Dynamic region-based wavelet compression for telemedicine application

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ABSTRACT

In this paper, a novel image compression scheme is presented, which is specially suited for image transmission over a narrow-band network typically required for telemedicine to remote regions. A wavelet compression algorithm is enhanced with the feature of dynamically compressing different regions of the image. This feature is provided while keeping the algorithm's embedding ability, which leads to a 'importance' embedding rather than the traditional 'energy' based embedding. To incorporate regions in a wavelet-based compression algorithm the region edges were carefully tuned to eliminate the negative influence that the wavelet transform has on the region algorithm. Tests of this new algorithm on standard test images and ultrasound images showed that both the dynamic and region-based features could be incorporated into the wavelet algorithm with only a small overhead.

Keywords: telemedicine, embedded zerotree, region-based compression, wavelet.

1 Introduction

This paper introduces a new image data compression algorithm motivated by the need for conveniently transmitting medical image data over low-bandwidth networks which is invoked by the growth of telemedicine.

Telemedicine[1] is the provision of health care services via interactive audio visual and data communications. It is a digitized and computerized process incorporating many technologies like communications, databases, user-interfaces and medical science while the foundation of it is communication. As the medical images may be very big, the transmission and storage of the medical image often causes difficulties. For example, a single 2048x2048 X-ray image may use 4 megabytes, and transmitting it over a telephone line operating at 9600 bits per second (bps) may take 1 hour, which would be very inefficient. So, if we want to get better performance, we'll have either to increase the bandwidth of the communication channel or to apply some compression during transmission. Furthermore, the situation of narrow-band communication will not be totally eliminated in the near future. In many remote countryside places, wide-band communication service may be unavailable; also, in moving vehicles, ships or planes, it is hard to achieve wide-band communication because of the limitation of the spectral resources. A compression ratio of at least 10:1 is highly required, and better could reach 30:1. Then for the previous example, the image could be transmitted in only a few minutes.

There already has been much research on image compression, and a large variety of algorithms have been proposed. A standard compression algorithm, JPEG, is available which will get good results on most images except when the compression ratio is high. In our experience, the block artifacts to which JPEG is susceptible appear when the image is represented by less than 2 bits per pixel(bpp). Recently, the wavelet transform was proposed[2] which can achieve a better compression ratio for many images without increasing computational complexity.

When using wavelet algorithms to compress an image with a ratio of 10:1 or even 30:1, down to below 1 bpp , the decompressed image's quality is enough for most uses. But for medical usage there are still some problems. First, as the medical image's quality may influence the diagnosis result, lossy compression has not yet been accepted for use in diagnostic usage. Second, unlike ordinary usage, which is mainly concerned with the overall impression of the image, medical imaging may be very concerned about the detail at some region (e.g. a pathologically important region), so the deviation caused by a 30:1 or 10:1 compression at that region may be unacceptable.

By considering the strict requirement of medical imaging and the fact of low-band communication in the future decade, the current image compression technology is still not adequate for the task. Some new technology is required.

2 Embedded Compression and Region Based Compression

One of the recent valuable achievements for providing better service on image transmission is *embedded zerotree wavelet image coding*(EZW).[3–5] 'Embedded' here means that the image is coded in such a way that encodings of the image at lower bit rates are always at the beginning of the bit streams of the encoding of the same image at higher bit rates. This leads to a result that a small leading part of the encoding bit-stream can provide a coarse reconstruction of the original image. With the use of embedded coding, we could already make our image transmission system more acceptable to the medical users. For example, we could first transmit a lower-quality image in minutes for initial viewing and could get a quick idea for the following steps of diagnosis, then with a following slower transmission of further detail to double check and draw a formal and legal conclusion; or we could let the remote expert browse the compressed images in the local image database by just transmitting the head part of them and then only the relevant images are transmitted in their entirety.

Interest in a medical image often can be confined to a specific region. A different bit-rate can be allocated to different spatial regions according to their 'importance' to the user. This kind of bit-rate allocation, different from the widely used optimal bit allocation[6] to minimize the total distortion such as the *mean squared error* (MSE) of the image, is a *region based bit-rate allocation.* A region based method provides another way solving the conflict between the high fidelity requirement for medical images and the low bandwidth communication.

3 Dynamic Embedded Image Coding

We have seen that both embedded coding and region based compression are helpful for our target of improving the image transmission performance for telemedicine usage, but up to now, we haven't found any research work which will work on both of them. In this paper, a new very flexible and high performance compression scheme called *dynamic region-based wavelet*(DRW) coding is implemented. It is an algorithm which provides region based compression; meanwhile, it is an embedded coding algorithm which also supports progressive transmission. Furthermore, this is a completely dynamic algorithm which can choose and change the *region of interest*(ROI) to encode on the fly. If no region of interest is selected, the algorithm will progressively encode the whole image until some target requirement such as bit-rate or distortion rate is reached. If a region of interest is selected, the successive bit-stream only progressively encodes that region(of course it will stop if some requirement is reached). The ROI could be changed to any shape and position in the middle of sending the previous ROI. If needed, after the encoding of the ROI, the remaining image could continue to be coded and transmitted until a bit-rate or some other requirement is reached.

As mentioned previously, the wavelet transform based compression has very good performance on both compression ratio and speed. The DRW algorithm inherits the high performance of wavelets and adds the novel feature of dynamic embedded coding.

4 Method

In the embedded zerotree wavelet (EZW) coding, the most critical concept is the *zero tree* and the *successive approximation*.

One property of the subband wavelet decomposition coefficients is that there are many small-valued coefficients in the high-frequency or fine-scale subband. With respect to a given threshold, these coefficients could be quantized to zero. The zero tree is used to efficiently code this quantized wavelet image by utilizing another property of wavelet images, i.e. the coefficient of a given scale is likely to be greater than the coefficient of the same orientation in the same spatial location at finer scales. If a coefficient is thresholded to zero, this coefficient and its *descendents* at finer scales are likely to form a zero tree.

Successive approximation is realized by first coding with a very coarse threshold (usually half of the maximum magnitude), then iterating by halving the threshold and redoing the coding. The fidelity is then revised, iteration after iteration. Full details of the method are given in Shapiro.[3] Looking at the successive approximation process of the EZW algorithm, we may regard the threshold as a 'fidelity requirement'. Choosing different thresholds means different fidelity requirements for the reconstructed image. Region-based image compression may be described as a compression which has different fidelity requirements for different regions. In the conventional EZW algorithm, the threshold is unique at every iteration; in other words, there is one fidelity requirement for the whole image. We conclude that, if we could specify different thresholds for different regions, the EZW coding could be upgraded to a region-based algorithm.

In the DRW method, the mask of the ROI is transformed into the wavelet domain and is called the *coding mask*. For each coefficient in the wavelet domain, a unique threshold is assigned (the initial values are all set to be half the maximum magnitude). Then, in the coding process, we choose only to code the coefficients in the coding mask. At each iteration, for every such coefficient, its related threshold is halved.

There are some important considerations here:

1. In the new method, when checking if a coefficient's value is zero or not, we check it against its own threshold, or its own fidelity requirement.

2. Sometimes, we may have case that when coding an in-mask coefficient, some of its descendents might be outside the mask. These coefficients are taken as zero to increase the possibility of forming zero trees, but the threshold of these outside coefficients are not halved, because they are not coded.

3. In the wavelet transform each point's energy spreads to its neighbor, and the reconstruction value is a weighted sum of its neighbors. The size of this neighborhood is dependent on the wavelet filter and the frequency of information. As the low frequency energy spreads much wider than the high frequency one, we couldn't just enlarge the mask at fixed width in the spatial domain. We found that enlarging the mask at the transform domain gets good results, because it gives different subbands the least necessary enlargement.

With this new algorithm, region based compression is performed as follows.First the mask is set to be the whole image, and the image is coded and transmitted until the required fidelity of non-ROI is reached. Then the mask is reduced to the ROI, and the image is coded and transmitted until the fidelity requirement under the coding mask is fulfilled. In the DRW algorithm, the mask can be changed dynamically, so that after the ROI is perfectly coded, the region of interest may be set back to the non-ROI, and the image is coded until its fidelity catches up with the ROI's. This leads to a progressive transmission of the image which is not just based on the

Figure 1: Original image – lena, 512x512 8-bit greyscale

compression	bpp	psnr	time EZW (seconds)	time DRW (seconds)
16:1	0.5	36.20	11.68	13.14
32:1	0.25	33.15	9.97	11.13
64:1	0.125	30.25	8.52	10.07

Table 1: Test result on lena (512x512 8-bit greyscale)– mask fixed to the whole image

energy, but based on the "importance" of the information.

5 Test Results and Performance

This algorithm has been implemented and tested on a Sun sparc 5 workstation running SunOS 4.1.3.

Table 1 lists PSNR and timing result on a test image "lena" shown in Figure 1, with the mask set to the whole image all the time.The new algorithm has the same PSNR performance as EZW, and the speed lag compared with EZW is acceptable.

Result Figure	bytes	bpp	psnr	psnr in ROI
Fig 2 (a)	1314	0.04	26.22	25.62
Fig 2 (b)	3645	0.11	26.63	36.91
Fig 2 (c)	3645	0.11	29.56	29.13
Fig 2 (d)	29056	0.89	37.31	37.04

Table 2: Test result on lena – dynamic rendering, ROI is shown on Figure 2 (b)

(a) (b) (c) (d)

Figure 2: Example of Dynamic Region-based Compression Algorithm:
(a) Mask set to whole image, first 1314 bytes
(b) Follows (a) , after a ROI is selected,and a total of 3645-bytes have been transmitted
(c) shows the first 3645 bytes if the whole image is transmitted
(d) shows without the ROI, 29056 bytes are needed to create the same fidelity within the ROI as shown in Fig 2(b)

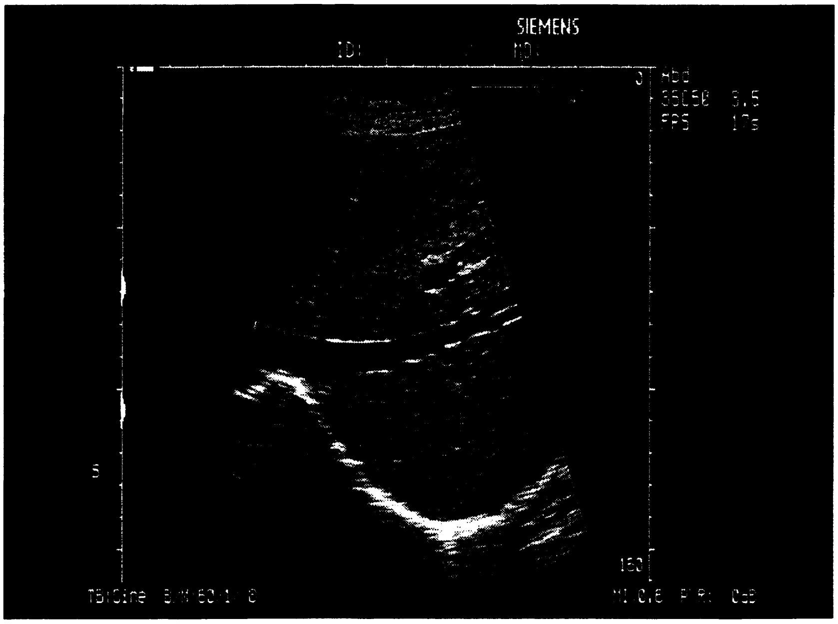

Figure 3: Original image ultrasound, 640x480 8-bit greyscale

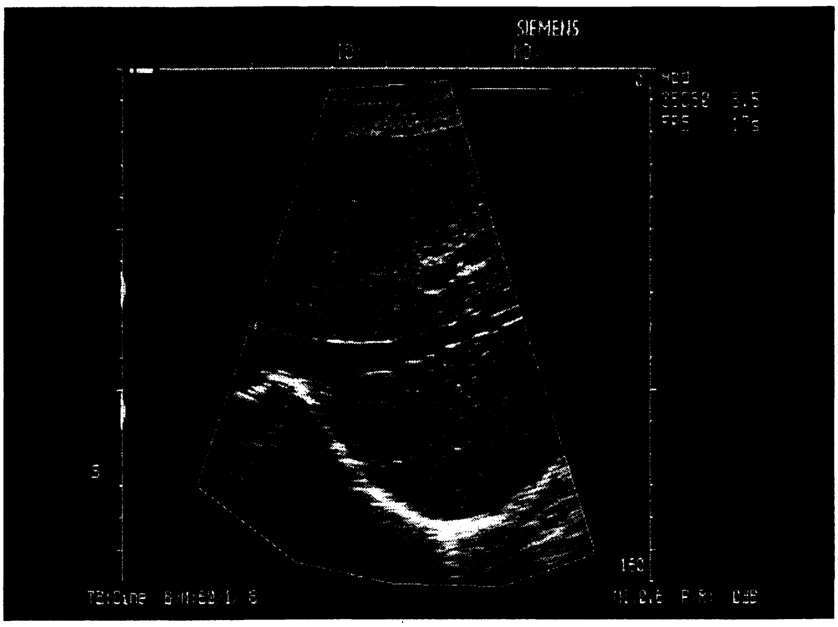

Figure 4: Figure 3 compressed with DRW at 0.21 bpp

in-region psnr (dB)	bpp DRW	bpp EZW
19.51	0.060	0.060
21.92	0.10	0.15
25.59	0.21	0.34
30.81	0.40	0.61
36.51	0.69	1.01
42.64	1.02	1.46
49.29	1.37	1.94
56.92	1.70	2.42

Table 3: Test result on Figure 3

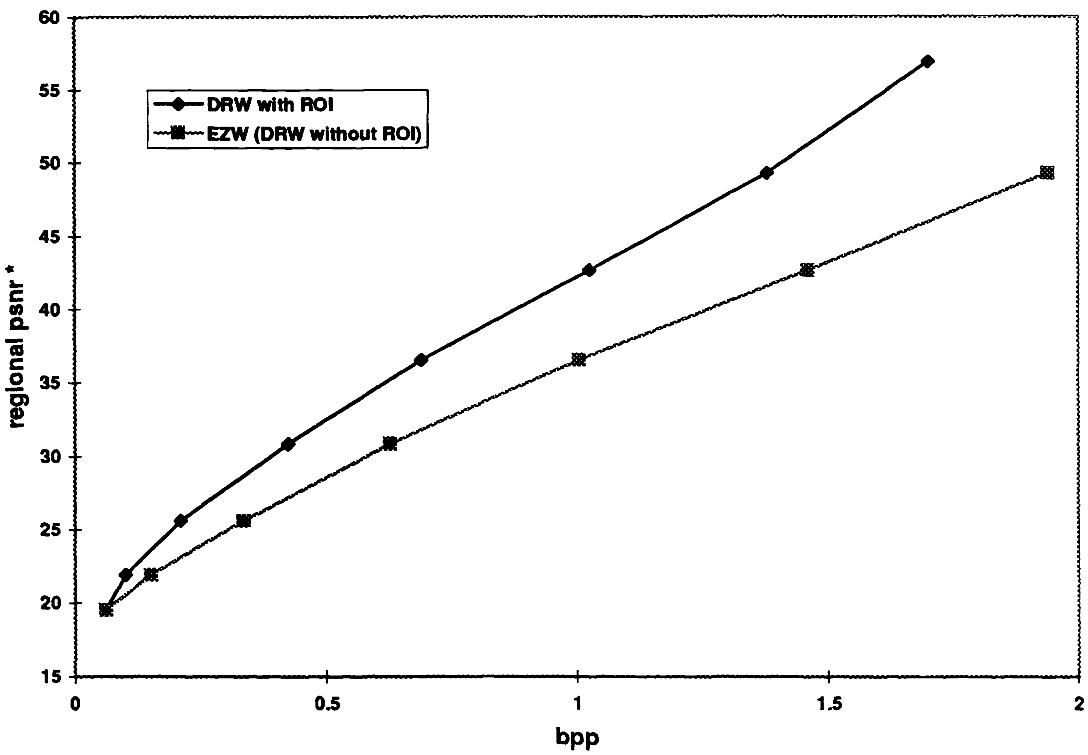

Figure 5: Performance of DRW and EZW on Figure 3
*the psnr of the region as plotted in Figure 4

Figure 2 shows an example of dynamic transmission of the lena image. Table 2 lists the PSNR performance of the example of dynamic transmission in Figure 2. Figure 2(a) shows a 0.04 bpp compression of the whole image; Figure2(b) and Figure 2(c) are both 0.11 bpp compression. Observe in Figure 2(c) how poor the selected region looks compare with Figure 2(b) after the same total number of bytes has been transmitted.

Notice that, if we go from Figure 2(b) and set the ROI back to the whole image and go on with the transmission, we could get exactly the same result as Figure 2(d) after 29472 bytes, compared with 29056 bytes of Figure 2(d). This shows that the region-based dynamic transmission has very small overhead.

Other tests were performed on ultrasound images, of which a typical one is shown in Figure 3. These images have text and large black spaces, which makes their compression characteristics rather different to the lena-like images, where meaningful medical data occupies the whole image. Fore these ultrasound images, it is reasonable to choose the ultrasound data as the ROI, as shown in Figure 4. Here, the DRW scheme gives the non-ROI only enough fidelity requirement to recognize the texts and scales. The saved bytes budget is used to make the ROI more detailed.

The psnr of the data within the ultrasound ROI are given in Table 3, after compression of the ultrasound image to different levels, using both the whole-image EZW compression, and also the DRW compression method. The DRW method always out-performs the conventional whole-image EZW compression. Note that for a within-region psnr of 30.81, the DRW method uses only 0.40 bpp whereas the EZW method requires 0.61bpp; from the original 8bpp data, the DRW method provides a 20 times compression, whereas the EZW method provides only 13.1 times compression. Figure 5 shows the result of DRW at 0.21 bpp, which has the same in-region psnr as the result of EZW at 0.34 bpp, hence 38% more compression is realized. Similar results were obtained for other grey-scale ultrasound images.

6 Conclusion

In this paper, we have introduced a new dynamic region-based wavelet image compression scheme which is based on a general, state of the art still-image wavelet compression algorithm. We have devised a mechanism to add a dynamic feature to the algorithm, and optimized the image partition for region-based coding in the wavelet domain.

The results of our DRW compression techniques on a standard test image and on several ultrasound images were compared with the conventional EZW algorithm. Our DRW algorithm shows an advantage because of its dynamic and region-based features. Further more, these features have little influence on the speed and compression ratio in comparison with the "mother" EZW algorithm. In low band-width communication, the DRW algorithm could be used to greatly reduce the transmission time for the receiver to get the most important information first.

7 Future Work

The choice of the wavelet filter is an important aspect of tuning any wavelet-based compression system. For region-based compression, the region segmentation performance of a filter could be take into consideration. The spectral characteristics of different medical image modalities may require different wavelet basis functions or different filters, and different wavelet compression techniques. We are currently investigating different wavelet algorithms for colour and greyscale ultrasound images where the texture needs to be retained for diagnoses. Another technical improvement may occur if we incorporate the dynamic region-based concept into other zerotree based algorithms such as the Said-Perlman algorithm[7] which has better performance than EZW.

Another aspect concerns the design of the Graphical User Interface for interactively drawing the ROI; we are working on designs for the GUI, including the possibility of automatic or semi-automatic segmentation of the ROI in ultrasound images to aid in data storage and display.

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9 REFERENCES

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