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Adaptive threshold-based block classification in medical image compression for teleradiology

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Abstract

Telemedicine, among other things, involves storage and transmission of medical images, popularly known as teleradiology. Due to constraints on bandwidth and storage capacity, a medical image may be needed to be compressed before transmission/storage. Among various compression techniques, transform-based techniques that convert an image in spatial domain into the data in spectral domain are very effective. Discrete cosine transform (DCT) is possibly the most popular transform used in compression of images in standards like Joint Photographic Experts Group (JPEG). In DCT-based compression the image is split into smaller blocks for computational simplicity. The blocks are classified on the basis of information content to maximize compression ratio without sacrificing diagnostic information. The present paper presents a technique along with computational algorithm for classification of blocks on the basis of an adaptive threshold value of variance. The adaptive approach makes the classification technique applicable across the board to all medical images. Its efficacy is demonstrated by applying it to CT, X-ray and ultrasound images and by comparing the results against the JPEG in terms of various objective quality indices.

Keywords: Data compression; Telemedicine; Teleradiology; Discrete cosine transform (DCT); Medical image compression

1. Introduction

One of the greatest challenges facing humankind is to make high quality health care available to all. The World Health Organization (WHO) recommends that the WHO and its member states must integrate the appropriate use of health telematics in the overall policy and strategy for the attainment of health for all [1]. *Health Telematics* or *Telemedicine* is the delivery of health care and the exchange of health care information across distance. Teleradiology, one of the most used clinical aspects of telemedicine, has received a focused attention in the past few years. Basically, teleradiology attempts to transfer medical images of various modalities, like computerized tomography (CT) scans, magnetic resonance imaging (MRI), ultrasonography (US), and X-rays, etc. from one location to another. These transfers may be from one hospital to another, from an imaging center to a hospital, or from an imaging center or hospital to a physician's desk. Due to the bandwidth or storage limitations, the radiological images may be needed to be compressed before transmission to a distant location, or storage on picture archiving and communication system (PACS), or storage on the smart card of the patient.

Recently, there has been considerable interest in applying the lossy or irreversible compression for medical data, wherein the loss of fidelity must be contained to minimize diagnostic errors [2]. Lossy signal compression is achieved by processing the signal in the spatial/time domain or a transform domain [3–5]. In the transform domain, an invertible transform maps the signal to a set of coefficients. The transform typically is required to convert the statistically correlated input samples to a set of uncorrelated coefficients. For the purpose of compression, the dominant transform coefficients are retained and the remaining ones are discarded. The retained coefficients are then quantized and encoded for either storage or transmission. A transform is efficient if it can compact the energy in fewest of coefficients [6].

Discrete cosine transform (DCT) [7] is among the most popular transform techniques for image compression because of its high energy compaction capability. In fact several techniques to

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that end have been proposed in the literature. The computation time of full frame DCT on a whole image is high, so the image is usually divided into non-overlapping blocks of appropriate size, e.g., 8×8 or 16×16 pixels. The DCT is then computed for each block and a quantizer is applied to the transform coefficients. Block-based DCT is a fundamental component of many image and video compression standards like JPEG (Joint Photographic Experts Group) [8].

Recently DCT has been used in medical image compression. Tai et al. [9] gave a segmentation technique for medical image compression based on the local energy magnitude for segmentation of blocks of the image into different energy levels. A 3D cuboid, which is formed by grouping together the blocks with same energy level, is compressed using 3D DCT. Wu et al. considered DCT as a band pass filter which decomposes a block into equal size bands [10]. The task of compression of medical images is utilizing the spectral similarity among bands. Wu gave an adaptive sampling algorithm for medical image compression using DCT. A classification of blocks was used to enhance the compression [11]. Although DCT has been used very effectively in these works without any intangible loss of information, there exists a lot of scope for further improvement especially on the classification of blocks. The present paper proposes the use of an adaptive threshold for classification of blocks. Sampling of DCT coefficients is used to compute a set of "significant" coefficients as the compressed data. The decoder retrieves the significant coefficients directly from the compressed data and calculates the other coefficients using linear interpolation.

An improved block classification technique based on adaptive threshold is put forward in Section 2, which also presents classification and sampling algorithms. Various parameters used for evaluation of reconstructed image quality and results are given in Sections 3 and 4, respectively. Finally, the conclusions are presented in Section 5. Section 6 contains a summary of the paper.

2. Image compression using proposed classification of blocks

2.1. Encoder configuration

The encoder configuration presented in Fig. 1 has been selected for the present work. In DCT-based compression schemes, the original image is often divided into smaller blocks to get the advantages of reduced computational complexity and

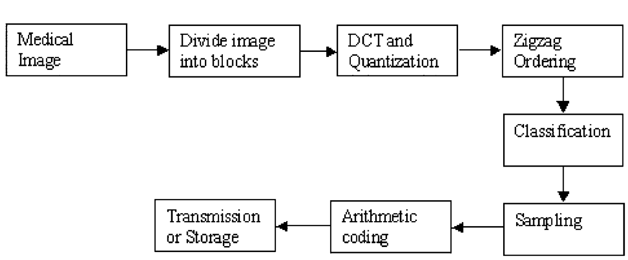

Fig. 1. Encoder configuration.

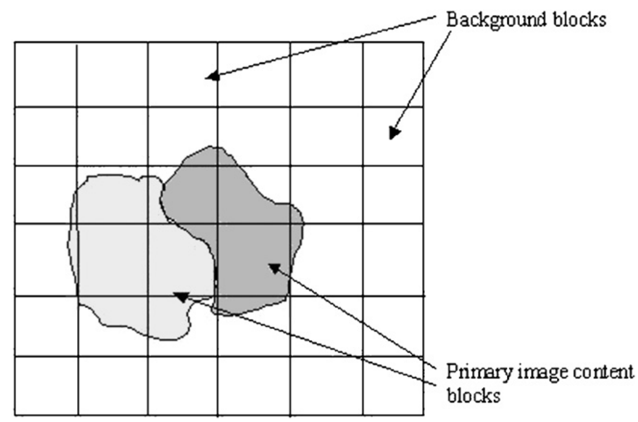

Fig. 2. Indicative medical image.

memory requirement. However, the achievable compression ratio (CR) reduces with smaller block size. Thus, a trade-off is to be maintained between computational complexity and CR in deciding the block size. In this work a block size of 16×16 pixels has been chosen [12]. Then the two-dimensional (2D) DCT is computed for each block and quantization is performed on the transform coefficients so obtained.

In the present study, sampling of 1D signals on the basis of the distortion area is carried out to compress medical images. However, the spectrum of medical images being 2D, a tool to transform 2D signals into 1D signals is required. The majority of the DCT coding schemes use *zigzag* scan for this purpose and the same is used here. The zigzag ordering helps to facilitate better entropy coding by first placing low-frequency coefficients, which are most likely to be nonzero, followed by high-frequency coefficients [8].

2.2. Proposed block classification technique

Medical images acquired in most radiological applications are visually examined by a radiologist. Therefore, any image compression method must ensure that there is no significant loss of diagnostic information for visual examination as well as subsequent medical image analysis. Medical images show characteristic information about the physiological properties of the structures and tissues. However, the quality and visibility of information depends on imaging modality and the response functions of the imaging scanner.

In medical images, most of the primary objects are typically located in the central region and the background is dark gray as shown in Fig. 2. Also the importance of every block inside the medical image is not the same. Thus the blocks can be classified into two categories, namely, *pure* and *complex*, based on variance in the block. The block with higher complexity has more information about the image, so more coefficients must be chosen to preserve the diagnostic information of the image.

As pure regions occupy most of the image and having minimum information content, better CRs can be obtained by retaining fewer coefficients in pure regions. As the nature of various imaging modalities is not similar, blocks of medical images from different modalities should be classified using an adaptive threshold, which would change with the imaging modality. It is proposed here to link the threshold with variance of blocks in an image. The allowable sampling distortion area limit (γ) for those regions located on the background is set higher as the primary image content in these regions is low.

2.3. Block classification algorithm

The variance in a data sequence $x(i)$ for a block can be obtained as follows:

$$\bar{x} = \frac{1}{n}\sum_{i=0}^{n-1} x(i), \tag{1}$$

$$v = \frac{1}{n}\sqrt{\sum_{i=0}^{n-1} (x(i) - \bar{x})^2}, \tag{2}$$

where $\bar{x}$ is the mean value of $x(i)$ and v is the variance of $x(i)$.

A threshold Th is then defined as

$$\mathrm{Th} = (v_{\min} + v_{\max})/2, \tag{3}$$

where $v_{\max}$ and $v_{\min}$ are maximum and minimum values of variance in the whole image. If variance v of a block is greater than the threshold Th, then the block is considered to be a complex block, else it is taken as pure.

Following is the algorithm used for the above computation process:

Here two classifications i.e. ($C = 2$) and a block size of 16×16 have been used; therefore, overhead cost is about 0.004 bits/pixel.

2.4. Sampling algorithm

To find the significant coefficients, a *sampling* algorithm is employed for the 1D coefficients that are generated by zigzag scanning. As the DC term is always considered an important sample, it is transmitted or stored in its original form. In this method initial points are selected and the distortion area is calculated. Approximate distortion can be found by the area formed by the straight line between the two significant coefficients and the original waveform [11]. The distortion area is the absolute sum of the differences between the predicted coefficients and the original ones. The algorithm for calculating distortion area is as follows:

d_area(): Calculates distortion area
Input: data sequence $x(i)$; start point $(a, x(a))$;
end point $(b, x(b))$;
Output: distortion area (δ)

Step 1: Create a linear equation between start point $(a, x(a))$; and end point $(b, x(b))$; using:

$$y'(x_i) = \frac{x(b) - x(a)}{b - a} \times (x_i - a) + x(a) \tag{5}$$

which estimates the value of y_i of any sample (x_i, y_i).

classify_block(): Classifies the blocks and sets the allowable distortion area limit
Input: Image of $N \times N$ Size
Output: distortion area limit (γ)

Step 1: Find the threshold (Th) for block classification using Eqs. (1)–(3).
Step 2: Decide the class of the blocks (pure or complicated)
if variance of block (v) > Th
/* Block is with more complexity */
Set the distortion area limit (γ) to a ***small*** value so as to accommodate more coefficients from this block.
else
/* Block is of pure nature with less complexity */
Set the distortion area limit (γ) to a ***large*** value so as to accommodate more coefficients from this block.
End
Step 3: Return γ.

The classification information must be transmitted to the decoder side for proper reconstruction of the image. The overhead (OH) of classification in terms of bits/pixel is defined as

$$\mathrm{OH} = \frac{\log_2(C)}{\mathrm{Blocksize}}\ \text{bits/pixel}, \tag{4}$$

where C is number of classifications.

Step 2: Calculate distortion area δ using equation:

$$\delta = \sum_{i=a+1}^{b-1} |x(i) - y'(i)|. \tag{6}$$

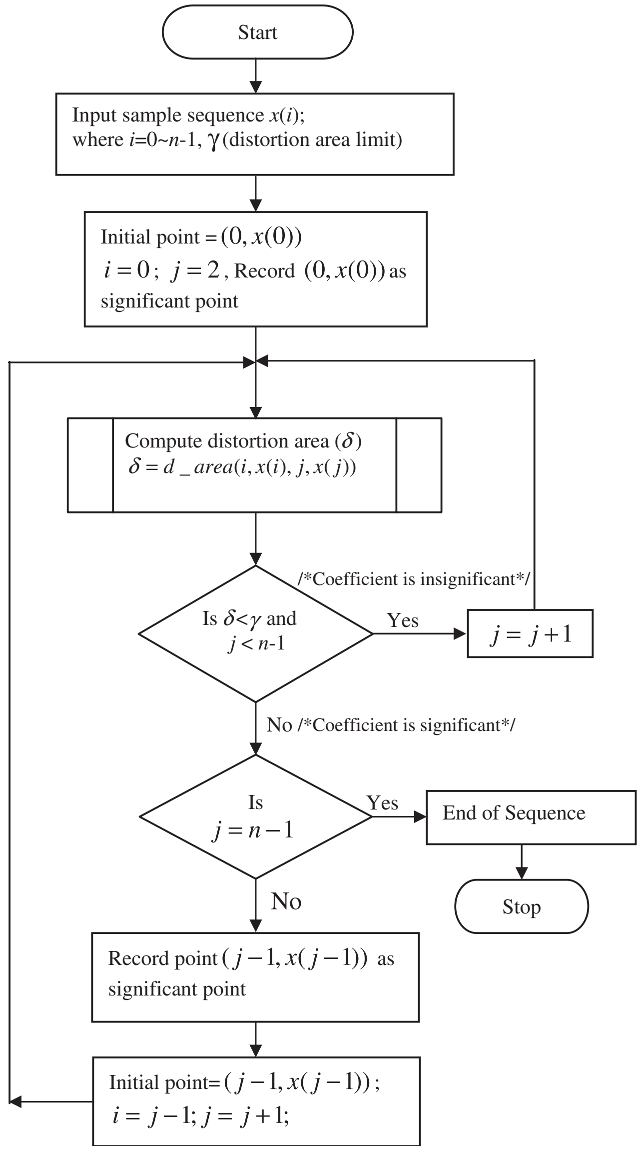

Fig. 3. Flow chart for finding significant coefficients in zigzag sequence.

Step 3: `Return` δ;
`exit ( );`

Let δ be the distortion area generated by p, $p(i)$ and $p(i+1)$. If $\delta > \gamma$ (distortion area limit), which is a constant specified by the user on the basis of classification of block, then p is selected as a significant sample, and the linear segment that connects by $p(i)$ and $p(i+1)$ is broken into two linear segments that connect $p(i)$ and p, p and $p(i+1)$, respectively. The same tests are carried out on each of these two linear segments repeatedly. The flowchart for finding the significant coefficients in zigzag sequence $x(i)$ is shown in Fig. 3.

Finally, arithmetic codes [13,14] for linear segments that connect the selected significant coefficients are generated and transmitted or stored. The decoder retrieves the significant coefficients from the compressed data directly and uses linear interpolation to reconstruct the other coefficients.

3. Reconstructed image quality assessment

A good processed image might be the one that is perceptually pleasing or useful in a specific application. There are three general approaches for quality measurement: (a) computable objective distortion measure such as mean squared error (MSE) or signal-to-noise ratio (SNR), (b) subjective quality as measured by psychophysical tests or questionnaires with numerical ratings, and (c) simulation and statistical analysis like diagnostic accuracy in medical images measured by clinical simulation and statistical analysis [15]. Approach (a) being the most scientific, has been chosen in the present work.

In this study following objective distortion measures have been applied:

(i) *MSE*: The MSE is defined as the mean of the square of the difference between the original and reconstructed pixels, x and x', and can be expressed as [15]

$$\mathrm{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[x_{i,j} - x'_{i,j}]^2, \tag{7}$$

where x and x' are the intensities of original and reconstructed pixels, respectively, $M \times N$ is the image size, and P is the maximum possible value of the pixel, e.g., 255 in an 8-bit gray level image.

(ii) *Peak PSNR*: The PSNR, in decibels (dB), can be evaluated as follows [15]:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{P^2}{\mathrm{MSE}}\right)\,\mathrm{d}B, \tag{8}$$

where P is maximum possible value of pixel, e.g., 255 in an 8-bit gray level image.

(iii) *Percent rate of distortion* (*PRD*): The PRD is another indicator of the reconstruction fidelity of compression method, and is given by [16]

$$\mathrm{PRD} = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[x_{i,j} - x'_{i,j}]^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}[x_{i,j}]^2}} \times 100. \tag{9}$$

(iv) *Correlation coefficient* (*CC*): The CC measures the degree to which the original and reconstructed images match and is given by [16]

$$\mathrm{CC} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} x_{i,j}x'_{i,j}}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(x_{i,j})^2}\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(x'_{i,j})^2}}. \tag{10}$$

(v) *Objective quality assessment using human visual system* (*HVS*) *properties*: In the last three decades, a great deal of effort has gone into the development of quality assessment methods that take advantage of known characteristics of the HVS. Very recently Wang et al. [17] developed a measure of structural similarity (SSIM) that compares local patterns of pixel intensities, normalized for luminance and contrast, based on the assumption that the HVS is highly adapted to extract structural information from the viewing field.

Suppose a and b are two nonnegative image signals. If one of the signals is considered to have perfect quality, then the similarity measure can be used as a quantitative measurement of the quality of the second signal as compared to original signal. It is computed as

$$\mathrm{SSIM}(a,b)=\frac{(2\mu_a\mu_b+C_1)(2\sigma_{ab}+C_2)}{(\mu_a^2+\mu_b^2+C_1)(\sigma_a^2+\sigma_b^2+C_2)}, \tag{11}$$

where μ_a, μ_b, σ_a and σ_b are mean intensities and standard deviations for a and b, respectively. C_1 and C_2 are constants. In discrete form σ_{ab} can be estimated as

$$\sigma_{ab}=\frac{1}{N-1}\sum_{i=1}^{N}(a_i-\mu_a)(b_i-\mu_b). \tag{12}$$

For image quality assessment, it is useful to apply the SSIM index locally rather than globally. The local statistics are computed within a local $w \times w$ square window, which moves pixel-by-pixel over the entire image. At each step, the local statistics and SSIM index are calculated within the local window. In practice, a single overall quality measure of the entire image is required. A mean SSIM (MSSIM) index to evaluate the overall image quality is computed as

$$\mathrm{MSSIM}(A,B)=\frac{1}{M}\sum_{i=1}^{M}\mathrm{SSIM}(a_i,b_i), \tag{13}$$

where A and B are the original and reconstructed images respectively; a_i and b_i are the image contents at the ith local window; and M is the number of local windows of the image.

4. Results

To demonstrate the effectiveness of the proposed method, it has been applied to 65 CT, 28 X-ray and 30 US images obtained from [18,19]. These are from various body parts like head, chest, and abdomen, etc. along with different abnormalities, e.g., hemorrhage, mass lesions, etc. The images are tagged and also contain the diagnostic information. The values of the distortion area limit for *pure* and *complex* sequences has been selected as 6.0 and 1.0, respectively, on the basis of bit rate and quality of reconstruction from empirical experiments. Modifying these thresholds affects the decoded quality and the bit rate.

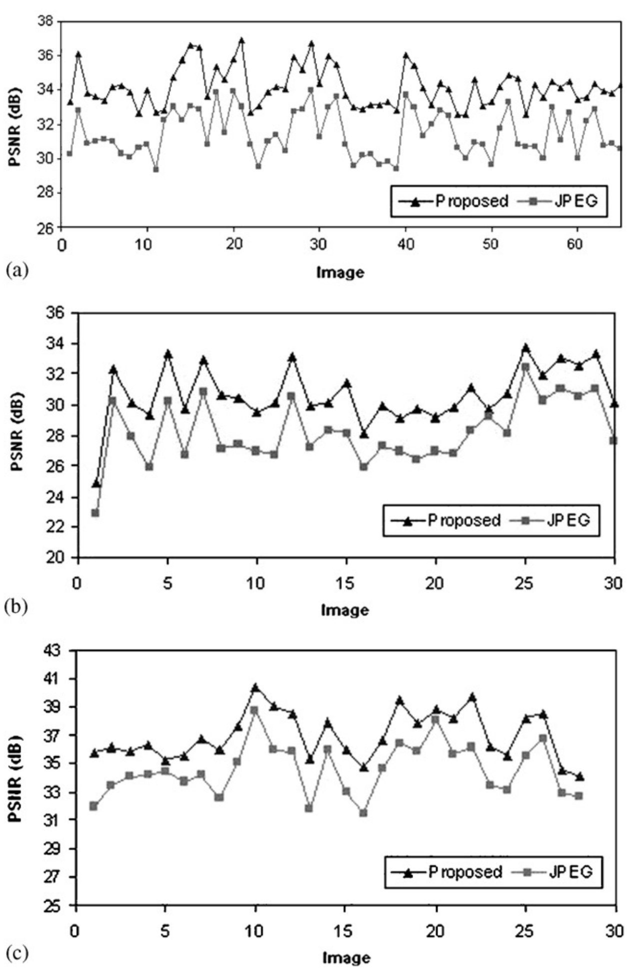

Fig. 4. PSNR comparison of proposed algorithm and JPEG for (a) CT, (b) US, and (c) X-ray images.

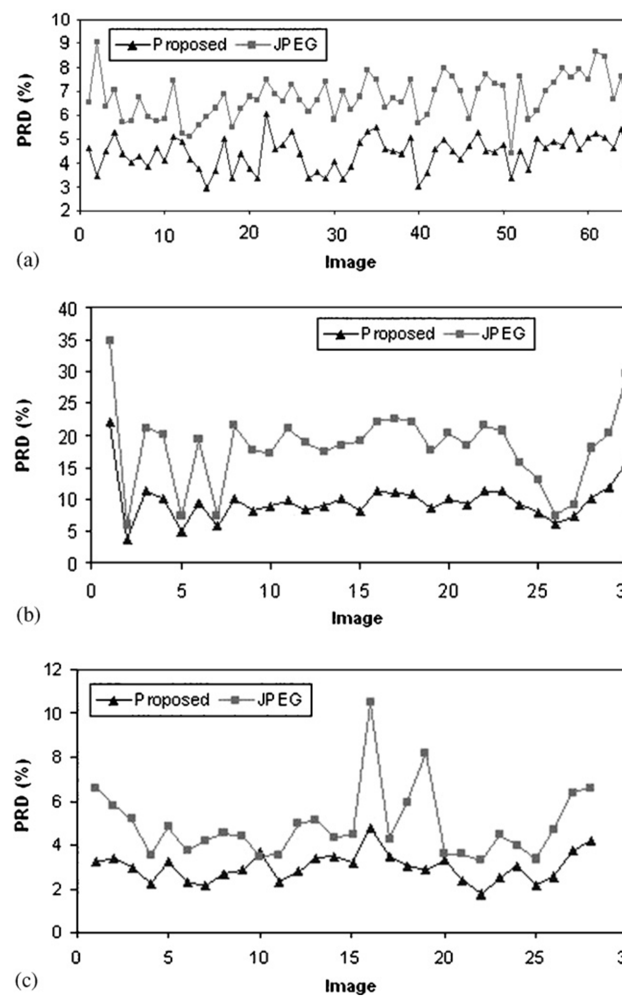

Fig. 5. PRD comparison of proposed algorithm and JPEG for (a) CT, (b) US, and (c) X-ray images.

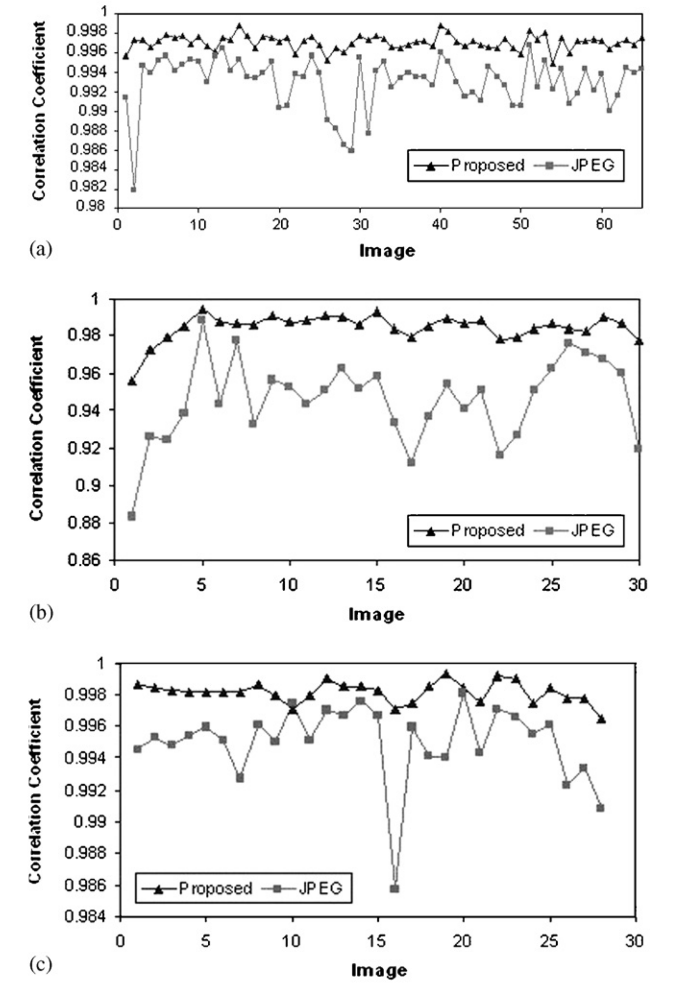

Fig. 6. Correlation coefficient comparison of proposed algorithm and JPEG for (a) CT, (b) US, and (c) X-ray images.

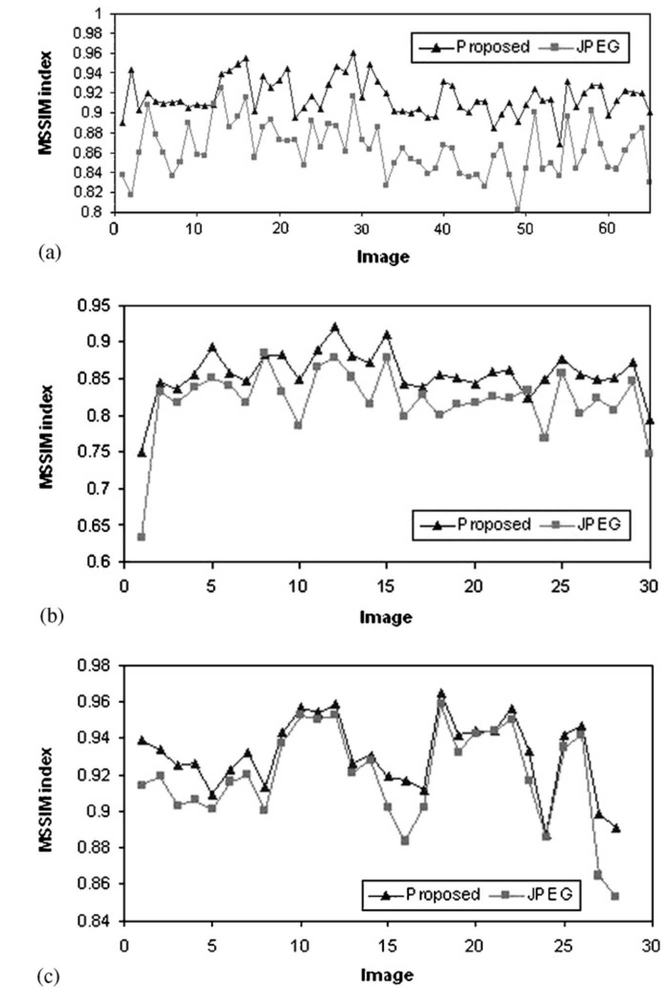

Fig. 7. MSSIM index comparison of proposed algorithm and JPEG for (a) CT, (b) US, and (c) X-ray images.

In general, optimal distortion area limit sets can be determined for every kind of medical image if repetitive experiments are conducted.

For comparison, a JPEG compressor also codes the same test images. The performance (PSNR) of the proposed method has been found to be much better than JPEG under the same bit rate or CR. Fig. 4(a) shows the comparison of the proposed algorithm with JPEG in respect of PSNR of different CT images.

It is found that there is an improvement of 2.73 dB on average in case of CT images. The proposed method gave best performance of 3.93 dB higher PSNR than JPEG and the minimum improvement of 0.59 dB higher than that of JPEG.

The comparison of PSNR values for US images is given in Fig. 4(b). It has been observed that there is an improvement of 2.53 dB on an average in case of US images. The proposed method gave best performance of 3.46 dB higher PSNR than JPEG and lowest improvement of 0.44 dB higher than that of JPEG.

Similarly, the comparison of PSNR for X-ray images is presented in Fig. 4(c). There is an improvement of 3.74, 2.39, and 0.72 dB for best, average, and worst cases, respectively, for various X-ray images when compressed using the proposed method over JPEG at same CR.

Hence it can be concluded that the proposed method outperforms the JPEG method in terms of PSNR. This conclusion is further supported by the other evaluation parameters also.

The comparisons of PRD for different images of CT imaging modality are presented in Fig. 5(a).

It is evident from Fig. 5(a), that the PRD is increased when the JPEG method is applied to compress a CT image at the same CR as in the proposed method, which is undesirable. For most of the CT cases, the PRD is significantly less in the proposed method as compared to JPEG.

Similar findings have been made for the images of other imaging modalities as presented in Fig. 5(b) and (c), respectively.

The comparison of CC for CT images is presented in Fig. 6(a). It can be observed from Fig. 6(a) that the proposed method preserves better correlation than JPEG for different CT images.

Results of CC given in Fig. 6(b) and (c) for different images of US and X-ray imaging modalities, respectively, further validate that proposed method is better than JPEG.

Fig. 8. CT image: (a) original image; (b) reconstructed image with proposed method; and (c) reconstructed image with JPEG.

Fig. 9. US image: (a) original image; (b) reconstructed image with proposed method; and (c) reconstructed image with JPEG.

Fig. 10. X-ray image: (a) original image; (b) reconstructed image with proposed method; and (c) reconstructed image with JPEG.

SSIM index is based on a measure of SSIM that compares local patterns of pixel intensities, normalized for luminance and contrast, based on the assumption that the HVS is highly adapted to extract structural information from the viewing field [15].

The higher the value of the MSSIM index the better is the quality of the image. When comparing the loss of information in the compressed medical images, it is desirable that a system, which gives higher values of MSSIM index, is considered better in terms of preservation of diagnostic information. For a perfect reconstructed image without any loss of information MSSIM index must be 1. MSSIM index comparison of various CT images is presented in Fig. 7(a). It can be seen from this that the proposed method preserves more diagnostic information as compared to the JPEG method.

Similar findings have been made for different images of US and X-ray imaging modalities whose results of MSSIM index comparison are given in Fig. 7(b) and (c), respectively.

Since a radiologist is the final observer for medical images to make a diagnosis, the test images and images decoded with proposed method and with the JPEG method were presented to an experienced radiologist for his opinion. The radiologist found that the images compressed with proposed method were better than the JPEG compressed images and retain more diagnostic information. Moreover, blocking artifacts are more prominent in the images compressed with JPEG than those of the proposed method. One typical CT image and its images decoded with the proposed method and JPEG are shown in Fig. 8.

Similar observations are made for images of US and X-ray imaging modalities as presented in Figs. 9 and 10, respectively.

The foregoing results clearly indicate that the proposed strategy is capable of yielding better performance than JPEG for given CR or bit rate for all the images. Also, the proposed method does not increase computational complexity. Thus it is very much applicable for teleradiological applications.

5. Conclusions

For teleradiology, the basic requirement of image compression is the preservation of diagnostic information in the reconstructed medical image. The proposed compression method is applied to different images of various imaging modalities. It proves wider applicability of proposed method. The comparison of the proposed technique with the JPEG compression has been done in terms of various objective quality performance indices and it has been demonstrated that the proposed technique outperforms the JPEG. The concept of adaptive threshold value based on variance (image complexity) has been introduced for the classification of the blocks, which improves the quality of the reconstructed medical images for the same CR and vice versa. The proposed method involves very simple computation making it suitable for teleradiology.

If the limit of the distorted area is set very high for achieving still higher CRs, the blocky effect will arise. Reducing blocking artifacts by using a smoothing filter (deblocking) would sacrifice the detailed characteristic of the major component in the medical image. Further investigations can be made to develop a deblocking technique that does not smooth out the important information in the reconstructed image.

For teleradiology application, it would be important to contain the additional computational burden.

6. Summary

Teleradiology applications require the compression of medical images for their fast transfer from one location to other. There is a restriction on the compression algorithm that loss of diagnostic information must be minimal for effective diagnosis. The purpose of this study is to develop a DCT-based compression algorithm, which preserves the diagnostic information while performing compression. The DCT blocks are classified on the basis of information content with a view to maximize CR without sacrificing diagnostic information. The paper presents a technique for classification of blocks using an adaptive threshold value based on variance. The adaptive approach makes the classification technique applicable across the board to all medical images. To demonstrate the efficacy of the proposed technique it has been applied on 65 CT, 28 X-ray and 30 US images obtained from http://www.mdchoice.com/xray/ctscan/Ct.asp and http://www.gehealthcare.com and the results are compared against the JPEG compressed images in terms of PSNR and CR. It has been found that for the same CR this method gives an average improvement in PSNR of 2.73, 2.53, and 2.39 dB for CT, US, and X-ray imaging modalities, respectively. The PRD values are less for the images compressed with the proposed method than for those compressed with JPEG. The performance of the proposed method is better than JPEG in terms of CC also. Further, to know the extent to which the diagnostic information is preserved during compression, MSSIM index has been evaluated; both on the original and reconstructed medical images. After comparing the results of the proposed method with JPEG, it has been found that more diagnostic information in terms of SSIM is preserved in the medical image compressed with the proposed method than in JPEG compressed images. The images compressed with DCT-based method suffer from blocking artifacts. These artifacts are more severe in the case of JPEG compressed images. Further investigations are to be made for reduction of these artifacts.

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