MEDICAL IMAGE COMPRESSION USING POST-SEGMENTATION APPROACH

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ABSTRACT

This paper presents a medical image coding technique that is suitable for interactive telemedicine over networks. The new encoding scheme allows a server to progressively transmit only a part of a compressed image over a network as requested by a client. This technique is different from the region scalable coding scheme in JPEG 2000 since it does not require that a region of interest (ROI) be defined when encoding occurs. In our proposed method, a medical image is encoded at full resolution and stored in the server. A user can receive a basic image at low resolution and then specify a ROI. The server can then provide full resolution for the ROI. Our technique allows a user to select the ROI after the compression has been done. We employ integer wavelet lifting to support lossless coding for medical images that strictly require lossless compression. This paper shows the benefits of the proposed technique with examples and simulation results.

1. INTRODUCTION

Current compression schemes produce high compression rates if loss of quality is acceptable. However, images for medical applications do not allow any deficiency in diagnostically important regions. The strict quality requirements along with the normally large size make it impractical to transmit the image through a network. This is the bottleneck of its use in telemedicine application. An approach that supports the transmission of the medical image with a high compression rate with good quality in the ROI is thus necessary. JPEG 2000 and other related research that supports ROI coding use the pre-segmentation approach [1, 2, 3] since the ROIs are identified and segmented before encoding. The challenge of the pre-segmentation approach is to obtain the segmentation automatically. Segmentation is one of the most significant and difficult tasks in the area of image processing. If a segmentation algorithm fails to detect the correct ROIs, then the result would be disastrous since the important diagnostic data in the original image would possibly be lost.

Our proposed region scalable coding scheme is a post-segmentation approach that can solve the problems associated with the pre-segmentation approach. In this approach, lossless compression is applied to the whole image and stored in the server. By applying special treatment (set partitioning and rearrangement) to the transformed data, small regions of an image are identified and compressed separately. This will allow a client to access a specific region of interest efficiently by specifying the ROI. The proposed coding method achieves high performance by using the integer wavelet transform with the lifting scheme, successive quantization, and partitioning that rearranges the wavelet coefficients into subsets. Each subset that represents a local area in an image is then separately coded using run-length and entropy coding.

Typically, medical images require huge amounts of data even though it may be compressed. Since lossless compression is applied to the image, a large amount of data is required to reduce the mean square error to an acceptable level for the high resolution images. We applied set partitioning in hierarchical trees (SPIHT) to a magnetic resonance image (MRI) using the integer wavelet transform to obtain perfect reconstruction of the image [4].

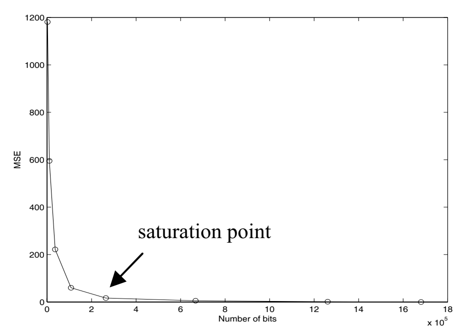

Figure 1: The number of bits versus mean square error with SPHIT

Fig. 1 shows an example of the relationship between amount of the data and quality of the image. As shown in the figure, the quality of the image begins to saturate beyond 200kbits. The total number of bits required for perfect reconstruction is 1.7Mbits, which is eight times larger than the amount of data around the saturation point. This proves the necessity of the region-scalable coding approach. As shown in the example, a server can send a doctor 20kbits of data that is visibly good enough to locate potential ROIs. Then, if a doctor finds a ROI, then he or she can request more data in only the ROI, which would dramatically reduce the amount of data that must be transmitted.

In the rest of this paper, details of the proposed approach will be discussed. In section 2, we will discuss our approach to achieve region scalable coding. In section 3, we will discuss the performance of the proposed technique using our simulation results. We summarize our research results in section 4.

2. APPROACH

2.1. Integer Wavelet Transform

For lossless coding it is necessary to make an invertible mapping from an integer image input to an integer wavelet representation. A new still image compression standard, JPEG 2000 is based on the DWT [5]. JPEG2000 employed the integer wavelet transform with lifting for lossless coding.

The lifting scheme presented by Sweldens [6] allows an efficient implementation of the DWT. Another of its properties is that perfect reconstruction is ensured by the structure of the lifting scheme itself. This allows the integer wavelet transformations to be used. It is a basic modification of linear transforms, where each filter output is rounded to the nearest integer. The integer wavelet transform can be used to obtain lossless compression[6]. In our approach, we use the integer wavelet transform with lifting for both lossy and lossless coding.

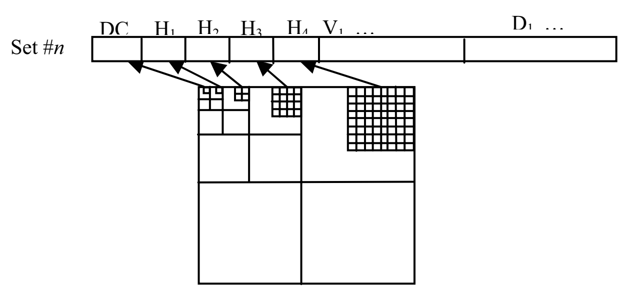

Figure 2: Set partitioning of the wavelet transform

2.2. Set Partitioning & Rearrangement

The wavelet coefficients are partitioned into subsets to achieve the proposed post-segmentation. A subset consists of a pixel in the lowest sub-band and its children from a quad tree structure. Each set represents a small area corresponding to a block in the spatial domain. Fig. 2 explains how the wavelet coefficients are rearranged to make up an image that consists of sets. A set is extracted from a wavelet image. Each set consists of one wavelet DC value and its children in horizontal (H_n), vertical (V_n), and diagonal (D_n) directions. Each element in each sub-band is arranged by the raster scanning order.

2.3. Successive quantization and Layering

In the post-segmentation approach, the ROI is not defined when encoding occurs. A whole image is encoded with full resolution. Entropy coding cannot be applied across the sets or bit-planes in the post-segmentation approach. This restriction degrades coding efficiency at the expense of region scalability. Details of successive quantization and layering are given as follows. In each set, a unique quantizer is used for quantization and layering. The quantizer Q1 is the quantizer with a center dead zone for the basic layer. In the basic layer, a threshold is used for the wavelet coefficients and they are quantized by Q1. In the enhancement layer, a threshold is used for the coefficients and they are quantized by Q2 with thresholds, (Tl, T2). The quantization occurs between Tl and T2 (Tl > T2). Nonzero values outside [Tl, T2) are set to zero in the enhancement layer. For further layering, the system requires a set of quantizers (Q1, …, QL, QL-1,) to produce one basic layer and (L - 1) enhancement layers. If we choose the step size for the threshold to be a power of two, then the quantization scheme would be similar to the successive approximation scheme used in SPIHT [4].

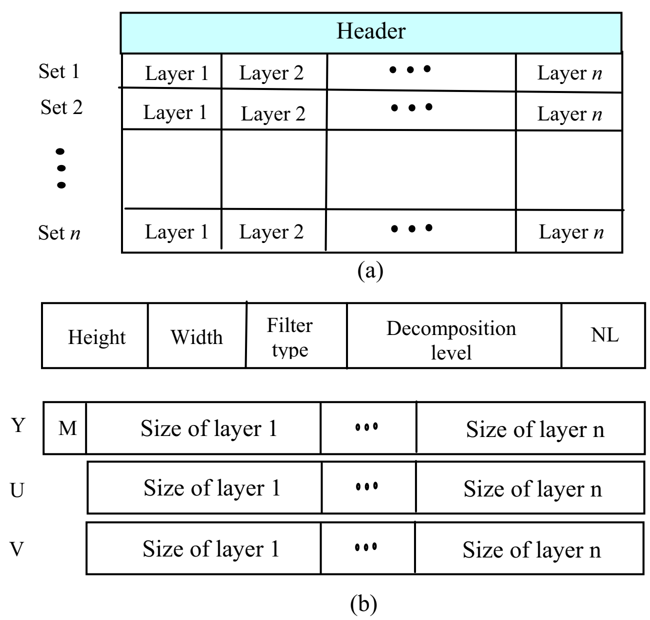

Figure 3: Set partitioning of the wavelet transform (a) structure of set partitioned image data (b) header information

Fig. 3 shows the set arrangement including header information. The header contains information regarding image properties, number of layers (NL), markers, and number of bits for each layer in each set.

The overhead for the header information is negligible compared to the image data. When each set is transmitted, the header does not need to be sent since reconstruction can be done without the header information. Therefore the header information does not affect the network traffic. Any sets corresponding to the ROI that a client requests can easily be extracted and transmitted due to the efficient structure of the encoded data. In the client site, a decoder keeps log information that records transactions between the server and the client. When we send the data, we split the requested data into several packets.

The structure of each packet is shown in Fig. 4. The first two bytes in the figure are the identifier (ID) of a set. This is followed by the set number (SN), number of layers, and size of image data in the set. The image data comes last.

ID	SN	NL	Length	Data
2bytes	2bytes	1byte	2bytes	Image data

Figure 4: Structure of the data packet

3. SIMULATION RESULTS

We used lossless coding using integer wavelet transform because of the strict requirements for telemedicine applications. However, when the image is decoded, only the ROIs are fully decoded. Therefore, we need to consider the properties of wavelets other than the properties normally considered for image compression such as energy compaction. One important property is how the length of the wavelets used affects the quality of the image near the boundary of the ROI. We evaluated three different types of wavelets to evaluate compression efficiency for ROI image compression. We evaluated the S transform, the 5/3, and the 9/7 integer wavelet transforms. We evaluated the impact of edge effects for the different wavelets as shown in Table 1. As shown in the Table 1, the 9/7 integer lifting shows the worst compression performance even though it has a very good energy compaction property [7]. The 5/3 wavelets also degrades the image quality near the boundary of the ROI, resulting in 50.51dB for the PSNR in the ROI. This phenomenon was caused by the interaction of the data at low resolution outside the ROI with the data at high resolution inside the ROI. There are some edge effects both inside and outside the ROI. We are concerned with the edge effects inside the ROI. The length of the wavelet determines the region of support for the wavelet used. The effects of the transition of the data at the edges of the ROI can potentially last for all the region of support around the edge. However, we can eliminate these effects within the ROI by extending the ROI by an amount equal to the region of support for the wavelet filter used. Thus, the wavelet with a shorter region of support has an advantage.

Table1: Comparison of Wavelet filters

Wavelets	$PSNR_{ROI}$ (dB)	Total bits (bits)
S	∞	220k
5/3 integer	50.51	250k
9/7 integer	47.64	250k

We now discuss the performance of our region scalable image compression (RSIC) method compared to other existing algorithms. We applied our RSIC to an ultrasound image and an MRI image. Fig. 5 shows an ultrasound image. As shown in Fig. 5, the image pixels within the ROI were perfectly recovered while the background was reconstructed at visually acceptable quality. As you can see, the letters in the background are readable.

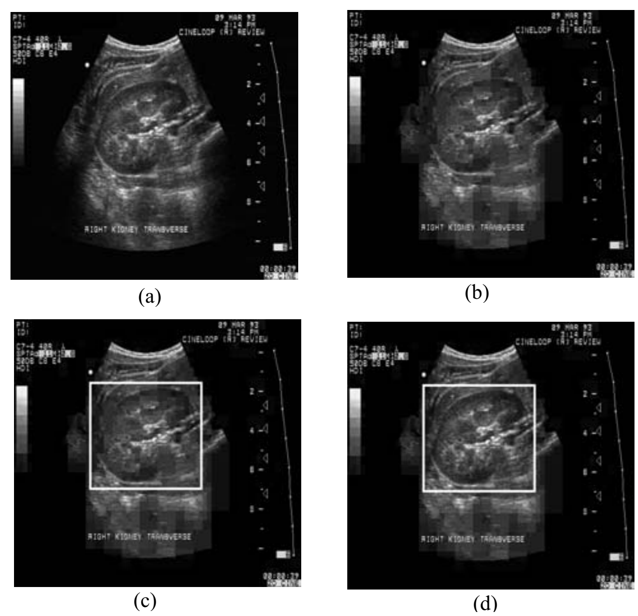

Figure 5: RSIC for Ultrasound (ROI: 15%) (a) original image (b) reconstructed image with basic quality (c) ROI selection from (b) (d) reconstructed image with updating ROI

Fig. 6 illustrates another example of using the RSIC. Fig. 6-(a) and Fig. 6-(b) show a normal spine image and an abnormal spine image. Fig. 6-(c) is a reconstructed image with basic quality from Fig. 6-(b). In Fig. 6-(d), the area in the white box is the ROI that contains an abnormality of the spine. A user can identify the clinical problem from the image with basic quality that was reconstructed with a small number of bits. If a user needs to see a ROI with higher quality, then the server can update only the ROI in addition to the previously decoded image. Since this technique is post-segmentation based, the client can interactively update as many ROIs as needed. Compression results for this approach are summarized in Table 2.

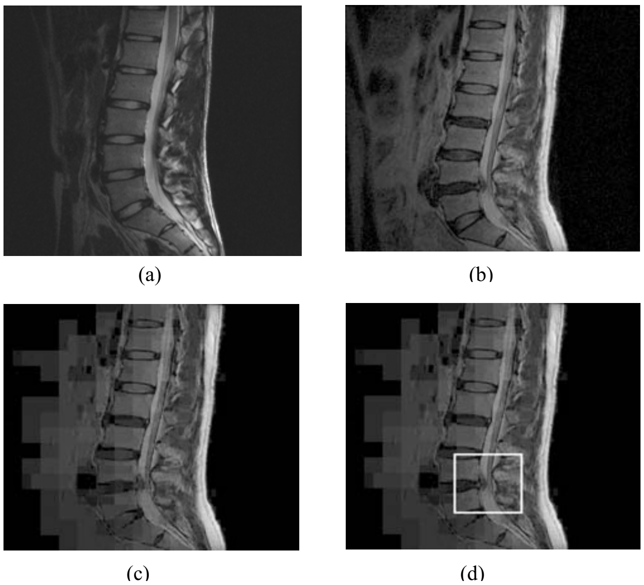

Figure 6: RSIC for MRI (ROI: 5%) (a) original image for a normal spine (b) original image for an abnormal spine (b) reconstructed image with basic quality (d) reconstructed image with ROI updated

Table 2: Coding Performance of RSIC

Area	Ultrasound		MRI	
	$PSNR_{ROI}$	Total bits	$PSNR_{ROI}$	Total bits
Background	28.12	212065	32.48	193843
ROI	∞	532836	∞	340129
Whole Image	∞	1097367	∞	1569233

Finally, Fig. 7 compares the performance of the RSIC with the EZW and SPHIT methods. The solid line with squares and the dashdotted line with circles show the results using the conventional method and the dotted line with circles shows the results using RSIC. The region of interest covers about 5 percents of the whole image. As shown in Fig. 7, RSIC saves many bits compared to EZW and SPHIT while keeping the image quality lossless in the ROI. RSIC saved the huge amount of bits compared to SPHIT at a full resolution.

4. CONCLUSION

The fully embedded scalability of the proposed coder allows us to transmit the basic layer with additional refinement data related only to a set or sets corresponding to the ROI in the image based upon a user's request. Our proposed RSIC technique also supports scalability for a pre-defined ROI. The main contribution of this research is that our proposed RSIC method allows a user to select the ROI at any time and then have the server to update only the ROIs requested. This is a very important feature for medical image communications that satisfies both the requirement of quality for the ROI and compression to make transmission of important medical images over networks feasible.

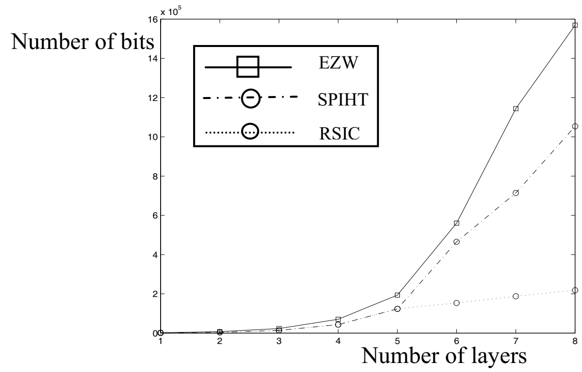

Figure 7: Comparison of EZW, SPIHT, and RSIC applied to a spine image

5. REFERENCE

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