Implementation and Performance Assessment of Gradient Edge Detection Predictor for Reversible Compression of Biomedical Images

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Abstract. Technological advancement of medical imaging techniques are progressing constantly, dealing with images of increasing resolutions. In hospitals, medical imaging techniques like X-rays, magnetic resonance imaging and computed tomography etc. are of high resolution consuming large storage space. Such high resolution of medical images transmitted over the network utilizes large bandwidth that often results in degradation of image quality. So, compression of images is only a solution for efficient archival and communication of medical images. Predictive based coding technique is explored in this paper for medical image compression as it performs well for lossless compression. This paper presents a comparative investigation on 2D predictor's coding efficiency and complexity on CT images. It was observed that among 2D predictors Gradient Edge Detection (GED) predictor gave better results than Median Edge Detector (MED) and DPCM. GED predictor at proper threshold value achieved approximately same results in terms of various performance metrics as Gradient Adaptive Predictor (GAP) though it is less complex.

Keywords: Compression · Predictors · Coding efficiency · Complexity

1 Introduction

Digital image processing has a great demand for transmission and storage of data efficiently with the rapid advancement in information and communication technology. In biomedical area, technology of medical images are progressing dramatically and dealing with images of increasing resolutions. Healthcare departments deal with abundant amount of medical images and terabytes of digital data is generated by hospital per year [1, 2]. Currently various medical imaging techniques are in use like magnetic resonance (MR), X-rays and computerized tomography (CT) that produce enormous amount of data as these techniques normally contains set of 2D frames that represent cross sectional part of human body. This growing amount of medical data makes a demand for effectual techniques of compression that are used for proper storage and communication [3]. Efficient compression techniques are required to deal

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with the rapid expansion of medical data, to save time and to shrink storage space. Additionally, telemedicine is an application that requires progressive lossy to lossless compression. Since compressed image file sizes require less time for transmission so it is valuable for telemedicine application [4]. Medical image compression has been proved as a very important aspect to get a successful real time application of telemedicine along with an efficient storage and transmission. Compression technique removes the irrelevant and redundant bits from the image and accelerates the transmission speed. Compression results in lesser number of bits to represent the information. An efficient compression technique can reduce file size and transmission time, i.e. improving effectiveness of the image transmission system. Generally used image compression techniques are discussed.

Lossy compression technique does not provide exact replica of original image but it results in higher compression ratio. Lossy technique system is not acceptable in medical field because any loss of information result in false and it may create issue. So it is not preferred technique for compression of medical images [5, 6]. Lossless compression of image is an appropriate technique in medical field as it results exact replica of original image [7]. Diagnosis of image cannot afford any deficiency in diagnostically important regions of interest (ROIs). Thus it is necessary to have an approach that brings a high compression rate maintaining good quality of medical images. There are many compression techniques available in literature like transformation coding, entropy encoding and dictionary encoding.

As it is essential that compression and reconstruction of signal should be efficient without any loss of medical information as little loss of data especially in medical field is unbearable because it may lead to diagnose mistakenly [8].

Related Work

It is seen in literature that predictive coding performs well for lossless compression technique and efficiency of compression system depends upon the choice of predictors. Choice of is necessary for predictor for efficient prediction results in reduction of redundancy from the image that further contributes for better compression ratio. Many researchers have reported applying predictive coding technique on medical images for lossless compression.

In [9], author reviewed various image compression techniques based on medical image compression. In the rising field of telemedicine and teleradiology, comparative analysis of compression techniques and their applications has been carried out. In [10] predictive coding with a simple context-based entropy coder is offered and different predictor efficiency were analyzed with higher bit depth, achieving approximately same bit rate as standard predictor algorithm. [11] In this paper, author examined various compression techniques and it was explored that although medical image compression is an emerging need, but it encounters higher dimensionality of challenges and complicatedness for catering the increasing demands of the medical science. Authors in [12] proposed threshold controlled gradient edge detection which combines MED predictor and GAP. It is seen that GED predictor can achieve comparable bit rates as more complicated GAP predictors. In [13], author has used differential pulse code modulation for image compression lossless and near-lossless compression method and due to its high compression ratio and simplicity; it is an efficient technique for lossless compression. Enhanced DPCM transformation is used in this method which has a good energy compaction and Huffman encoding was used for image coding. In [14], proposed prediction based algorithms on the detection of edges and assessment of local gradients. MED and GAP were analyzed and comparative analysis of these predictors were also done in terms of entropy. Authors in [15] adopted a compression method that is based on a combination between predictive coding and bit plane slicing for compression of medical and natural image samples. High system performance is achieved by this lossless compression technique with high compression ratio. The main objectives through this research paper are to find the more efficient prediction algorithm by comparing different 2D predictors for image prediction. Another objective of this paper is to analyze the effectiveness of varying resolution values on entropy of prediction error image. The rest of this paper is organized as follows. In Sect. 2, details of prediction based compression is presented. In Sect. 3 results and discussion are shown. Conclusion of paper is drawn in Sect. 4.

2 Materials and Methods

2.1 Data Set

Different medical images of CT-scan are collected from CIPR [16] and OSRX [17] for validation, testing and examine coding efficiency of different predictors on patient's medical images. Details of CT medical test samples are shown in Table 1. These datasets are commonly used datasets having CT images of varying resolutions. In this research work, CT images are taken to test the algorithms and there is no effect in the performance of algorithms with varying image modality, resolution and number of images.

Table 1. Dataset details of CT medical test images

TAG	Sequence name	Modality	Image size
CIPR-CT-01	CT_Aperts	CT	256 × 256
CIPR-CT-02	CT_carotid	CT	256 × 256
CIPR-CT-03	CT_skull	CT	256 × 256
CIPR-CT-04	CT_wrist	CT	256 × 256
OSRX_CT_01	BREBIX	CT	512 × 512
OSRX_CT_01	MAGIX	CT	512 × 512
OSRX_CT_02	CEREBRIX	CT	336 × 336

2.2 Predictive Based Lossless Image Compression

Additional amount of bits and information that do not provide any relevant information is called redundancy [18]. Neighboring pixels in an image are related to each other and correlation between these pixels results in interpixel redundancy. Neighboring pixels are used to calculate the value of current pixel and difference between adjacent pixels can be used to represent an image to reduce the interpixel redundancy. Basic Scheme of predictive coding technique is shown in Fig. 1.

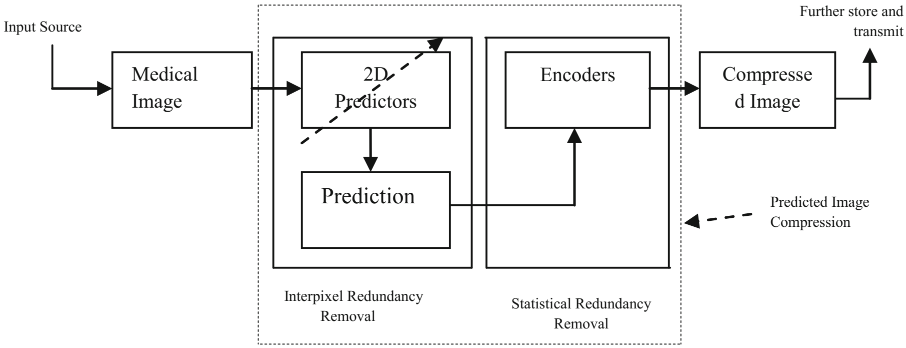

Fig. 1. Scheme of predictive coding technique

In predictive coding technique, interpixel redundancy is removed by 2D predictors and statistical redundancy is removed by encoders like Huffman and Arithmetic coding.

2.3 2D Predictors Used in Predictive Based Coding Techniques

Most important part of lossless predictive coding technique is prediction as it exploits interpixel redundancy from the image. 2D predictors can also be used for removing redundancy from volumetric images when operated slice by slice. 3D volumetric medical data is splitting into 2D image slices and separately enhance and predicted by the 2D predictor algorithms. Basic arrangement of pixels in causal template is denoted as follows:

$$\left.\begin{array}{l} X_{i,j} = X[i, j],\ X_N = X[i, j-1],\ X_W = X[i-1, j], \\ X_{NW} = X[i-1, j-1],\ X_{NE} = X[i+1, j-1], \\ X_{NN} = X[i, j-2],\ X_{WW} = X[i-2, j],\ X_{NNE} = X[i+1, j-2]. \end{array}\right\} \quad (1)$$

Where $X_{i,j}$ is current pixel and X_N (North pixel), X_W (West pixel), X_{NW} (North–West pixel), X_{NE} (North-East pixel), X_{NN} (North-North pixel), X_{WW} (West–West pixel) X_{NNE} (North-North-East pixel) are neighbour pixels in causal template. The various 2D predictors taken into consideration in the work are Median Edge Predictor (MED), Gradient Adjusted Predictor (GAP), Differential Pulse Code Modulation (DPCM) and Gradient Edge Predictor (GED).

Median Edge Detection Predictors (MED): The value of current pixel $X_{i,j}$ is predicted by Median edge detector that selects the median value among neighboring pixels X_N, X_W and $X_W + X_N - X_{NW}$ (pixels are shown in Eq. 1). It is uses three causal pixels which are used to select one of the three sub-predictors depending upon whether it is horizontal edge or vertical edge [19].

Gradient Adjusted Predictors: GAP is based on the gradient estimation which is done around the current pixel. It can adapt itself to the intensity gradients of immediate neighbors of predicted pixel. For gradient estimation six causal pixels are used and predicted value is determined on some threshold. Threshold use in this predictor is fixed and typical values of threshold are 8, 32 and 80 [12].

Differential Pulse Code Modulation (DPCM): Differential encoding compression method predicts the current signal value based on the past encoded signal values. Error signal is obtained by taking difference of original value and predicted value and then encoded. It gives good compression ratio for images with high correlation between neighbouring pixels [20]. Error signal having peaked histogram is containing small error value.

Gradient Edge Detection: MED and GAP predictors have their own merits and demerits and GED predictor takes the advantage of both predictors. It is finest combination of simplicity and efficiency. It uses local gradient estimation on proper threshold value (T) as that of GAP and chooses between three sub predictors, defined as in MED predictor [4]. Threshold values used in standard GAP predictor are fixed but in GED predictor value of threshold is user defined. On proper threshold value GED provides efficient results as that of GAP. Like MED, it is also simple to implement. Algorithm of GED is as follows:

$$\left.\begin{array}{l} \mathrm{Av} = |\mathrm{NW}-\mathrm{W}| + |\mathrm{NN}-\mathrm{N}| \\ \mathrm{Ah} = |\mathrm{WW}-\mathrm{W}| + |\mathrm{NW}-\mathrm{N}| \\ \text{if } \mathrm{Av}-\mathrm{Ah} > \mathrm{T}, \mathrm{Px} = \mathrm{W} \\ \text{else if } \mathrm{Av}-\mathrm{Ah} < -\mathrm{T}, \ \mathrm{Px} = \mathrm{N} \\ \text{else } \mathrm{Px} = \mathrm{N}+\mathrm{W}-\mathrm{NW} \\ \\ \text{where, T = Threshold} \\ \text{Av, Ah = vertical and horizontal gradients} \\ \text{Px = Predicted pixel} \end{array}\right\} \qquad (2)$$

2.4 Performance Metrics

Different predictors for medical images are examined with various evaluation metrics as entropy, Peak Signal-to-Noise Ratio, Structural Similarity Index (SSIM). Entropy is final step in predictive coding technique that removes the statistical redundancy from the image [21, 22]. Entropy of an image is calculated as:

$$H(X) = -\sum_{\mathrm{x}} \mathrm{p(x)log\ p(x)} \qquad (3)$$

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

Quality of an image is express in terms of PSNR and its typical value is 30 db for 8 bit depth. It depends upon Mean Square Error (MSE), lower the value of square error higher will be PSNR and better quality of an image is obtained [23]. PSNR is calculated by

$$\begin{aligned} \mathrm{PSNR} &= \frac{10\log_{10}(255)^2}{\mathrm{MSE}} \\ \mathrm{MSE} = \frac{1}{\mathrm{MN}}\sum\sum &\frac{\mathrm{error}^2}{\mathrm{rows} \times \mathrm{columns}} \\ \mathrm{RMSE} &= \sqrt{\mathrm{MSE}} \end{aligned} \tag{4}$$

SSIM is the combination of luminance, contrast and structure and based on mean and variance. Value of SSIM is lies between 0 and 1 and predicted image is more similar to original image if SSIM approaches to 1 [8].

$$\mathrm{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)} \tag{5}$$

3 Results and Discussion

Results of several 2D predictors of predictive coding technique for the various CT-scan databases are presented, implemented in MATLAB 2013.

Medical images of Computed Tomography (CT) are compressed using 2D predictors MED, DPCM, GAP and GED are obtained and shown in Figs. 2, 3. It is found that interpixel redundancy is better removed by GAP than the MED and DPCM predictor as GAP provides less entropy and RMSE of prediction error image. Results of GED predictor are approximately same as that of GAP predictor. Original image and residual image obtained from MED, GAP, DPCM and GED predictors are shown in Figs. 2, 3 with their corresponding histograms.

3.1 Comparative Analysis of 2D Predictors for Computed Tomography (CT) Images

Analysis in Terms of Entropy: Comparative analysis is carried out for different samples of CT medical images taken from different database. These images are tested by all four predictors MED, GAP, DPCM and GED, which provides better assessment in contrast to entropy, PSNR, RMSE and SSIM. As GED predictor is based on threshold value and we got 44 as a optimal threshold when it is tested for different values of threshold from 8 to 256 at the difference of 16. Resolution Independent Gradient Edge Predictor (RIGED) is a GED predictor with threshold value 44 for efficient prediction. So for 8 bit depth images RIGED is efficient. It is estimated that performance of RIGED is better obtained than MED, DPCM and GAP as it takes the advantage of simplicity and efficiency from standard MED and GAP predictors.

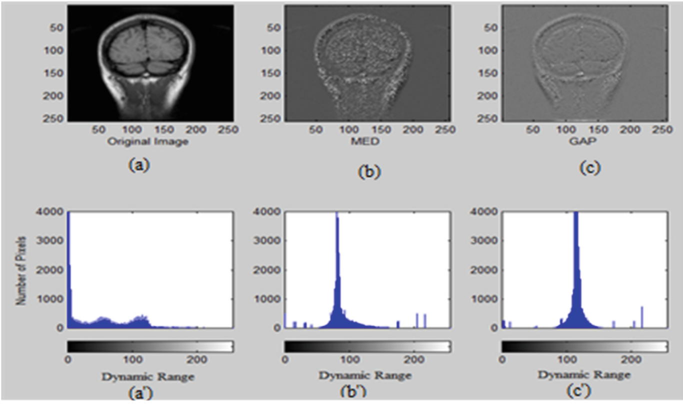

Fig. 2. (a) Original CT-scan image of brain, residual image obtained from (b) MED and (c) GAP predictors (a'), (b'), (c') corresponding histograms.

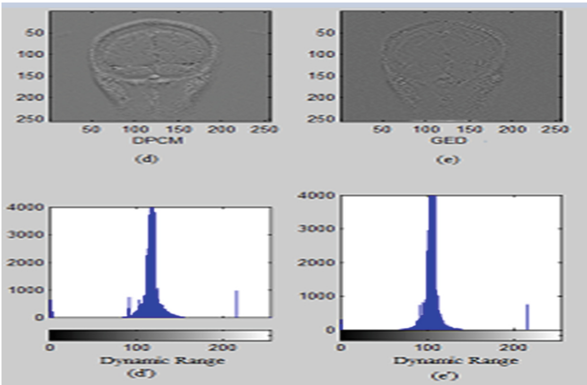

Fig. 3. Residual image of CT obtained from (d) DPCM and (e) RIGED predictors (d'), (e') respective histograms.

RIGED gave better results than MED and DPCM predictor and approximately same results as that of GAP even it is less complex than GAP. Entropy values of prediction error image obtained from MED, DPCM, GAP and RIGED for different CT images are represented in Fig. 4.

It is clear from above figure that for different CT image samples, entropy after prediction by 2D predictor is less as compare to entropy of original image. So it is depicted that lower number of bits are required to encode the image if prediction is done before encoding. Efficiency of predictor depends upon the entropy value, lower the entropy value, more efficient is the predictor. From the above figure, it is clear that RIGED achieved minimum value of entropy so it is efficient than other predictors.

Analysis of 2D Predictors for CT Images in Terms of Entropy Value for Varying Image Resolutions: Analysis of 2D predictors for CT images of varying resolutions is

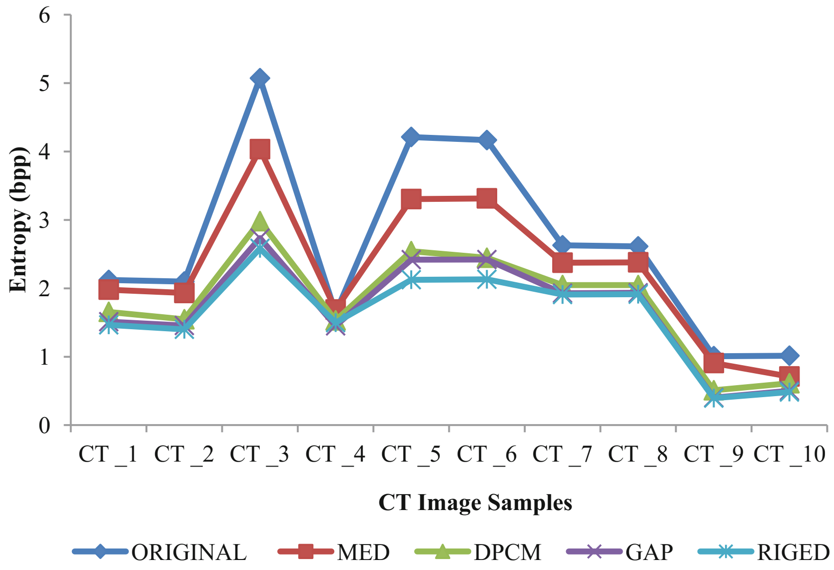

Fig. 4. Entropy values of original image residual image predicted from MED, DPCM, GAP and RIGED predictor for CT image samples.

also carried out in terms of entropy values. Average entropy values for different resolution obtained from 2D predictors are represented graphically in Fig. 5. It is depicted from the figure that entropy value obtained from lower resolution image is larger than higher resolution image. When resolution increases, entropy value of images decreases as shown in figure below. Entropy values obtained from different 2D predictors for 256 × 256 resolution is large as compare to 512 × 512. For resolution in between 256 × 256 and 512 × 512, entropy values are lie between the entropies of 256 × 256 and 512 × 512.

3.2 Analysis in Terms of Other Performance Metrics

In Terms of Root Mean Square Error: Analysis of 2D predictors is also done with reference to other performance metrics. Root mean error square of prediction error image or residual image is obtained that is shown in Table 2. Lower the value of RMS, better will the prediction and interpixel redundancy is also better removed. It is clear from the table below that RMSE of residual image calculated from GAP is lowest as compare to MED and DPCM. RIGED gave better results than MED, DPCM and approximately same values of error as that of GAP. GED is optimum combination of simplicity and efficiency. It is pointed that RMSE of prediction image is better obtained by RIGED as compare to other predictors.

In Terms of Peak Signal to Noise Ratio: Peak signal-to-noise ratio is also calculated for different image samples of CT-Scan as shown in Table 3 similar to the previous discussion. Optimal result of PSNR is achieved by RIGED. MED predictor gave lowest

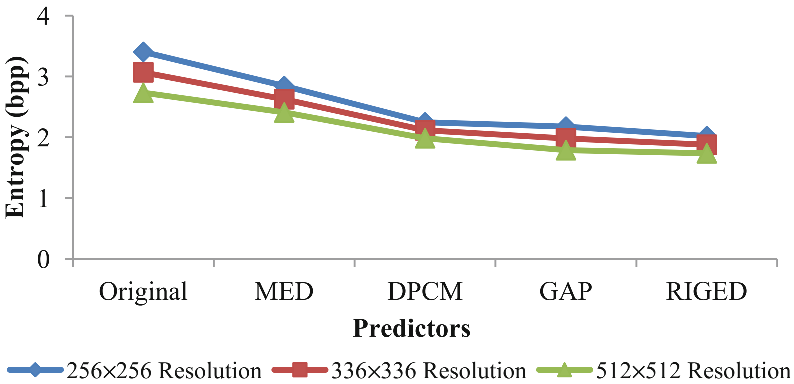

Fig. 5. Average entropy values of original image residual image predicted from MED, DPCM, GAP and RIGED predictor for CT image samples having different resolution.

Table 2. RMSE values for CT images having different resolutions

Medical images test samples	Image size	RMSE			
		MED	DPCM	GAP	RIGED
CT_1	256 × 256	18.707	4.231	3.888	3.695
CT_2	256 × 256	18.328	4.112	3.792	3.574
CT_3	256 × 256	33.618	5.1679	3.736	3.269
CT_4	256 × 256	11.245	5.405	4.377	4.836
CT_5	512 × 512	34.148	10.124	14.741	14.671
CT_6	512 × 512	33.724	9.998	14.497	14.434
CT_7	512 × 512	29.449	8.916	7.796	8.313
CT_8	512 × 512	30.219	9.075	8.190	8.680
CT_9	336 × 336	3.463	1.387	1.336	1.298
CT_10	336 × 336	5.221	1.235	1.145	0.996

value of PSNR as compare to other predictors but it has advantage of simplicity. GAP achieved good results in terms of PSNR but it is computationally complex predictor. RIGED achieved comparable values of PSNR and it is also simple to implement.

In Terms of Similarity Index: Another quality parameter Structural Similarity Index (SSIM) is also calculated for predicted image. It shows the similarity between predicted image and original image. Its value is in the range from 0 to 1 and if the SSIM of predicted image approaches value 1 then it is more similar to original image whereas approaching to 0 shows the dissimilarity between the images. Values of SSIM for various CT images from 2D predictors are given in Table 4.

It is seen from the above Table that RIGED achieved maximum values of SSIM for different CT test image. RIGED is highly efficient than other 2D predictors and it is also simple to implement.

Table 3. PSNR values for CT images having different resolutions

Medical images test samples	Image size	PSNR			
		MED	DPCM	GAP	RIGED
CT_1	256 × 256	22.690	35.600	36.337	36.778
CT_2	256 × 256	22.868	35.849	36.557	37.067
CT_3	256 × 256	17.599	33.864	36.702	37.840
CT_4	256 × 256	27.111	33.473	35.310	34.441
CT_5	512 × 512	17.463	28.023	24.760	24.801
CT_6	512 × 512	17.571	28.132	24.905	24.943
CT_7	512 × 512	18.749	29.126	30.293	29.735
CT_8	512 × 512	18.525	28.973	29.866	29.360
CT_9	336 × 336	37.341	45.286	45.619	45.863
CT_10	336 × 336	33.774	46.296	46.970	48.158

Table 4. SSIM values for CT images having different resolutions

Medical images test samples	Image size	SSIM			
		MED	DPCM	GAP	RIGED
CT_1	256 × 256	0.980	0.832	0.988	0.989
CT_2	256 × 256	0.981	0.836	0.989	0.990
CT_3	256 × 256	0.972	0.414	0.983	0.983
CT_4	256 × 256	0.944	0.859	0.960	0.957
CT_5	512 × 512	0.989	0.714	0.990	0.993
CT_6	512 × 512	0.989	0.724	0.990	0.993
CT_7	512 × 512	0.978	0.847	0.985	0.987
CT_8	512 × 512	0.979	0.846	0.986	0.987
CT_9	336 × 336	0.992	0.975	0.993	0.992
CT_10	336 × 336	0.995	0.965	0.996	0.997

4 Conclusion

For the lossless compression of medical images, predictive coding performs better as it is simple to implement and most essential it provides lossless compression with less storage space, low bandwidth and less transmission time. Different 2D predictors MED, DPCM, GAP and RIGED are used in this research work to removes interpixel redundancy of the image. Performance parameters such as entropy, RMSE, PSNR and SSIM are calculated after prediction for all these predictors. It is calculated from various experiments conducted that GED predictor at good threshold value (RIGED) can achieve comparable results as that of most efficient GAP predictor. RIGED is also simple to implement as that of MED and also provides efficient results.

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