reconstruction methods in compressive sensing for biomedical images. *Journal of Global Pharma Technology*, *6*, 134-143.

Shanmathi, G., & Maniyath, S. R. (2017). Comparative study of predictors used in lossless image compression. *Asian Journal of Applied Science and Technology*, *1*(5), 10-13.

Shrikhande, N. R., & Bairagi, V. K. (2013). Prediction based lossless medical image compression. International *Journal of Electronics and Communication Engineering and Technology*, *4*(2), 191-197.

Thombare, S. (2016). Low-complexity, lossless volumetric medical image compression with PPM-5 & linear. *International Journal of Innovative Research in Computer and Communication Engineering*, *4*(10), 17140-17144.

Weinberger, M. J., Seroussi, G., & Sapiro, G. (2000). The LOCO-I lossless image compression algorithm: principles and standardization into JPEGLS. I*EEE Transaction on Image Processing*, *9*(8), 1309-1324.

Wu, X., & Memon, N. (1996, May 9). CALIC a context based adaptive lossless image codec. In *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing* (Vol. 4, pp. 1890-1893). Atlanta, GA, USA.