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Irreversible wavelet compression of radiological images based on visual threshold

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***Abstract*—Visually lossless irreversible coding permit compression algorithms to improve the compression gain without disturbing the visual image quality. This paper proposes a novel coding scheme in which wavelet based visual model is embedded into lossless compression algorithm to compress the volumetric medical image data. Obtained experimental results are compared with numerically lossless compression schemes such as Differential Pulse Code Modulation (DPCM), Joint Photographic Experts Group-Lossless (JPEG-LS), JPEG-2000 and High Efficiency Video Coding (HEVC). The proposed method achieves reduced bit rate without deteriorating the visual quality of the resulting images.**

Keywords—Discrete Wavelet transform, Vision model, Visually lossless compression, Volumetric MRI and CT images

I. Introduction

Noninvasive methods used for the diagnosis of various diseases have strict requirement with contrast and spatial resolution of radiologic images. They demand volumes of such images with all possible views making storing and transmission of medical images a challenging one in applications like teleradiology or Picture Archiving and Communications Systems (PACS). This problem is addressed with different types of compression algorithms [1]–[3].

Although radiologists and health care technology communities prefer lossless algorithms, irreversible algorithms which preserve visual quality of medical images are promising due to the fact that human vision is an imperfect sensor. Many of the image processing algorithms exploit this limitations of Human Visual System (HVS) to enhance the performance of the system. Since human observers are the receivers of the visual information present in the image, characteristics of HVS plays a prime role in applications related to coding of images. To preserve the visual quality of image in a lossy compression scheme, determination of acceptable visual threshold is important.

Assessment of visual lossless compression algorithm on two dimensional Radiography, mammogram and Computed Tomography (CT) medical images have demonstrated improvement in the compression ratio without affecting the visual quality of the medical images [4]–[6]. Studies on image data compression with visually lossless schemes indicates that the range of compression ratio with perceptually lossless threshold is between 4:1 and 20:1 depending on the image type, image content, bits per pixel (bpp) and type of compression algorithm [7]–[9].

In this paper a wavelet based visually lossless irreversible image coder is proposed for volumetric gray scale radiologic images. Many sequences of Magnetic Resonance Imaging (MRI), X-ray angiogram and CT slices are considered as test data, since they have different textures and large number of edges. Visually lossless coding system identify and measure the information present in the image which is relevant to human vision while coding images. It is achieved by finding the image dependent visible threshold to determine the allowed amount of degradation in the image in such a way that original and decoded images are identical to human observer. One of the important property of HVS is that the human eyes understand the image through frequency and orientation. This property is taken into consideration through wavelet based compression. The correlation present between successive image slices is removed with block matching algorithm.

Performance of the proposed Visually Lossless Coder (VLC) is compared with the lossless compression based on HEVC standard [10] for sequences of CT, MRI and X-ray angiogram data. In HEVC inter-picture, intra-picture and 2D coding procedures are embedded making it a hybrid video encoder. Both inter-picture coding and intra-picture coding make use of predictive coding, while inter-picture coding use motion compensation and estimation making it suitable for volumetric medical image compression.

This paper is organized as follows. Section II briefly describes wavelet based vision model. Section III explains visually irreversible compression scheme for volumetric medical images. Section IV presents the simulation results and Section V concludes the work.

II. Visual model

Selection of a vision model is the first step in implementation of visually lossless coder. Number of vision models are developed in spatial domain as well as in the transformed domain (such as Discrete Cosine Transform and Discrete Wavelet Transform (DWT)) [11]. In this stage the perceptual redundancy present in image is measured through JND profile. Currently, DWT is the commonly used tool due to its suitability for both vision models and image coding systems [11] and hence DWT based vision model was chosen.

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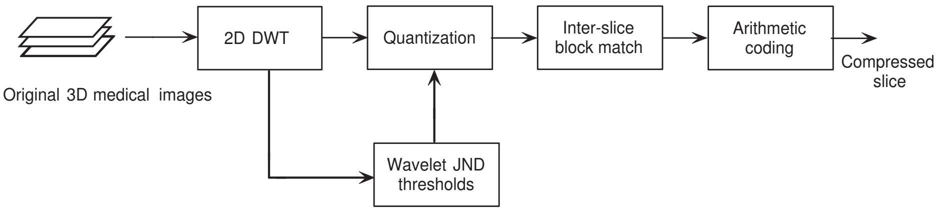


Fig. 1. Block diagram of the proposed method

The perceptual model needs one JND threshold, $v_{JND}(\lambda, \theta, [m, n])$ for each DWT coefficient at location $([m, n])$ within subband (λ, θ), where λ is the transform level and θ is the orientation.

In this work, three visual phenomena are considered to model HVS : contrast sensitivity, luminance masking, and contrast masking [12]. The JND threshold $v_{JND}(\lambda, \theta, [m, n])$ is computed as

$$v_{JND}(\lambda, \theta, [m, n]) = JND_{\lambda,\theta} a_l(\lambda, \theta, [m, n]) a_c(\lambda, \theta, [m, n]) \tag{1}$$

where $JND_{\lambda,\theta}$ is the base detection threshold for a subband (λ, θ), $a_l(\lambda, \theta, [m, n])$ is the luminance masking adjustment, and $a_c(\lambda, \theta, [m, n])$ is the contrast masking adjustment.

The base detection threshold $JND_{\lambda,\theta}$ provides the relative variation in the observable signal over a background with uniform intensity. A mathematical representation of JND threshold is given by [12]:

$$JND(\lambda, \theta) = \frac{1}{A_{\lambda,\theta}} a 10^{k\left\{log\left(\frac{g_\theta f 2^\lambda}{r}\right)\right\}^2} \tag{2}$$

where a, k, f and g_θ are constants. Values of these constants are listed in Table I. $A_{\lambda,\theta}$ is the amplitude of the DWT 9/7 basis function related to level λ, orientation θ and visual resolution of the display in pixels/degree r. Table II lists the $A_{\lambda,\theta}$ values for a 5-level 9/7 DWT decomposition [12].

TABLE I. Parameters for the DWT threshold model

a	k	f	g_{LL}	$g_{HL,LH}$	g_{HH}	r (pixels/degree)
0.495	0.466	0.401	1.501	1.0	0.534	35

TABLE II. Basis function amplitude $A_{\lambda,\theta}$ for a 5 level 9/7 DWT

Orient	DWT				
	1	2	3	4	5
LL	0.62171	0.34537	0.18004	0.09140	0.045943
LH, HL	0.67234	0.413177	0.22727	0.11792	0.059758
HH	0.72709	0.49428	0.28688	0.15214	0.077727

The base detection threshold values change with the background intensity levels. Hence mean luminance of the local image region needs to be considered when calculating detection threshold. Therefore to account for this variation a luminance masking correction factor is applied to the contrast sensitivity function. The luminance masking correction factor is approximated as:

$$a_l(\lambda, \theta, [m, n]) = \left(\frac{v_{\lambda_{max}, LL, m', n'}}{v_{mean}}\right)^{a_T} \tag{3}$$

where $v_{\lambda_{max}, LL, m', n'}$ is the DWT coefficient in the LL subband that corresponds to location $(\lambda, \theta, [m, n])$. The parameter a_T controls luminance masking, a value of 0.649 was used.

Contrast masking is another factor that influence the detection threshold. It is due to the fact that the visibility of one image element changes with the presence of another image component. Contrast masking estimates the variation in the noticeable detection threshold as a function of the contrast of the masker. The contrast masking effect can be framed as [12]:

$$a_c(\lambda, \theta, [m, n]) = a_{c\_self}(\lambda, \theta, [m, n]) a_{c\_neigh}(\lambda, \theta, [m, n]) \tag{4}$$

where $a_{c\_self}(\lambda, \theta, [m, n])$ is the self contrast masking adjustment factor and $a_{c\_neigh}(\lambda, \theta, [m, n])$ is the neighborhood contrast masking adjustment factor.

A sufficiently large coefficient at the location $(\lambda, \theta, [m, n])$ increases the detection threshold. This variation in detection threshold is incorporated through self contrast masking adjustment factor $a_{c\_self}(\lambda, \theta, [m, n])$. In DWT based reconstructed images, the signal formed by DWT coefficient $c(\lambda, \theta, [m, n])$ is superimposed on other signals formed by the neighboring wavelet coefficients. This phenomena is taken in to account through neighborhood contrast adjustment factor $a_{c\_neigh}(\lambda, \theta, [m, n])$. So there is some masking effect contributed from spatially neighboring signals in wavelet domain.

III. Visually lossless image coding

To decode an image of superior visual quality with lesser bit rate, image compression algorithm not only remove the statistical redundancies but also the perceptually unimportant contents from the image volume. The main aim of visually lossless coder for medical images is to minimize the energy of each slices by removing visually insignificant information. Block diagram of the proposed VLC is shown in Figure II. The important components of the compression system are 2D DWT, wavelet based JND estimator, inter-slice block matching routine and arithmetic encoding. In this proposed method slice redundancy available in the image data volume and human visual features are considered to compress the 3D image data.

DWT is used to decorrelate an image into various spatial-frequency and orientation subbands. It is performed with 9/7 biorthogonal filters. After an image is transformed into five levels of its spatial-frequency subband representation, the DWT coefficients within each subband are quantized to eliminate the visually redundant information in such a way that absolute value of quantization error is below the JND value forming the image compression algorithm as an visually

TABLE III. COMPARISON OF VISUALLY LOSSLESS BIT RATES (BPP) OBTAINED WITH LOSSLESS BIT RATES OF DPCM, HEVC, J2K AND JPEG-LS [10]. MEASURED VISUAL QUALITY OF DECODED IMAGES (PSNR, VIF AND SSIM) ARE ALSO TABULATED.

Image (slices:pixels per slice:bpp)	Visually lossless compression								Lossless compression [10]			
	Performance with $q = 3$				Performance with $q = 7$				DPCM	HEVC	J2K	JPEG-LS
	bpp	PSNR (dB)	VIF	SSIM	bpp	PSNR (dB)	VIF	SSIM	bpp	bpp	bpp	bpp
1. Angio-1 (151:512×512:12)	4.17	72.90	0.98	0.99	3.83	59.72	0.83	0.97	5.10	5.30	4.78	4.74
2. Angio-2 (271:512×512:12)	4.66	72.92	0.98	0.99	4.02	59.65	0.82	0.97	5.17	5.38	4.81	4.78
3. Angio-3 (186:512×512:12)	4.27	72.60	0.98	0.99	3.77	58.83	0.82	0.96	5.55	5.60	5.12	5.08
4. CT-1 (596:512×512:12)	3.96	73.05	0.98	0.99	3.10	60.15	0.82	0.97	4.95	5.28	4.66	4.65
5. CT-2 (637:512×512:12)	3.92	73.10	0.98	0.99	3.21	60.69	0.83	0.98	4.93	5.38	4.42	4.52
6. CT-3 (82:512×512:12)	3.89	73.07	0.98	0.99	3.54	61.26	0.82	0.96	4.18	4.51	3.98	4.00
7. MRI Brain (100:256×256:8)	2.75	50.00	0.97	0.99	1.34	39.38	0.75	0.95	3.29	3.44	3.46	3.30
8. MRI Cord (11:512×512:8)	2.55	50.02	0.97	0.99	1.29	41.27	0.76	0.97	3.11	3.58	2.78	2.84
9. MRI Knee (50:512×512:8)	1.26	53.9	0.98	0.99	1.22	41.55	0.76	0.97	1.55	1.62	1.59	1.48

lossless non-invertible process. Let $c(\lambda, \theta, [m, n])$ denote a DWT coefficient at location $([m, n])$ within subband (λ, θ) and $cd_q(\lambda, \theta, [m, n])$ is the corresponding quantized DWT coefficient through truncation of $c(\lambda, \theta, [m, n])$. So

$$cd_q(\lambda, \theta, [m, n]) = \lfloor \frac{c(\lambda, \theta, [m, n]}{q} \rfloor \times q \tag{5}$$

where $\lfloor\ \rfloor$ is the truncation function and q is an integer.

Finally, if the absolute value of the difference of the quantized DWT coefficient $cd_q(\lambda, \theta, [m, n])$ and reference DWT coefficient $c(\lambda, \theta, [m, n])$ is below the JND threshold $v_{JND}(\lambda, \theta, [m, n])$, the reference DWT coefficient $c(\lambda, \theta, [m, n])$ at location $[m, n]$ is replaced by the corresponding quantized DWT coefficient $cd_q(\lambda, \theta, [m, n])$.

A. Inter-slice block matching:

There is structural correlation between the stack of medical image slices because each slice generated is usually a cross section of human body and is parallel to adjacent slices. In this stage compression ratio is improved by exploring the correlation in the slice direction. The inter-slice block matching is used to estimate current slice of residual image using the previous image. Inter-slice block matching routine is applied separately for different subbands to exploit correlation between adjacent image slices.

Image slice obtained after eliminating visual redundant information, is split into non-overlapped blocks of 8x8 and a 16x16 search window is defined in the previous image slice. Since there is a resemblance between the two image slices there must be a best match for each block in previous image slice. For blocks with all values zero, block matching algorithm is not applied. A unique displacement vector is chosen to indicate decoder about this particular case while reconstructing the image. There is a need for a criterion for defining the best match. Sum of Absolute Difference (SAD) is used to select the best match.

Block with minimum SAD is considered as the best match. Corresponding displacement vector and block matching residual of the current block is taken for further processing. Adaptive arithmetic coding is the final step which is applied on block matching residual image.

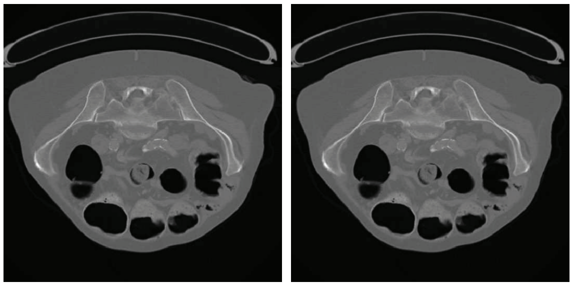
B. Metrics for Evaluating Compression Algorithms

The traditional image quality metrics such as Peak Signal to Noise Ratio (PSNR) and Relative (RE) do not model human perception accurately. Visual Information Fidelity (VIF) [13] and Structural Similarity index (SSIM) [14] are some of the HVS based quantitative performance metrics used to evaluate the quality of the reconstructed image followed by lossy compression for natural images. These statistical metrics are applied to evaluate the perceptually lossless coding algorithm since they closely emulate the HVS.

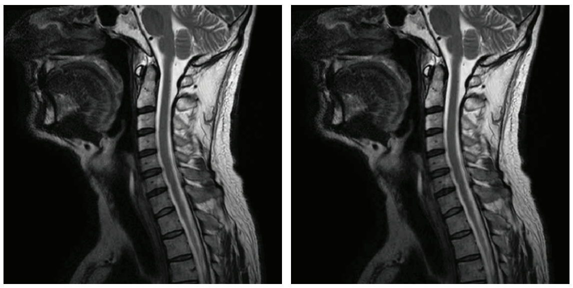
IV. SIMULATION RESULTS

The proposed algorithm has been simulated using Matlab® on an Intel® Core™ i5 Processor. The coder is developed for a viewing distance of 24 inches and for a display with around 35 pixels/degree display visual resolution. Images are decorrelated using 9/7 wavelet filter DWT with 5 frequency levels. The value of parameters *a*, *k*, *f*, *r* and g_θ used in the JND model are based on the experiment carried with various models to reveal the threshold for gray scale DWT coefficients with noise as a function of spatial frequency and orientation θ [12].

Both neighborhood contrast adjustment and self contrast adjustment factors are considered as discussed in Section II. The performance of proposed VLC is tested on volume of MRI, CT and X-ray image data whose details are summarized in Table III, column 1. Volumes 1-3 comprise X-ray images of a vascular study of a human heart. Sequences 4-6 are CT scanning axial view images of a human thorax. Sequence 7 comprises MRI scanning axial view slices of a human brain



(a) Reconstructed CT-3 image: Slice number 50
(i) bpp=3.89; PSNR=73.07 dB (ii) bpp=3.54; PSNR=61.26 dB



(b) Reconstructed MRI Cord image: Slice number 5
(i) bpp=2.55; PSNR=50.02 dB (ii) bpp=1.29; PSNR=41.29 dB

Fig. 2. Visual clip of selected decoded image slices.

and volumes 8-9 is the sagittal view of MRI scanning of human spinal cord and knee respectively.

Performance of VLC and numerically lossless compression algorithms on test data base is given in Table III. Wavelet based VLC is compared with the state of art codecs such as DPCM, JPEG-LS, JPEG2000 image coding standard and HEVC video coding [10]. JPEG-LS is a near lossless/lossless compression standard for natural images and is based on prediction, residual modeling and context-based coding of the residuals. JPEG2000 is the compression standard available for natural images and it is used in DICOM standard. JPEG2000 employs 2D integer wavelet transform. HEVC is a standard codec for the compression of video. It employs multi frame motion compensation and estimation.

DWT coefficients are truncated for various integer values q (equation 5). Visually lossless bit rates given in Table III are obtained by setting the value of q to 3 and 7 to eliminate visual redundancy. Wavelet based VLC with $q = 3$ reduces the bit rate by 20.66% compared with DPCM, 28.24% compared with HEVC, 14.60% compared with J2K and 13.28% compared with JPEG-LS. Wavelet based VLC with $q = 7$ reduces the bit rate by 61.54% compared with DPCM, 72.56% compared with HEVC, 53.85% compared with J2K and 52.1% compared with JPEG-LS. The proposed coder achieves VIF of 0.98 out of 1 and SSIM of 0.99 out of 1 which proves that the coder is indeed visually lossless at the lower bit rates. Figure 2 shows reconstructed images with proposed VLC for the selected image slices of CT-3 and MRI Cord images.

V. Conclusion

Numerically lossless compression methods fail to yield good compression, even though radiologists prefer them. In case of lossy compression techniques discarding any information could affect the diagnosis on the process of improving the compression ratio. So a wavelet based visually lossless approach is proposed to have both better image quality and compression ratio in one coding system. In this coder amount of visually irrelevant information discarded is controlled by a vision model embedded into the lossless compression of medical images. Performance evaluation shows that the proposed method achieve bit-rate savings over standard lossless compression techniques without loss of visual quality.

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