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ORIGINAL PAPER

THE VALUE OF COMPRESSED MEDICAL IMAGES IN DIAGNOSTICS: JPEG 2000 LOSSY COMPRESSION OF CT AND MRI IMAGES

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ABSTRACT

Background: Hospitals and clinical environments are rapidly moving toward the use of digital medical images. Digital images are acquired mainly for diagnostic reasons, important for the documentation of the patient's case, and offer an alternative to analog film-based systems. However, medical images occupy a substantial amount of digital storage space. Image compression is important in reducing medical image transmission time and storage requirements while maintaining relevant diagnostic information. Without image compression, medical images' data would overload the network and make telemedicine impractical. The issues of how and to what extent medical images can be compressed and retain their diagnostic value still remain.
Aim: The goal of this study was to determine the level to which medical images can be compressed in order for reconstructed images to be acceptable for diagnostic purposes.
Methods: We performed compression and reconstruction of The Digital Imaging and Communication in Medicine (DICOM) images obtained from two different modalities: computed tomography (CT) and magnetic resonance imaging (MRI). Image compression and reconstruction were performed using the JPEG 2000 compression standard which uses the biorthogonal CDF 9/7 wavelet for lossy compression.
Results: Based on the results obtained from objective Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) measures, and subjective evaluations, we showed that an MRI image can be compressed to 45:1 (0,1768 bpp) without losing its diagnostic value, while a CT image can be compressed to 32:1 (0,25 bpp). The correlation between each objective and subjective measure was found.
Conclusion: JPEG 2000 compression standard which uses the biorthogonal CDF 9/7 wavelet for lossy compression can be used to achieve efficient compression of CT and MRI images without compromising their diagnostic quality.

Key words: *lossy image compression, JPEG 2000, radiology*

INTRODUCTION

Hospitals and clinical environments are rapidly moving toward digitization as well as capturing in native digital format, processing, storage, and transmission of medical images (i.e. telemedicine). A digital medical image is acquired mainly for diagnostic reasons and it is an important item in the documentation of the patient's case.[1] Medical images are currently handled by information technology (IT) systems (i.e. PACS, discussed below) oriented toward acquiring, archiving, transmitting and accessing medical images which represent modern counterparts of traditional archives of exposed plates. These systems serve for either long or short-term storage of images acquired using various methods of medical imaging (i.e. CT, MRI, X-ray), as well as for transmitting images for remote diagnostics or consultations. Therefore, computer image analysis represents a very potent tool supporting the diagnostic process.

Along with their immense benefits, medical images occupy a substantial amount of storage space and thus overload the communication between components of Picture Archiving and Communication Systems (PACS).

The average digital information storage space requirement of a PACS system for archiving medical images is 40 terabytes[2] (on average, 1000 images of about 500 megabytes in size get generated per patient[3]), while the network communication requirement is based on a high speed transfer (high-speed networks) of minimum 100 megabytes per second.[4] Sizes of medical images generate serious problems during their transmission. Problems would not be so noticeable if most of the time the need was only for a single transfer of a medical image, from the place where it is generated to the place where it is archived. Within PACS systems, in practice medical images are transmitted to other computers (or some other devices) where they are additionally processed i.e. viewed, analyzed, compared to other medical images from the same patient or from different patients. Depending on network capacity, the time required for transmission increases with the size of a medical image. If the number of requests is too high, it is possible for the network to get overloaded, and also that certain packages get lost during transmission which could lead to errors in the interpretation of medical images.[5] Due to the critical nature of medical image data, partial/impaired reconstructions due to lost data should not be used for medical evaluation. The real problem arises due to the retransmissions required when earlier delivery attempts fail due to network conditions. The only solution to the problem of archiving and distributing medical images in a practically useful manner is the use of an appropriate digital image compression method.

Image compression plays a vital role in reducing the data set size required to store and represent images while maintaining relevant diagnostic information. Rapid technology development enabled in many domains wide-spread commercial usage of digital image processing methods which were until recently available only to well equipped research laboratories.[6] In all these applications, such as video conferencing, videotelephony, multimedia systems, processing and storage of documents, systems of standard and high resolution TV picture transmission, biomedicine and others, image compression methods have important roles. Image compression methods are necessary in order to decrease the memory usage or required capacity of telecommunication channels, since this involves transmission or inscription of large amount of data required for image representation. In fact, the storage of one digital monochrome image with the resolution of 512×512 pixels requires 256 KB of memory, while the storage of an image in color of the same resolution requires 768 KB.[6] The storage of a monochrome video sequence of the same resolution, with 25 images/s, requires 6.4 MB/s, while a video sequence in color requires 19.2 MB/s. As the resolution increases, memory and bandwidth requirements increase proportionally. Due to the great need for image compression, compression methods have been intensively developed in the past twenty years and the research in this area continues to be significant and high paced. Methods have been developed that allow compression of a still image up to 50 times without a significant impact on the quality of the reproduced image. In regards to a sequence of images e.g. video data, the level of compression can be even greater.

Medical image compression is specific in that errors, distortions in the reconstruction of a compressed image have to be minimized in order to allow an accurate, reliable diagnosis, while still achieving high compression efficiency.[7] No consensus exists about compression techniques and compression factors that need to be used.[8,9] In general data compression methods are classified into two categories: lossy (irreversible) image compression and lossless (reversible) image compression. Lossy compression methods allow high compression ratios although they do not allow exact image recovery after compression, while lossless compression methods allow exact recovery of the original image, but they achieve much lower compression ratios, around 1.5:1 to 3:1.[8,10,11,12,13] However, even though the original image is not perfectly reproduced by lossy compression methods, the reproduction may be good enough so that there is no perceptible image degradation or compromised diagnostic value. Additionally, since higher degrees of compression are possible using lossy techniques, these methods may be considerably more beneficial in decreasing the time and cost required for image transmission, and decreasing storage requirements. Furthermore, the United States Food and Drug Administration (USFDA) accepts the use of compression technology as part of teleradiography systems and PACS applications, although it states that images that have been compressed using lossy methods have to be provided with instructions which explain the effects of lossy compression on image quality.[9]

In this study, we applied a lossy compression technique in order to evaluate the level to which CT and MRI images can be compressed without losing their diagnostic value. Image compression and reconstruction were performed using the JPEG 2000 compression standard which utilizes the biorthogonal CDF 9/7 wavelet transform for lossy compression and both objective and subjective methods were applied to carry out this evaluation.

MATERIALS AND METHODS

In this study, CT and MRI images were compressed at different compression ratio values, using the JPEG

2000 compression standard which utilizes the biorthogonal CDF 9/7 wavelet transform. For evaluating the quality of reconstructed images we used both objective and subjective methods. PSNR and MSE were used as objective measures, while medical doctors (radiology specialists) carried out the subjective evaluation. They reviewed reconstructed images, compared them to the original image and evaluated their quality from the perspective of diagnostic value. The correlation between objective and subjective measures was also examined, as described below.

The Objective Evaluation of the Quality of a Compressed Image

The evaluation of the quality of a compressed image gives information on how and to what level the lossy compression method used influences image quality. An image can be treated as a matrix, where image elements (pixels) correspond to matrix elements. The evaluation procedure is based on determining differences between certain elements of an input and an output matrix. This allows the comparison of the efficiency of different compression methods, as well as different compression ratio values of one particular compression method.

At the compression system input there is a matrix *A* with elements a_{ij}, where $i \in [1...M]$, and $j \in [1...N]$. M is equal to the number of image elements in the vertical direction, and N is equal to the number of image elements in the horizontal direction. *MxN* is the total number of image elements in an image. At the compression system output matrix, *A'* is generated with a'_{ij} elements. The difference between matrix *A* and *A'* represents the loss of quality, in other words an error. The error is bigger with a higher compression ratio. The compression ratio can be adjusted to user's request and thus directly impact the amount of data needed for presentation of a compressed image, and the quality of a reconstructed image.

The difference between matrix A and A' can be presented using the mean square error (MSE - Mean Square Error):

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left[a_{ij} - a'_{ij}\right]^2$$

The amplitude of image elements has a range of $[0.2^n-1]$, where *n* is the number of bits needed for presentation of the amplitude of elements of the original image. MSE does not take into account the amplitude of image elements thus the Peak Signal-to-Noise Ratio (PSNR) is used:

$$PSNR = 20\log_{10}\frac{2^n - 1}{MSE^{\frac{1}{2}}} = 10\log_{10}\frac{\left(2^n - 1\right)^2}{MSE}$$

If it is assumed that n=8 bits/image element then:

$$PSNR = 10\log_{10}\frac{\left(2^n - 1\right)^2}{MSE} = 10\log_{10}\frac{255^2}{MSE},$$

PSNR gives an objective measure of the fidelity of a compressed image.

Subjective Evaluation Method

The subjective evaluation emphatically examines quality and at the same time considers image intelligibility. When taking the subjective test, observers focus on the differences between the reconstructed image and the original image; they note certain details where information loss cannot be accepted. The representative subjective measure is Mean Opinion Score (MOS)[14]

$$MOS = \sum_{i=1}^{5} ip(i)$$

where i is grade (score) and p(i) is grade probability (normalized frequency of occurrence).

In our experiments, we used the absolute score scale (Table 1) in order to seek the consistency between subjective and objective measures. The adopted testing methodology was the double-stimulus impairment scale method with the five-grade impairment scale. When the tests span the full range of impairments (as in our experiment) the double-stimulus impairment scale method should be used. The double stimulus impairment scale method uses both reference and test conditions, which are arranged in pairs, such that the first signal (stimulus) in the pair is the intact reference and the second signal is the same signal with impairments. The original source image without compression was used as the reference condition. The two stimuli were displayed in sequence one after another and the observers were asked to vote on the second keeping in mind the first. Each observer compared the reconstructed images with the original one to evaluate their quality and grade them. A score of 5 represents no perceivable impairment (Excellent), score of 4 represents a small amount of impairment which can be ignored (Good), score of 3 implies impairment which can be seen evidently and cannot be accepted (Poor), score of 2 implies a significant amount of impairment which cannot be accepted (Bad) and finally a score of

1 implies very heavy impairment, therefore cannot be tolerated (Very Bad).

Table 1. *Mean Opinion Score (MOS) method used for subjective evaluation*

Score	
5	Excellent
4	Good
3	Poor
2	Bad
1	Very Bad

Wavelet Transformation

The Discrete Wavelet Transform (DWT) is the mathematical foundation of the wavelet-based image compression scheme. Traditional two-dimensional (2D) DWT first performs row filtering on an image followed by column filtering. This gives rise to a signal decomposition with four wavelet subbands as shown in Figure 1 (A). The Low-Low (LL) subband contains the low-frequency content of an image in both the horizontal and the vertical dimensions. The High-Low (HL) subband contains the high-frequency content of an image in the horizontal and the low-frequency content of the same image in the vertical dimension. The Low-High (LH) subband contains the low-frequency content of an image in the horizontal and the high-frequency content of the same image in the vertical dimension, and finally, the High-High (HH) subband contains the high-frequency content of an image in both the horizontal and the vertical dimensions.

Each of the wavelet coefficients in the LL, HL, LH, and HH subbands represents a spatial area corresponding to approximately a 2 X 2 area of the original image.[15] For an n-scale DWT decomposition, the coarsest subband LL is further iteratively decomposed in a similar manner. Figure 1(B) shows the subbands obtained for a three-scale wavelet decomposition. As a result, each coefficient in the coarser scale represents a larger spatial area of the image but a narrower band of frequencies.[16]

The two approaches that are used to perform the DWT are the convolution based filter bank method and the lifting based filtering method. Between the two methods, the lifting based DWT is preferred over the convolution based DWT for hardware implementations due to its simple and fast lifting process. Besides this, it also requires a less complicated inverse wavelet transform.[16-20]

Lifting Based 9/7 DWT

The irreversible 9/7 filter is selected in our proposed work since it provides a lossy transformation. In the implementation of lifting-based 9/7 DWT,[20,21,22] three computation operations — addition, subtraction, and shift — are needed. The lifting process is built based on the split, prediction, and updating steps. The input sequence is first split into odd and even components for the horizontal filtering process. In the prediction phase, a high-pass filter is applied to the input signal which results in the generation of the detail coefficients. In the updating phase, a low-pass filter is applied to the input signal which leads to the generation of the approximation coefficients. Likewise, for the vertical filtering step, the split, prediction, and updating processes are repeated for both sets of coefficients i.e. detail and approximation. Table 2 represents coefficients and the lifting implementation of the 9/7 DWT filter used in JPEG 2000.[23]

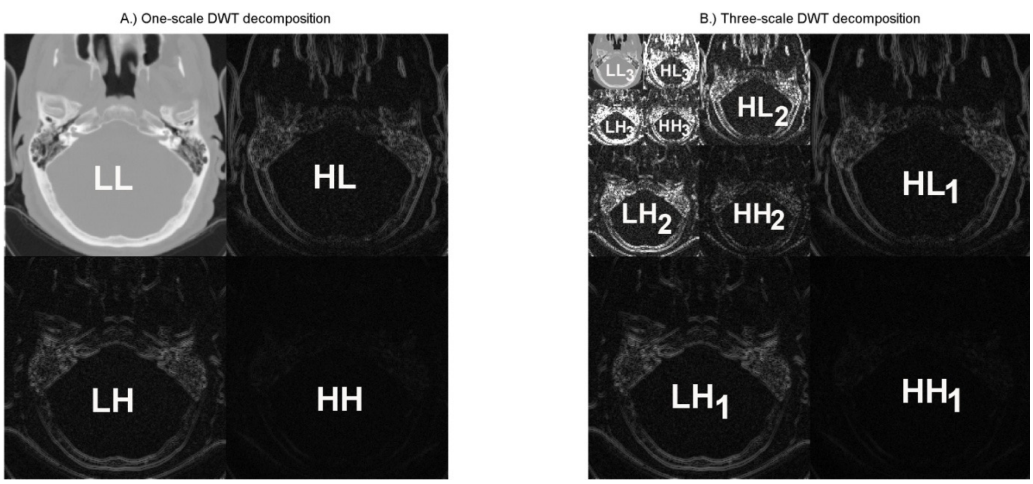

Figure 1. *2D wavelet decomposition*

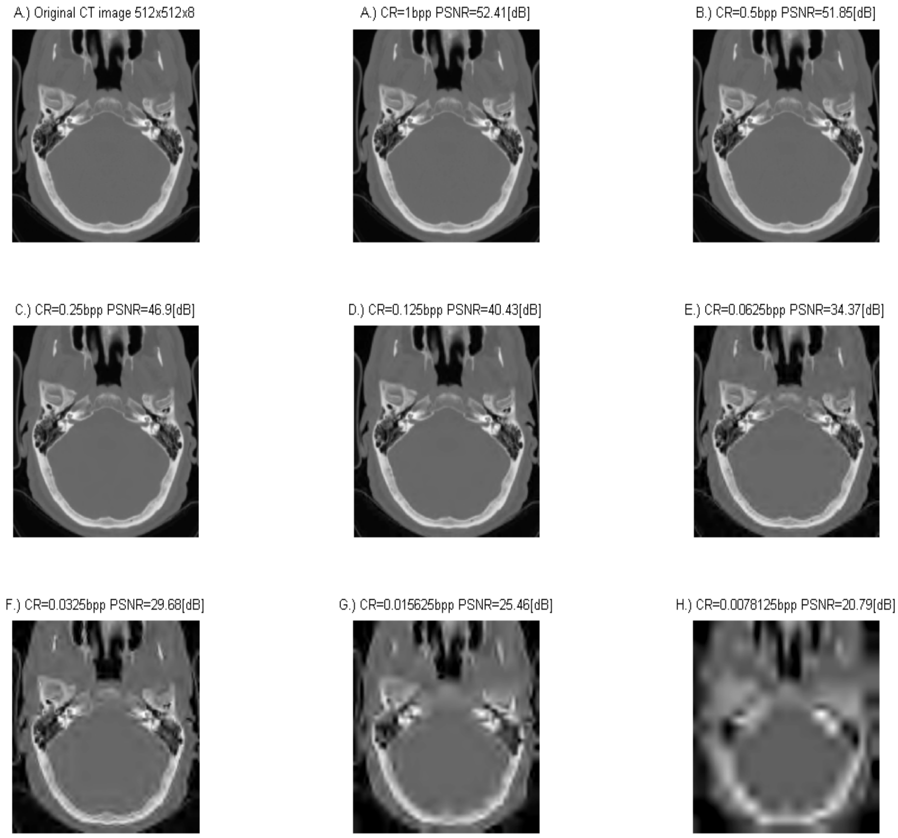

Figure 2. *(A-I) Reconstruction of a compressed CT image with different compression ratios*

Table 2. *Coefficients and the lifting implementation of the 9/7 DWT filter*

I	Low pass filter h_0	High pass filter h_1
0	0.85269867900889	0.78848561640637
1	0.37740285561283	-0.41809227322204
2	-0.11062440441844	-0.04068941760920
3	-0.02384946501956	0.06453888262876
4	0.03782845550726	

RESULTS

Using the MATLAB program (MATLAB Version 7), we implemented the JPEG 2000 compression standard which uses the biorthogonal CDF 9/7 wavelet for lossy compression. Two original DICOM images of size 512x512 and of 8 bits per pixel pixel-depth taken from two modalities: CT and MRI were processed. Images were compressed at eight different compression ratio values and objective scores were calculated using MSE and PSNR which were also implemented in the MATLAB programming environment. The reconstructed images, for each modality, were obtained for the following eight compression ratio values: 8:1 (1 bit per pixel - bpp), 16:1 (0.5 bpp), 32:1 (0.25 bpp), 64:1 (0.125 bpp), 128:1 (0.0625 bpp), 256:1 (0.0325 bpp), 512:1 (0.015625 bpp) and 1024:1 (0.0078125 bpp) (Figures 2 and 3). In all figures and tables, compression ratios are presented as equivalent bit rates. Test results, obtained by both objective and subjective measures as described above, are shown graphically in Figures 4-6. Tables 3 and 4 summarize the results for PSNR and MSE for these images, respectively.

For the subjective measure, both the original and the reconstructed images were shown on radiology-diagnostic monitor Barco E-3620 to eight radiology specialists (observers) from the University Clinical Center Tuzla (UCC) who evaluated and graded reconstructed images (Table 1). Observers assessed the degree of impairment of each test image using the five-grade impairment scale with half grade accuracy. Observers were carefully introduced to the method of assessment, nature of impairment, the grading scale and timing. All images were displayed using IrfanView v3.92 image viewing program (Irfan Skiljan, Graduate of Vi-

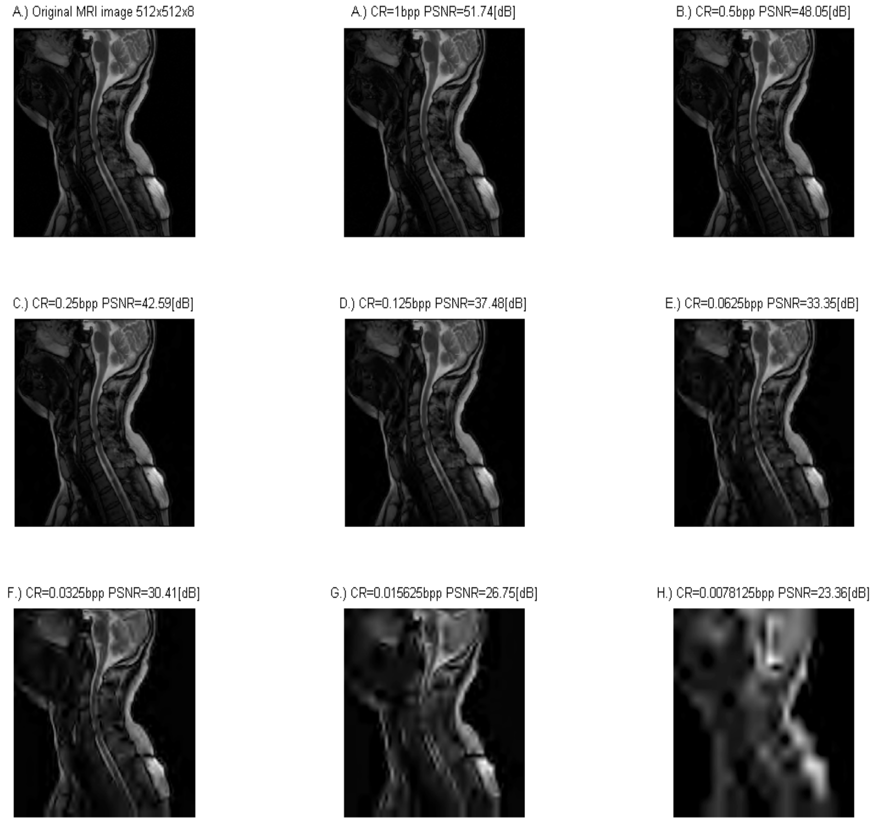

Figure 3. *(A-I) Reconstruction of a compressed MRI image with different compression ratios*

enna University of Technology, Austria). As described above, the score of 4 was taken as the smallest acceptable score, satisfactory for the diagnostic criteria. The average subjective scores for both CT and MRI images are shown in Table 5 and also illustrated graphically, using MATLAB program, in Figure 6.

Furthermore, in order to examine the reliability of the objective picture quality measures, we calculated the correlation between the numerical objective quality measures and MOS values (Table 6.). As a measure of the coherence between these two classes of picture quality measures, the Pearson product-moment (r) was used.[24] The possible values of r are between -1 and +1; the closer r is to -1 or +1, the better the correlation is. In our experiment, PSNR had a high correlation with MOS and that correlation was significant ($p<0.01$), which showed that the objective picture quality measure used was reliable for this study.

DISCUSSION

A large number of new medical images are created daily that need to be transmitted and archived long-term. Sizes of these images represent serious problems that can increase the transmission time, which consequently leads to a substantially longer delay in image retrieval and slows down treatment of patient's condition. The digital information storage volume needed as archiving space of these images can strain the hospital budget as well as the physical space available for storage. Thus image compression techniques are used in order to reduce the file sizes of these images (measured in bits or bytes) but still retain their diagnostic value.

In this study, we evaluated compression and reconstruction of two different medical image modalities (CT and MRI) over a range of compression ratios using the JPEG 2000 compression standard which utilizes the biorthogonal CDF 9/7 wavelet for lossy compression. For these radiology applications, our results showed that the compression ratio of up to 32:1 (0,25 bpp) was acceptable for CT images, and the compression ratio of up to 45:1 (0,1768 bpp) was acceptable for MRI images. Based on the quality of reconstructed images, the PSNR obtained was between 46.90dB to 52.41dB for CT scan images and between ~40.00dB

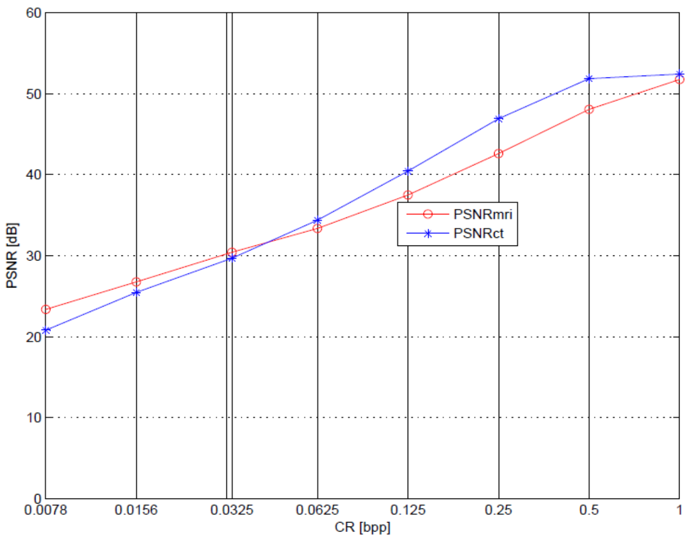

Figure 4. *PSNR against compression ratio for MRI and CT images*

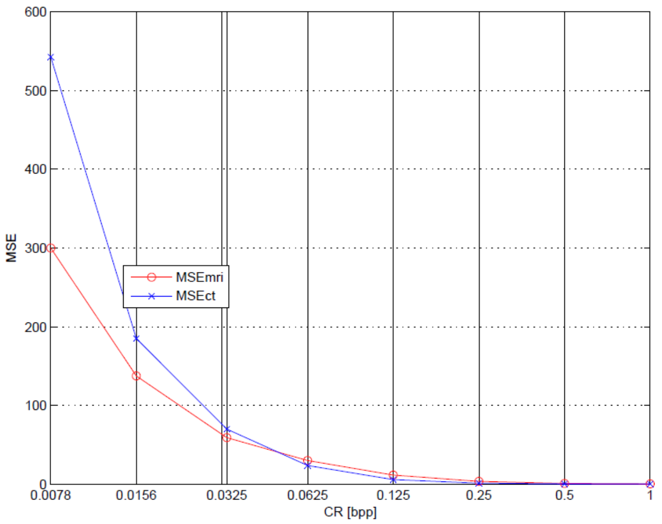

Figure 5. *MSE against compression ratio for MRI and CT images*

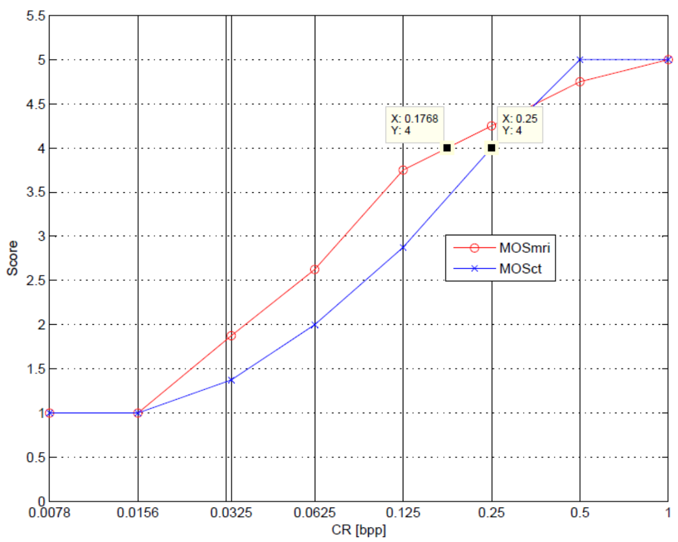

Figure 6. *Average score in terms of subjective score against compression ratio for MRI and CT images*

to 51.74dB for MRI. Subjective evaluation was carried out by eight radiology specialists

In the literature, as also adopted in our study, the highest compression ratio of an image is determined based on the quality of the compressed image (i.e. the PSNR and MSE values, and subjective analysis).[14] However, research has shown that these values can vary depending on the methods used for objective and subjective evaluations. The problem arises since, as discussed before, no consensus exists about types of compression techniques and compression ratios used. The results reported in the literature have shown that acceptable compression ratio values can vary significantly.[5,25,26] Using the standard JPEG 2000 compression technique it has been shown that the compression ratio of 14:1 does not compromise diagnostic quality,[27] although some researchers have achieved compression ratios of up to 24:1 and 140:1.[28,29,30,31] However, some of these results have to be taken with caution, since subjective analysis has not always been carried out by the radiology specialists.[14] Visually acceptable or unacceptable does not necessarily mean that the ratio is or is not diagnostically suitable because this depends on which disease is under consideration and this could be most accurately determined by the experts.[6]

Furthermore, studies have shown that for practical benefit compression ratios of at least 10:1 or more should be used for medical images.[25,26] Previously, JPEG 2000 has been successfully used for the compression of Computer Radiography (CR) images. The authors have found that compression ratios as high as 20:1 can be utilized without affecting diagnostic quality,[10] although CT and MRI images were not examined in this study. On the other hand, in a study similar to ours, Ghrare and colleagues have used wavelet transform techniques to evaluate an acceptable compression degree for reconstructed CT and MRI images compressed at different compression ratios.[32] Their results were similar to data obtained in our study, showing that the compression ratio of 30:1 is acceptable for CT images and the compression ratio of 40:1 is acceptable for MRI. Even though we have achieved only slightly higher compression ratios, it is important to mention that we have used much stricter subjective evaluation criteria. In particular, unlike in Ghrare et al., the subjective evaluation in our study was carried out by the radiology specialists, the score of 4 was considered to be the lowest diagnostically acceptable score and the results of subjective evaluation were calculated based on the true average of MOS scores (Figure 6), no rounding up was performed. In Ghrare et al., the score of 3 was accepted as satisfactory and the average scores were rounded up which allowed them to obtain higher acceptable compression ratios for the

Table 3. *PSNR results for reconstructed MRI and CT images*

CR [bpp]	1	0.5	0.25	0.125	0.0625	0.0325	0.015625	0.0078125
PSNRmri*	51.74	48.05	42.59	37.48	33.35	30.41	26.75	23.36
PSNRct**	52.41	51.85	46.90	40.43	34.37	29.68	25.46	20.79

**PSNRmri = PSNR for MRI image; ** PSNRct = PSNR for CT image*

Table 4. *MSE results for reconstructed MRI and CT images*

CR [bpp]	1	0.5	0.25	0.125	0.0625	0.0325	0.015625	0.0078125
MSEmri*	0.436	1.019	3.580	11.626	30.068	59.155	137.445	299.896
MSEct**	0.373	0.425	1.327	5.891	23.749	69.979	185.052	542.531

**MSEmri = MSE for MRI image; **MSEct = MSE for CT image*

Table 5. *MOS evaluation results for all observers for reconstructed MRI and CT images*

CR [bpp]	1	0.5	0.25	0.125	0.0625	0.0325	0.015625	0.0078125
MOSmri*	5	4.75	4.25	3.75	2.625	1.875	1	1
MOSct**	5	5	4	2.875	2	1.375	1	1

**MOSmri = Mean Opinion Score for MRI image; **MOSct = Mean Opinion Score for CT image*

Table 6. *Correlation between CR, MSE, PSNR and MOS*

		CR	MSEct	PSNRct	MOSct
MOSct	*Pearson Correlation*	.852**	-.628	.983**	1
	Sig. (2-tailed)	.007	.095	.000	
			MSEmri	PSNRmri	MOSmri
MOSmri	*Pearson Correlation*	.789*	-.800*	.976**	1
	Sig. (2-tailed)	.020	.017	.000	

*** Correlation is significant at the 0.05 level (2-tailed).**
**** Correlation is significant at the 0.01 level (2-tailed).**

subjective evaluation.

Overall, our study showed that the JPEG 2000 compression standard which utilizes the biorthogonal CDF 9/7 wavelet transform for lossy compression is a valid method to use for compression of CT and MRI images where even at higher compression ratios reconstructed images retained their diagnostic values. Our results were comparable and somewhat higher than the results reported in other studies using different compression methods, and showed a significantly high correlation between the objective and subjective measures used.

CONCLUSION

Compression techniques reduce the file size required to store and transmit digital medical images while maintaining relevant diagnostic information. Compression of medical images makes the use of digital medical images more economically viable and allows physicians a faster access to these images. Even a minimal compression ratio of 2:1 can have a significant impact on the speed of representation of digital medical images and can provide significant cost savings.

In this paper, two different medical image modalities were compressed and decompressed using the JPEG 2000 compression standard which utilizes the biorthogonal CDF 9/7 wavelet transform for lossy compression. Compression was performed at different compression ratios and its results were evaluated using objective and subjective testing. The quality of reconstructed images was measured using objective measures such as MSE and PSNR. The subjective evaluation was carried out by eight radiology specialists. The correlation between each objective measure and subjective measure was found. We demonstrated that for a compression system a group of numerical objective measures could reliably be used to specify the magnitude of degradation in reconstructed images. Based on the compression ratios of reconstructed images judged to be acceptable for diagnostic purposes, the PSNR values obtained were between 46.90dB to 52.41dB for CT scan images and between ~40.00dB to 51.74dB for MRI. Thus, for radiology applications, the compression ratio of 32:1 (0.25 bpp) was acceptable for CT images, and the compression ratio of 45:1 (0.1768 bpp) was acceptable for MRI images.

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