Reversible data hiding for medical images using segmentation and prediction

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Abstract- *Data hiding and embedding techniques assumes an important role to ensure safe and secure sharing of data in the modern era as data hacking is becoming very common. Unified data embedding and scrambling method along with reversible histogram shifting serve this purpose. Here the problem is once the embedded data is extracted the quality of the output image gets affected. In this study, Quad tree segmentation is used in segmentation of the image and neighborhood prediction method is used to embed data into a digital image in order to improve the quality of the output or reconstructed image. Prediction error is calculated and adjusted to minimum. The predicted pixels from the segmented image are vacated and the secret data pixels are inserted into those positions. The embedded image is extracted using reversible technique. The quality of the host image and the reconstructed image is measured by SSIM value. With the current experiment a SSIM value of 0.999is achieved for the reconstructed image.*

Index Terms: *DATA EMBEDDING, NEIGHBORHOODPREDICTION, RECONSTRUCTION, QTS,SSIM*

I. Introduction

THE internet, a worldwide communication network has revolutionized our daily life like nothing before. The World Wide Web allows people to share information and the E-mail technology connects people in far-flung corners of the world. A new paradigm of commerce allows individuals to shop online thus, millions of unsecured computer networks are communicating continuously among each other. The security of stored information depends upon the security of the other computer to which it is connected or it is being communicating. We are sensing a need to improve information security in the recent past due to the growing threat of cyber-attacks. There are possibilities that, personal and other business information become casualties if data is left undefended. For fond memories we need to keep information about every aspect of our life and there lies threat of this information being misused or being hacked.

In other words, information is an asset that has a value like any other asset [1].To be secure, information needs to be hidden from unauthorized access, protected from unauthorized change and should be made available to an authorized entity when it is needed.Network security is a set of protocols that allows using the internet comfortably without worrying about security attacks. The most common tools for providing network security are cryptography (an old technique that has been revived) and steganography.

Cryptography a word with Greek origin means “Secret Writing” [2]. However we use the term to refer the science and art of transforming messages and enabling them secure and immune to attacks. The word steganography, in Greek means “Covered Writing”; it’s an art of concealing the message by covering it with something else. The key concept behind steganography is that the message to be transmitted is not detectable by the casual eye. In fact people who are not intended to be the recipients of these messages should not even suspect that a hidden message exists [3]. The combined, steganography and cryptography can provide two levels of security to stored information’s. A computer program can encrypt a message using cryptography and hide the encryption within the image using steganography.

Data hiding plays a major part in transmission of patient records in the medical field and can have wide applications in the field of Tele- medicine. Modern medical equipments produce mass digital images and data day by day. The integrity of such records needs to be protected from unauthorized modification and observation. Water marking can be used as an effective tool to secure medical information, but with cryptography, confidentiality and integrity of information can be achieved by hiding the Electronic Patient Record (EPR) data in corresponding medical images. Simultaneously, care should be taken that the diagnostic quality of the medical images should not be compromised. Data hiding in the field of medical images opens up new challenges and is becoming a new research focus.

In general data hiding technique for digital content can be classified into two, one is data embedding and the other is data encryption[4]. Data embedding is further classified in two categories, reversible and irreversible. Irreversible technique has many disadvantages; reconstruction of the original image results in permanent loss of information after embedding and the host image cannot be completely recovered or the quality achieved is very poor. On the other hand, with reversible technique, the quality of the reconstructed image can be completely recovered.

The present study was conducted using, quad tree segmentation for segmenting images, neighborhood prediction to embed data and reversible technique for extraction of data. A quad tree is a tree data structure in which each internal node has exactly four blocks. A main point of quad tree segmentation is the evaluation criterion of image segmentation. In a quad tree decomposition, a judgment is first made to see whether a block can be represented by a single gray value or whether it must be divided into four sub blocks. Quad trees are most often used to partition a two-dimensional space by recursively subdividing it into four quadrants or regions [5], [6]. A reversible technique means the original input image can be losslessly restored after the embedded information is extracted.

In the present study some of the most efficient techniques suitable for data hiding in medical images were discussed.

II. Related work

In this section, reversible data hiding methods in literature are reviewed. In spatial domain, Histogram shifting, Vector quantization and SMVQ are most recently used methods of data hiding.

Xiao Bo *et al.* proposes “Reversible Data Hiding using Histogram Shifting in Small Blocks”[7] to reversible data hiding in bitmap image. Embedding is not carried out in the whole image but in small blocks in order to enhance the capacity. Firstly, the blocks are classified, and then, coding methods specific to each type of block are designed. Secondly, some blocks become unavailable for a second time embedding after the first one, while others are naturally unavailable. So as to separate these two kinds of blocks from each other, the status of blocks are defined, and a scheme of reserving blocks for taking identification information is proposed. Thirdly, the overall procedure of data embedding, extracting and image recovering are summarized.

Test results on well-known images demonstrate the effectiveness of the new approach. The new method increases the total capacity of reversible data hiding to 1-4 times of the conventional method, and surprisingly, it also improves the PSNR value at the same time.

It is discussed about Histogram Shifting Algorithm to

improve the PSNR value. This measure is simple to calculatebut sometimes doesn't align well with perceivedquality by humans. For example, the PSNR for a blurred imagecompared to a unblurred image is quite high, even though the perceived quality is low. But it does not concentrate on the SSIM value. The Structural Similarity Index Measure (SSIM) [8] of quality works by measuring the structural similarity that compares local patterns of pixel intensities that have been normalized for luminance and contrast.

Rahmani *et al.* proposes a “Reversible data embedding scheme based on search order coding for VQ index tables”[9]. Thispaper describing vector quantization (VQ)-compressed images based on search order coding (SOC). Data is embedded by choosing one of the possible ways to represent each embeddable index and outputted code is legitimate SOC code. The proposed scheme has two advantages. First it is more secure, comparing with previous SOC based schemes that generate non-legitimate codes as output. Second it can be used beside other schemes to embed moredata and also it is a solution for the problem of transmission of side information of schemes which their outputs are legitimate VQ codes. But this work does not concentrate on thequality of the image. After extraction the output image and original image does not achieve the quality metrics.

Chia-Chen Lin and Xue-Bai Zhang proposes “A High Capacity Reversible Data Hiding Scheme Based on SMVQ”(side match vector quantization)[10]. According to the scheme, they can directly reconstruct the original SMVQ compression code for the receiver to store the cover image in a saving storage space after extracting the secret messages. As an improvement to the existing techniques, they used a data-reading approach in which the data were divided into three categories and an ordering method was used to distinguish between the odd and even positions of the codeword. The experimental results demonstrated that this scheme enhances the embedding capacity and image quality to a certain limit but the process does not achieve a high quality.

III. Data hiding using quadtree segmentation with neighborhood prediction method

In this study the input image is segmented using quad tree segmentation method, neighborhood prediction method is used to predict pixel values of the segmented image, the data is embedded by replacing predicted pixels and reversible technique is used to reconstruct the embedded image.The block diagram for the proposed method is shownin fig-1.

Fig.1 Block Diagram for Prediction and Reconstruction

i). Quad tree Segmentation

Compared with other imaging technique,MRI imaging technique has the advantages of relatively high tissue contrast resolution,direct,non-invasive and non-ray examination ability and has been widely used in medical imaging[11]. The MRI scan image is given as input to the quad-tree segmentation (QTS).Quad tree decomposition is a simple technique for image representation at different resolution levels,which partitions an image into variable block size region based on a quad tree structure[12], [13], 14].Studies have demonstrated that quad tree based image segmentation can be effective and an efficient mechanism for isolatingblocks of distinct perceptual significance and thereby allowing different coding strategies that are perceptually suited to the individual segment categories. It divides a square image into four equal-sized square blocks, and then tests each block to see if it meets some criterion of homogeneity as shown in fig-2. If a block meets the criterion, it is not divided any further. If it does not meet the criterion, it is subdivided again into four blocks, and the test criterion is applied to those blocks. This process is repeated iteratively until each block meets the criterion. The result can have blocks of several different sizes.Quad tree segmentation is a segmentation based on equality inspect image. The following defines the concept of quad tree method:

R said that an image, segmentation is an process which divided into n sub-regions R1,R2,…,Rn and it must satisfy the following conditions:

1. $\cup_{i=1}^{n} R_i = R$

2. R_i is a connected domain. i=1,2,…,n.

3.$R_i \cap R_j = \emptyset$ for all i and j, i≠j.

4. $P(R_i)$ = True, for i = 1,2,…,n.

5. $P(R_i \cup R_j)$ = False, for any adjacent area: R_i and R_j

WhereP(R_i) is defined in the set of points R_i predicate logic, ∅ is the empty set[15].

In QTS method, MRI scan image is used as host image. First of allthis process decides on whether a further division is required or not. For that, the payload is found out for each sub blocks individually. If the payload size of the four blocks is larger than that of incoming block, then the incoming block is further divided into another four sub blocks. The process is continued until all the block partitions are traversed.

Generate a histogram h(x) of the original image or the host image I. Find the maximum and minimum points M and Z respectively from the histogram using the eqn.(1) and (2) .

$$M = arg_x \max h(x) \quad \text{------- eqn.(1)}$$

$$Z = arg_x \min h(x) \quad \text{-------eqn.(2)}$$

The host image I is divided in to sequence of non-overlapped blocks b1,b2…bp. Here the payload for the actual secret data is calculated using the eqn.(3).

$$PL(I) = h(M) - \log(N)^2 \times h(Z) - 16 \quad \text{---------eqn.(3)}$$

The total payload size is defined by the eqn.(4)

$$PL1(I,P) = \sum_{i=1}^{P} h_i(M_{i,1}) - (\log N)^2 \times \sum_{i=1}^{P} hi(Z_{i,1}) - P \times 16 \text{-------eqn.(4)}$$

Where ($M_{i,1}$) and ($Z_{i,1}$) is the pair of maximum and minimum points of the i^{th} image block and I =1.. P. When total payload size of the incoming block is higher than the actual payload of the block, the incoming block is partitioned into four sub blocks otherwise the incoming block is considered as a terminal node. Therefore no further partition is needed.

ii). Neighborhood Prediction Method (NPM)

After getting segmented image,Neighborhood prediction method was applied to predict pixel values in the image. Each pixel prediction is based on threshold value. In this case the threshold is chosen by 1≤ e≤31.The segmented image block pixels are stored as row and column. The target pixel is estimated by using NPM and the neighboring pixels are stored as future reference as shown in fig.2.

a	b	c
d	X	e
f	g	h

Fig.2. Single block with neighborhood of the target pixel X

Each prediction error denoted as e is computed as e=x-xp. Where x and xp are the original and predicted value. The e is analyzed to decide if the corresponding pixel location is suitable for data embedding. In particular, if e falls within the predefined range as expressed in eqn.(5) ,

$$-\varepsilon \leq e \geq \varepsilon \quad \text{--------eqn.(5)}$$

Where $\varepsilon \in N$, then it is utilized for data embedding purpose. Otherwise it will be left unmodified. I classify all pixels in an image into three categories, namely, not-predicted (NP), predicted but not embedded (PN) and predicted-and-embedded (PE). Here,the set of NP consists of all the reference points in every other column and row, which is utilized to predict the rest of the pixels using the proposed NPM method. Next, PN refersto a pixel whose prediction error (*e*)fails the condition in eqn.(5). In other words, PN is a pixel that cannot be predicted accurately by the proposed NPM method, and it is not considered for data embedding. Thus, PN holds the original pixel value. Finally, PE refers to a pixel that satisfies eqn.(5), and it is utilized for data embedding. Here, the prediction error (*e*) is stored as external information. In this case, where an external information is required to extract the embedded information and to reconstruct the original cover image. The actual intensity value is stored (ie., NP and PN), no information is embedded. In other words, the pixel value is either not predicted or it is predicted but not vacated for data embedding because the error fails eqn.(5). Therefore, there is no embedded information to be extracted and there is no modification the host image which needs to be restored. NPM is the efficient pixel estimation technique which can be used in various applications, including biomedical image segmentation, data embedding and pattern recognition.

iii). Reconstruction

In the existing methods three levels of predictions are used and with increase in the levels of prediction the *e* also increased, thus reducing the quality of reconstructed image.

Here, in this study, quad tree segmentation process is used. In quad tree segmentation, the host image is segmented into four blocks, thus reducing the image size. Application of neighborhood prediction method, predicts the pixels suitable for data embedding and other pixels remains unchanged. External information and not-predicted (NP) pixels are used to reconstruct the image. With the pixel values of NP and PN remaining unchanged only the values of PE pixels are reconstructed with pixels of secret data which I intends to embed into the image. The *e*pixels storethe external information. The XOR process mixes and converts the values of PE and *e* into the embedded image. The *e* values are captured at higher accuracy to improve the quality of reconstructed images.With the reversible method the pixels used in embedding data are reconstructed to the original values, so that I get the host image unchanged.

IV. Experimental Results and Discussion

The present study wasa comparison of check board prediction method and quad tree segmentation with neighborhood prediction method for SSIM values ie., the quality of the reconstructed image and was implemented using Matlab R2012a Version 7.14.0739. MRI scan digital images taken as the test images are considered for experimental purposes. MR images which include brain,neck,head,knee and abdomen, the image size of which is 512 pixel ×320 pixel,with both horizontal and vertical resolution at 96 dpi, 8 bit depth grayscale was used. It was verified by visual inspection that the host image is severely disturbed by embedding secret information into it. The distortion level was controlled by changing ε. It was also verified that whether the embedded information can be completely extracted and whether the quality of the reconstructed image is controllable.

In the present study, the quality of the reconstructed image was investigated using check board prediction method and was compared with the quality of the reconstructed image using quad tree segmentation andneighborhood prediction method. The image metrics are measured with SSIM value. The Structural Similarity Index Measure (SSIM) of quality works by measuring the structural similarity that compares local patterns of pixel intensities that have been normalized for luminance and contrast and the quality metric is based on the principle that the human visual system is good for extracting information based on structure.

The study was conducted using check board prediction method and it was found that, for MR image of brain, when ε=0 and at L=1 I got the SSIM value of 0.9791while for L=2 I got SSIM=0.9662and at L = 3 the same was observed as 0.9533. While, when ε=1 and at L=1 I got the SSIM value of 0.9795 while for L=2 I got SSIM=0.9685 and at L = 3 the same was observed as 0.9561. Similarly when ε=25 at L=1 I got the SSIM value of 0.8968 while for L=2 I got SSIM=0.8925 and at L = 3 the same was observed as 0.8967.

For MR image of Neck, when ε=0 and at L=1 I got the SSIM value of 0.9793 while for L=2 I got SSIM=0.9666 and at L = 3 the same was observed as 0.9580. While, when ε=1 and at L=1 I got the SSIM value of 0.9779 while for L=2 I got SSIM=0.9645 and at L = 3 the same was observed as 0.9573. Similarly when ε=25 at L=1 I got the SSIM value of 0.8900 while for L=2 I got SSIM=0.8972 and at L = 3 the same was observed as 0.8929.

For MR image of head, when ε=0 and at L=1 I got the SSIM value of 0.9784 while for L=2 I got SSIM=0.9682 and at L = 3 the same was observed as 0.9536. While, when ε=1 and at L=1 I got the SSIM value of 0.9794 while for L=2 I got SSIM=0.9686 and at L = 3 the same was observed as 0.9538. Similarly when ε=25 at L=1 I got the SSIM value of 0.8987 while for L=2 I got SSIM=0.8979 and at L = 3 the same was observed as 0.8975.

For MR image of knee, when ε=0 and at L=1 I got the SSIM value of 0.9773 while for L=2 I got SSIM=0.9620 and at L = 3 the same was observed as 0.9587. While, when ε=1 and at L=1 I got the SSIMvalue of 0.9740 while for L=2 I got SSIM=0.9652 and at L = 3 the same was observed as 0.9558. Similarly when ε=25 at L=1 I got the SSIM value of 0.8933 while for L=2 I got SSIM=0.8931 and at L = 3 the same was observed as 0.8942.

For MR image of abdomen, when ε=0 and at L=1 I got the SSIM value of 0.9739 while for L=2 I got SSIM=0.9668 and at L = 3 the same was observed as 0.9529. While, when ε = 1 and at L=1 I got the SSIM value of

0.9746 while for L=2 I got SSIM=0.9621 andat L = 3 the same was observed as 0.9533. Similarly when ε = 25 at L=1 I got the SSIM value of 0.8949 while for L=2 I got SSIM=0.8977 and at L = 3 the same was observed as 0.8963.

In all the images used, it was found that when ε is increased the SSIM values are found to be decreasing;similarly if the levels are increased from 1 to 2 and 3 for each of the ε the SSIM values are found decreasing. It's observed that the

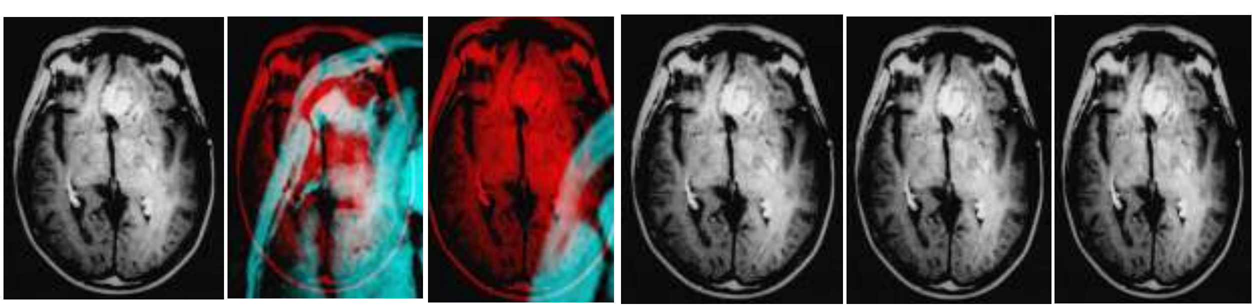
quality of images was found superior when the SSIM values are approaching 1.

Similarly the SSIM value for reconstructed image from various MRI scan images for various combinations of ε and L were studied using check board prediction method and the results are reported in Table I and the quality of the images at various levels of data embedding is shown in Fig.3

Table 1: SSIM Values for Check Board Prediction Method

Image	ε=0			ε=1			ε=2			ε=8			ε=25		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Brain	0.9791	0.9662	0.9533	0.9795	0.9685	0.9561	0.9783	0.9628	0.9556	0.9592	0.9474	0.9378	0.8968	0.8925	0.8967
Neck	0.9793	0.9666	0.9580	0.9779	0.9645	0.9573	0.9973	0.9668	0.9529	0.9746	0.9621	0.9533	0.8900	0.8972	0.8929
Head	0.9784	0.9682	0.9536	0.9794	0.9686	0.9538	0.9795	0.9685	0.9561	0.9583	0.9428	0.9339	0.8987	0.8979	0.8975
Knee	0.9773	0.9620	0.9587	0.9740	0.9652	0.9558	0.9772	0.9668	0.9580	0.9546	0.9466	0.9356	0.8933	0.8931	0.8942
Abdomen	0.9739	0.9668	0.9529	0.9746	0.9621	0.9533	0.9785	0.9667	0.9540	0.9594	0.9420	0.9340	0.8949	0.8977	0.8963

Fig. 3 Quality of the Images at Various Levels of Data Embedding Using Check Board Prediction Method



(a) (b) (c) (d) (e) (f)

(a) input image (b) CBP image for level 1 (c) prediction image for level 2 (d) final predicted image (e) text embedded image and (f) outputimage

The study was repeated using quad tree segmentation combined with neighborhood prediction method inorder to prove its superiority over the existing methods. Here also the same MR images of brain, neck, head, knee and abdomen were embedded with the data and the SSIM values were recorded at each levels.

For MR image of brain, when ε=0 the SSIM value was found to be 0.9946. While, when ε=1 I got the SSIM value of 0.9965, similarly when ε=25 I got the SSIM value of 0.9233.

For MR image of neck, when ε=0 the SSIM value was found to be 0.9994. While, when ε=1 I got theSSIM value of 0.9929, similarly when ε=25 I got the SSIM value of 0.9276.

For MR image of head, when ε=0 the SSIM value was found to be 0.9991. While, when ε=1 I got the SSIM value of 0.9971, similarly when ε=25 I got the SSIM value of 0.9260.

For MR image of knee, when ε=0 the SSIM value was found to be 0.9993. While, when ε=1 I got the SSIM value of 0.9975, similarly when ε=25 I got the SSIM value of 0.9249.

For MR image of abdomen, when ε=0 the SSIM value was found to be 0.9973. While, when ε=1 I got the SSIMvalue of 0.9995, similarly when ε=25 I gotthe SSIM value of 0.9237.The study reveals that when ε=0 the highest possible SSIM values was achieved and with increased ε values the SSIM values were found decreasing. i.e., the highest image quality for the reconstructed image was found with ε=0 and the lowest image quality was found with ε=25.

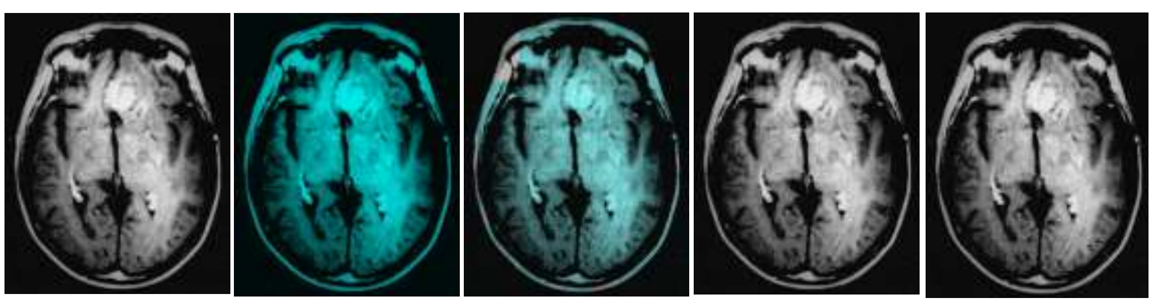
Similarly the trend observed in the present study was when the ε values lies between 0-2 there was a marginal difference in the SSIM values and when the ε values are increased beyond 2 there was a significant decrease noticedin the SSIM values. It is concluded that lower the prediction error threshold value, better the quality of the reconstructed image. The SSIM values for reconstructed image from various MRI scan images at different ε values were studied and the results arereported
in Table 2.

The image quality achieved at various levels of data embedding using the quad tree segmentation and neighborhood prediction methods depicted in Fig.4

Table 2: SSIM Values for Present Study Using Quad Tree Segmentation and Neighborhood Prediction Method

Image	ε=0	ε=1	ε=2	ε=8	ε=25
Brain	0.9946	0.9965	0.9994	0.9795	0.9233
Neck	0.9994	0.9929	0.9958	0.9754	0.9276
Head	0.9991	0.9971	0.9933	0.9746	0.9260
Knee	0.9993	0.9975	0.9980	0.9779	0.9249
Abdomen	0.9973	0.9995	0.9951	0.9768	0.9237

Fig. 4 Quality of the Images at Various Levels of Data EmbeddingUsing Quad Tree Segmentation and Neighborhood Prediction Method

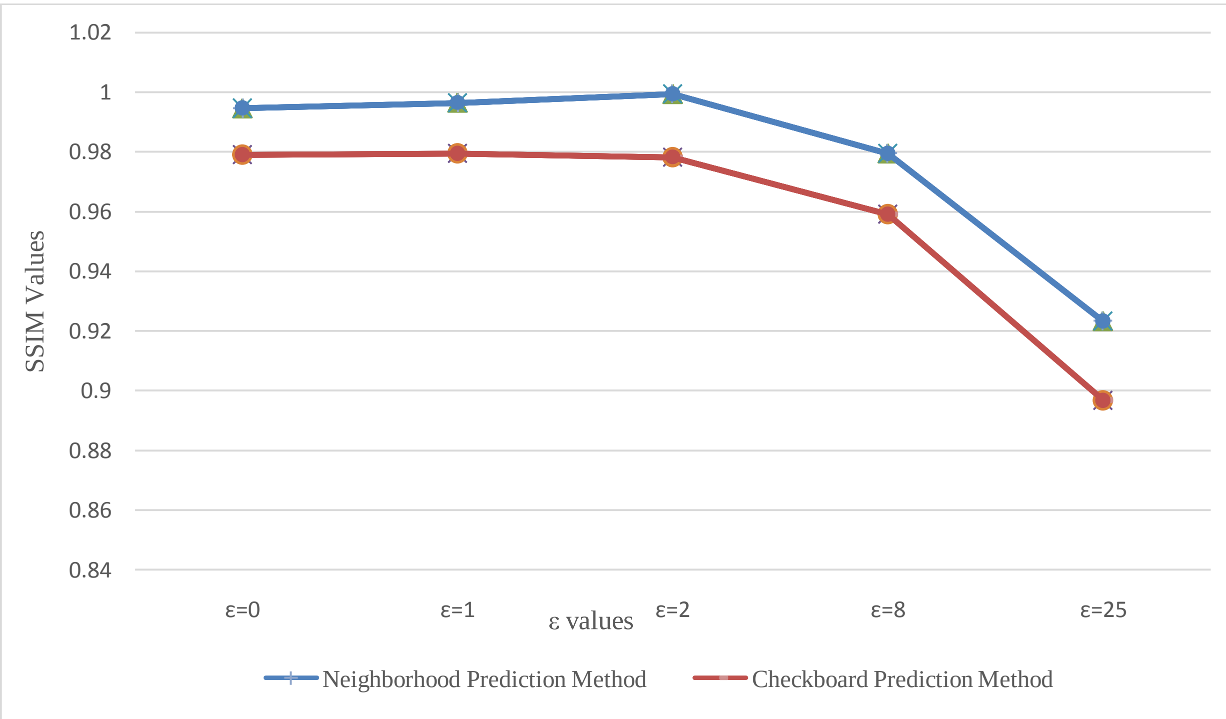


(a) (b) (c) (d) (e)

(a) input image (b) decomposed image blocks (c) decomposed image (d) text embedded image (e) output image

For MR image of brain, by using checkboard prediction method the higher SSIM value achieved at ε=0 and L=1 was 0.9791 while by using quad tree segmentation and neighborhood prediction method, the maximum SSIM value achieved was found 0.9946 when ε=0. For MR image of neck the higher SSIM value achieved at ε=0 and L=1 was 0.9793 while by using quad tree segmentation and neighborhood prediction method, the maximum SSIM value achieved was 0.9994 when ε=0. For MR image of head the higher SSIM value achieved at ε=0 and L=1 was 0.9784 while by using quad tree segmentation and neighborhood prediction method, the maximum SSIM value achieved was 0.9991 when ε=0. For MR image of knee the higher SSIM value achieved at ε=0 and L=1 was 0.9773 while by using quad tree segmentation and neighborhoodprediction method, the maximum SSIM value achieved was 0.9993 when ε=0. For MR image of abdomen the higher SSIM value achieved at ε=0 and L=1 was 0.9739 while by using quad tree segmentation and neighborhood prediction method, the maximum SSIM value achieved was 0.9973 when ε=0. In all the cases it was found that the SSIM values obtained in the present study were more than the SSIM values obtained from other existing methods, which suggests data embedding using quad tree segmentation and neighborhood prediction method is superior and yields better results in terms of quality of the reconstructed image. The performance comparisons using SSIM values of check board prediction method for brain image with L=1 and quad tree segmentation with neighborhood prediction methods are given in Fig.5

Fig.5 Performance Comparisons for CBP and NP Methods



V. Conclusion

In this work, data hiding techniques *viz*, QTS and NPM are used for embedding data in the image; QTS is used for segmentation and NPM for prediction. The image quality is measured by SSIM value. If SSIM value =1 then get exactly the quality of the input image as the quality of the output image. The existing methods gets an highest SSIM value of ≥ 0.979, while in the present study I got the highest SSIMvalue ≥0.999 for various MRI scan images, which suggest this method using quad tree segmentation and neighborhood prediction method is superior to the existing methods in data embedding and hiding for medical images.

VI. Future scope

In this case I am not concentrating for effective payload of the image. In future, I can concentrate the effective payload and also apply this method for various biomedical images and compression techniques.

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