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Progressive Image Transmission for Medical Applications based on Wavelet Transform with a Non-uniform Scalar Quantization Scheme

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Abstract— **The Progressive Image Transmission (PIT) technique has been used to alleviate the communication problem related to transmit large volume of medical image data. In this study, we propose a novel PIT algorithm based on wavelet transform, DPCM coding and non-uniform scalar quantization. Experimental results have confirmed the efficiency of the proposed scheme. The achieved bit rate for the first recognizable picture can be as low as 0.05 bit/pixel transmitted in less than 1.0 second for a 512×512 256-gray scale medical image. The reconstructed image shows higher quality than that obtained by the Set Partitioning in Hierarchical Trees (SPIHT) algorithm, which makes it a winning choice for medical image transmission through low speed communication channels.**

I. Introduction

Current digital medical imaging equipment tends to create large volumes of data in an image database. Transmission of those images with high resolution over relatively low speed channels like a wireless or a dial-up connection will cause a serious delay problem. For example, transmitting a set of 100 CT slices, with each slice made of 512×512 pixels and 16 bits/pixel (bpp), through a dial-up connection with a connection speed of 33.6 Kbps (56K modem) [1] will take about 3.5 hours. Conventional technologies of transmitting images row by row usually make users out of patience or even give up. To overcome this problem, progressive image transmission (PIT) techniques were introduced [2], which usually compresses and gradually transmits the coded bit-streams under certain constraints.

The principle of PIT is to transmit the least amount of data necessary to generate a recognizable approximation of the original image, and further transmit the detailed content to refine the existing images and achieve a high-resolution reconstruction. The receiver side always has an approximation of the original image instead of a fraction at each transmission stage.

In this paper, we present a novel PIT algorithm featuring 2-D wavelet transform, DPCM coding and a nonuniform scalar quantization scheme. The advantage of this scheme lies in its high performance and yet simple implementation. The rest of the paper is organized as follows. Section II describes the wavelet transform-based compression scheme. In Section III, a progressive image transmission algorithm under both the transmission bit-rate and the resolution constraints is presented. The simulation using clinical medical images has been performed to test the performance of the proposed algorithm, and the results are reported in Section IV. Finally, Section V concludes the paper.

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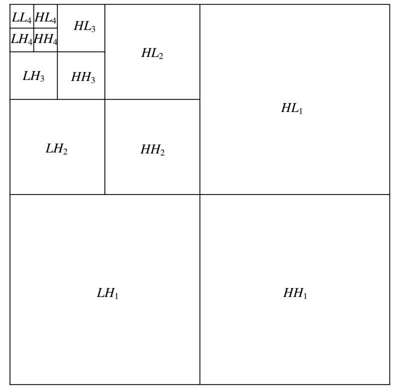

Fig. 1. Illustration of a 4-level 2-D wavelet transform

II. Wavelet Transform based Compression Scheme

A. 2-D wavelet transform

Wavelet transform decomposes the original image into one low frequency subimage LL_n and several subimages (HL_k, LH_k, HH_k, $k = n, n-1, ..., 1$) bearing high frequency details along the horizontal, vertical and diagonal directions, respectively. Fig. 1 illustrates a 4-level 2-D wavelet transform decomposition [3].

B. DPCM lossless coding for approximation subimage

The coarse approximation subimage LL_n contains much richer energy content than the detail subimages, and it is crucial to the reconstructed image quality. As a result, a lossless DPCM coding scheme is applied on it. DPCM is a predictive coding scheme, which is done by encoding the difference or residual between the source and its predicted value from previous source values [4]. We apply a 3rd-order 2-D linear prediction for the coarse approximation given as

$$\widehat{x}(i,j) = a_1 x(i,j-1) + a_2 x(i-1,j) + a_3 x(i-1,j-1) \quad (1)$$

The difference subimage $E(i,j) = x(i,j) - \widehat{x}(i,j)$ obtained from the original and predicted subimages can then be encoded by entropy coding [5].

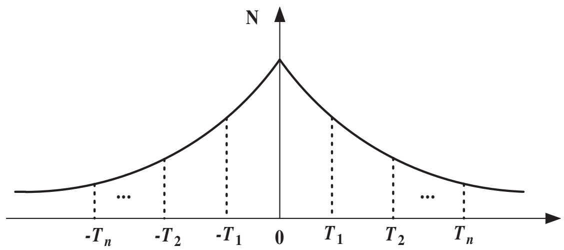

Fig. 2. The distribution of high frequency wavelet coefficients

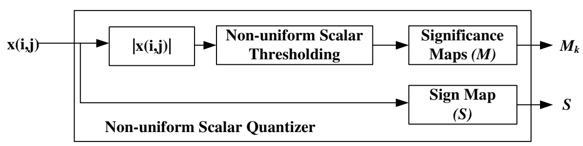

Fig. 3. New quantization scheme

C. Non-uniform scalar quantization for detail subimages

The wavelet transform coefficients of detail subimages (HL_k, LH_k, HH_k, $k = n, n-1, ..., 1$) are quantized using a non-uniform scalar quantization scheme. As pointed out in [6], the wavelet decomposition level and the coefficient amplitude together determine the coefficient weight, and they have significant effects on the quality of the reconstructed image. Experimental results also show that those subimages carrying lower frequency information are of more importance in the reconstructed image quality. Therefore, the wavelet coefficients in the higher-level detail subimages (see Fig. 1) should be handled with high fidelity. The majority coefficients in the detail subimages have low amplitudes and they can be discarded without comprimising the visual quality [7]. On the other hand, the high amplitude coefficients, although the number is small, could lead to significant quality loss, and thus must be handled carefully.

Our experimental results [6] show that the distribution of wavelet coefficients in each detail subimage fits the Laplacian function as shown in Fig. 2. In Fig. 2, T_1, T_2, ..., T_n refer to the quantization thresholds, and quantization intervals are denoted as $Q_k = [T_{k-1}, T_k]$, $k = 1, 2, ..., n$. For each subimage, the threshold is set according to the sampled standard deviation δ.

This quantizer defined by quantization thresholds and intervals treats the magnitude and the sign of a wavelet coefficient separately. Fig. 3 illustrates this scheme. The significance map $M(i,j)$ and sign map $S(i,j)$ are given as follows:

$$M(i,j) = \begin{cases} 1, & |x(i,j)| \in Q_k \\ 0, & |x(i,j)| \notin Q_k \end{cases} \tag{2}$$

$$S(i,j) = \begin{cases} 1, & x(i,j) \geq 0 \\ 0, & otherwise \end{cases} \tag{3}$$

After quantization, all the derived significance maps and the associated sign maps from quantizer tend to be sparse and are encoded by the entropy coding scheme [5].

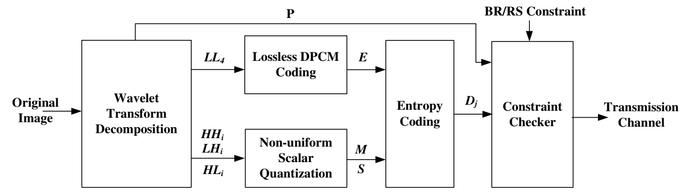

Fig. 4. Block diagram of proposed PIT algorithm

III. Progressive Transmission Algorithm

The PIT is achieved by orderly transmitting hierarchical levels one after the other going from the lowest resolution level (top level) to the highest resolution level (bottom level) [2]. Under the resolution constraints or the bit rate constraints, the image at the current stage can be reconstructed successively by combining the reconstructed image at the previous stages and the quantized subimage with resolution between the previous and the current stages [8].

A. Resolution and bit rate constraints

The resolution constraint specifies the maximum number of scales to be scanned during the non-uniform scalar quantization process. When the resolution constraint is specified, a set of bit rates based on the coefficient distribution is applied to achieve gradually refined reconstruction [9].

The constraint can also be set according to bit-rate. This PIT method can be implemented by changing the resolution at different stages while the bit rate is kept constant [8]. To produce the low- to fine-resolution images at each stage, the maximum number of scales to be scanned varies. This approach leads to a refinement of some coefficients from higher frequency bands of the wavelet space, and therefore, provides more details in the reconstructed image. The basic design procedure remains the same as that for the resolution constraint.

B. Proposed PIT algorithm

Following the wavelet transform-based compression scheme presented in Section II, we propose a PIT algorithm as shown in Fig. 4. The wavelet-transform decomposition is first applied to the original image, to obtain the low frequency and a set of high frequency subimages. A header packet is generated containing the required information for image reconstruction such as original image size, subimage size, specified resolution/bit-rate constraint, and transmission order. The low frequency subimage is processed using the lossless DPCM coding method. For each high frequency subimage, the non-uniform scalar quantization scheme is applied. After that, the DPCM coding and non-uniform quantization outputs are entropy encoded to form the data streams. The data streams are checked under the resolution or the bit rate constraint to satisfy the transmission requirements before they are transmitted orderly through the transmission channel. That is, the low frequency subimage is transmitted first so that the receiver end can generate a coarse approximation for quick recognition, followed by the transmission of the detail subimages from high level to low level that can keep refining the coarse version.

IV. Simulation

A. Parameter selection

Parameter selection has dramatic impacts on the medical image compression. We use an MRI head image with size of 128×128 pixels and 8 bit/pixel as the training image to tune the parameters for wavelet transform decomposition and DPCM predictor as well as non-uniform quantization thresholds. From our extensive experimental results, we have found that the 'db6' wavelet (out of totally 38 commonly used wavelet filters) achieves the best overall performance. The decomposition level is set to 4 to achieve the best trade-off between the number of zeroed coefficients and the computational cost. Our results are in consistence with those reported in [10]. The optimal linear predictor of a 2-D autoregressive (AR) process is $\widehat{x}(i,j) = 0.9 * x(i,j-1) + 0.9 * x(i-1,j)$ - $0.81 * x(i-1,j-1)$. Accordingly, we set $[a_1, a_2, a_3]$ = [0.9, 0.9, -0.81].

For the non-uniform scalar quantization, the thresholds and intervals are determined based on the Laplacian distribution of wavelet coefficients. For the subimage in the fourth level, the quantization interval are set to [0, $\delta/8$), [$\delta/8$, $\delta/4$), [$\delta/4$, $\delta/2$), [$\delta/2$, δ), [δ, 2δ), [2δ, 3δ), [3δ, ∞) to preserve as much information as possible; and in the third level, the intervals [0, δ/4), [δ/4, δ), [δ, 2δ), [2δ, 3δ), [3δ, ∞) are chosen; in the second and the first levels, the intervals are [0, δ), [δ, 2δ), [2δ, 3δ), [3δ, ∞) and [0, 2δ), [2δ, ∞).

B. Experimental results

We present the simulation results of the proposed PIT algorithm designed under the resolution and the bit rate specifications. A set of 20 clinical medical images with 256 gray levels is applied to evaluate the performance of the proposed PIT algorithm.

1) Simulation result for resolution constraint: The resolution constraints I_i can be chosen as $I_4 = 2^{-4}$, $I_3 = 2^{-3}$, $I_2 = 2^{-2}$, and $I_1 = 2^{-1}$, corresponding to scales m = 4, 3, 2, and 1. At each stage, i.e., for a specific resolution i, the bit rate varies according to the size of the subimages at that scale. Here we only display the experimental results of $I = 2^{-4}$ on a clinical 45° macular retinal image with size of 512×512 pixels and 8 bits/pixel. Table I and Fig. 5 show the first eight transmission stages. In the very first stage, the low frequency approximation with a size of 32×32 pixels is transmitted, and a reduced-sized approximation is reconstructed on the receiver side for quick recognition. For easy comparison, the reconstructed image is zoomed in/up to the same size of the original image. One can see that the first stage reconstruction is rough and all the vessels are blurred. Even so, much of the content is still recognizable and the user can decide whether to continue the transmission or stop it. Starting from the second stage, the reconstructed image is obtained by using the wavelet coefficients from detail subimages plus the existing approximation. It can be seen that the big vessels start to appear in stage 2 and the small vessels gradually become visible in the following stages. In the sixth stage, the blurred details get refined and almost all small details appear in the reconstructed image. In the eighth stage, the accumulated bit rate is 0.7 bits/pixel and PNSR value is 42.69 dB. The reconstructed image has fairly good quality containing all the detail information to meet the diagnosis requirements.

TABLE I

Resolution constraint $I = 2^{-4}$

Stage	Indiv. BR	Accumu. BR	Distortion	PSNR
1	0.05	0.05	9.80E-03	35.77
2	0.05	0.10	8.30E-03	36.49
3	0.05	0.15	6.30E-03	37.64
4	0.05	0.20	5.40E-03	38.32
5	0.10	0.30	1.40E-03	39.34
6	0.11	0.41	9.84E-04	40.93
7	0.11	0.52	8.09E-04	41.78
8	0.21	0.73	1.89E-04	42.69

TABLE II

Bit rate constraint BR = 0.5

Resolution Constraint	MSE	PSNR
$I = 2^{-4}$	43.35	31.76
$I = 2^{-3}$	28.34	33.61
$I = 2^{-2}$	21.48	34.81
$I = 2^{-1}$	18.75	35.40

2) Simulation result for bit rate constraint: Table II and Fig. 6 summarize the simulation results with bit rate constraint = 0.5 for an MRI spine image. It can be seen that under the same bit rate, if the scanning scale equals to 4, most of the edges are quite blur. If the scanning scale is reduced to 3, more details appear and the edges become sharper. Further improvement can be achieved if the scanning scale equals to 2. When the scale becomes one, the reconstructed image has the best quality among all scanning scales. One can notice that by scanning only one finer scale of wavelet coefficients, the image quality changes significantly while the bit rate is still kept the same.

3) Performance comparison: The performance of the proposed algorithm is compared with the well-known image coding algorithm Set Partitioning in Hierarchical Trees (SPIHT) [11]. We use the PSNR as an objective measure of the reconstructed image quality to compare the performance of the proposed algorithm and SPIHT at different bit-rates. The compression results of a Digital Subtraction Angiography (DSA) Liver image with a size of 256×256 pixels and 8 bit/pixel are shown in Fig. 7. One can see that the performance of the proposed algorithm is much better than that of SPIHT under the same bit rate specification by preserving more detailed information at early transmission stages (Bit Rate < 2.0).

V. Conclusion

In this paper, we have presented a new PIT algorithm which allows both the bit rate and the resolution constraints to be specified at each transmission stage. The proposed algorithm features wavelet transform, DPCM coding and a non-uniform scalar quantization scheme. In specific, the wavelet

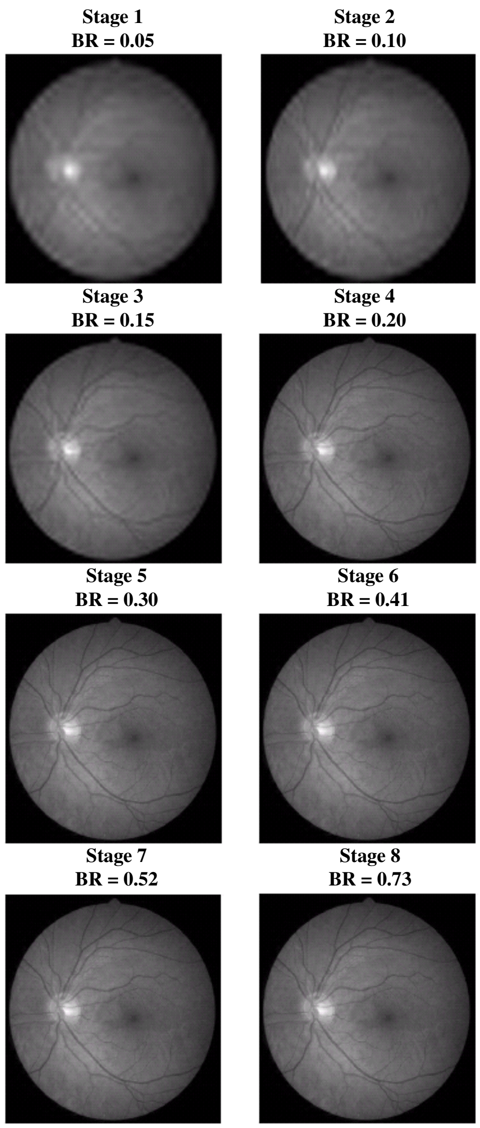

Fig. 5. Retinal images generated at a resolution constraint of $I = 2^{-4}$ and different bit rate constraints

transformation is used to obtain a multiresolution representation of an original image. The lossless DPCM coding scheme is then applied on the low frequency subimage, and the non-uniform scalar quantization technique is used to successively coding each high frequency subimage. Simulation results have confirmed the efficiency and implementation simplicity of the proposed algorithm.

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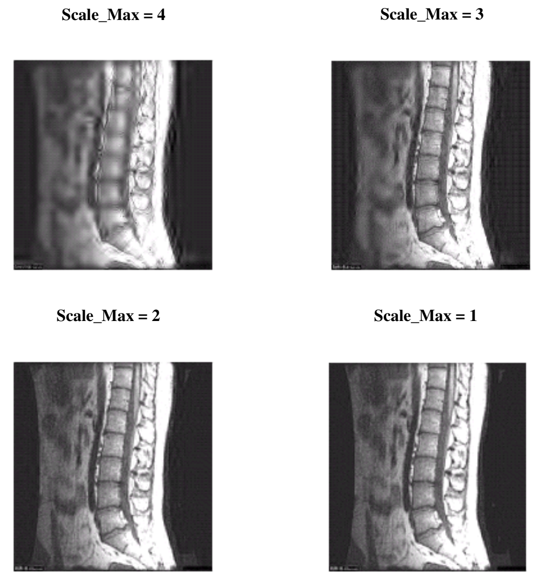

Fig. 6. Spine images generated at bit rate constraint BR=0.5

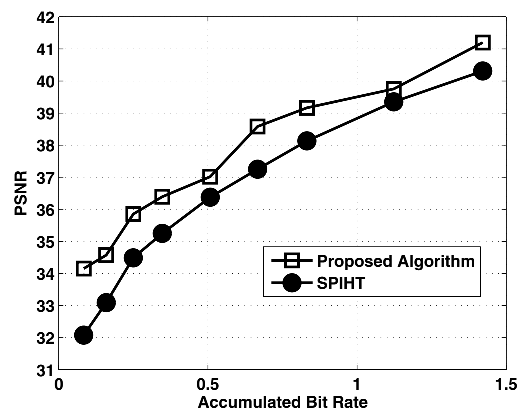

Fig. 7. Performance comparison of different algorithms in PSNR

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