Echocardiography Sequential Images Compression Based on Region of Interest

Wenjing Jia, Xiangjian He, Qiang Lin

Abstract– **This paper describes the studies on methods of compression for medical echocardiography sequence, or called ultrasound sequential images in this paper. The aim is to find a combination of methods, which achieves the highest overall compression performance. Our approach is based on region of interest (ROI), i.e. to segment the image into several regions according to their spatial characteristics, and then compress them separately with different methods. In doing so, we are able to achieve a relatively high compression ratio of about 7.2 while preserving the lossless contents of important regions.**

Index Terms– **Echocardiography Sequence, Image Compression, Region of Interest.**

I. Introduction

Data compression techniques play a key role as a leveraging technology in data-management systems, which reduce the storage requirements and transmission time, making the data management more effective and efficient. Most of the compression algorithms can be divided into two classes according to their principles: redundancy removal and entropy encoding. The performance of an image compression algorithm can be measured by its compression ratio (CR), i.e.

$$CR = \frac{Size\ of\ original\ image\ in\ bits}{Size\ of\ compressed\ image\ in\ bits} \tag{1}$$

For a group of data that is in some way related to each other, like the pixel values of an image, if a portion of the pixel value is known, the likelihood of making a good estimation is high by applying some rules of prediction. This redundancy removal procedure is often exploited in many applications including speech and image coding. Moreover, in order to make the resulting output of this process amenable to more compact representation, an entropy coding is often used. Two commonly used entropy-coding algorithms are Huffman coding [1] and Arithmetic coding [2].

Generally there are two categories of image compression: lossy and lossless. Lossless compression ensures complete data fidelity after the reconstruction, and yet the compression ratio is limited in general to 2:1 to 3:1. The application of lossy techniques results in information loss to some degree, but it can provide more than 10:1 compression ratio with little perceptible difference between reconstructed images and original images. Lossy compression techniques have been widely utilized for image compression [3]. However, unlike other compression applications such as TV and multimedia systems, some applications, like medicine, cannot afford any deficiency in diagnostically important regions (i.e. Region of Interest, ROI) so as not to contribute to diagnostic errors. So an algorithm that brings high compression ratio without loss of information in the ROI is thus necessary. A hybrid-coding scheme seems to be the only solution to this twofold problem. The general theme is to preserve quality in diagnostically critical regions, while highly compressing the other regions by high compression ratio algorithm.

In this study, we put special emphasis on the ultrasound sequential images (i.e. images with a strong correlation between temporally consecutive frames), where the medical information of the single frame is coming from the fan-shaped region in the middle part of the image, or in some applications, the electrocardiogram (ECG) in the bottom part of the image will be used also. As a consequence, in this context, we apply lossless coding scheme only to the ROI, whereas the rest of the image is processed in different channels. To exploit the interframe redundancy, we applied lossless interframe image compression using 3-dimensional differential pulse code modulation (3-D DPCM) due to its computational ability.

To our knowledge, this is one study concerned with the detection of motion information of ultrasound sequential images. The main research in this area is to mine dynamic information of human heart. Q. Lin et al. [4] have developed a system used to analyse cardiac ultrasound images. The development of compression technology will also allow for efficient use of automatic detection techniques in analysis of human heart motion information.

The paper continues as follows: Section II gives a review of lossless intra- and interframe image compression techniques. In section III, a description of investigated ROI-based compression schemes is given, and the results are given in Section IV. Section V gives our conclusions and discusses possible future work.

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ICITA2004 ISBN 0-646-42313-4

II. REVIEW OF LOSSLESS IMAGE COMPRESSION

A. LOSSLESS INTRAFRAME COMPRESSION

In [5], Kuduvalli and Rangayyan presented a performance comparison of several reversible image compression techniques. The source images they used were mammograms and chest radiographs with 10-bit intensity pixels, and the compression performance was presented in terms of average bit rate per pixel. The algorithms studied by Kuduvalli and Rangayyan can be categorized into four groups as follows,

1) Only entropy coding (including Huffman coding and Arithmetic coding)
2) Linear predictive coding followed by entropy coding.
3) Transform coding followed by entropy coding.
4) Linear interpolative coding followed by entropy coding.

The main results of these four techniques presented in the article are summarized in Table 1, which are already changed into compression ratio.

Tablel 1. Performance of Lossless Compression

Compression Technique	Compression Ratio
Entropy coding	1.1-2.0
Linear predictive coding	2.5-4.0
Transform coding	1.3-2.2
Linear interpolative coding	1.7-2.9

These results showed both the relative strength of the various coding techniques, as well as the CRs achievable with the lossless intraframe coding techniques. Among the values listed, linear predictive coding followed by entropy coding method has the best performance. In this paper, we also take a similar approach and our research show comparative performance with different algorithms in the context of a segmented image.

B. LOSSLESS INTERFRAME COMPRESSION

In most of the cases, ultrasound images are part of a complete sequence. The only part that is variable for each image in a sequence is the medical part. The background information and the text do not change or their change can be omitted from one frame to another. In order to exploit this correlation information, many ROI based algorithms were proposed.

S.B. Gokturk et al. [6] proposed a hybrid coder that uses a motion compensated coder in the overall image and entropy minimizing lossless coder for coding the error in the ROI region. In their application, the colon wall is segmented through a sequence of 3-D morphological image processing techniques at first. Then, motion vectors are coded for each block of the image. Finally, the error between the real image and the motion predicted image is coded for ROI blocks. However, the motion of the heart is identically different from that of other apparatus in human body, such as colon, because the movement of the heart cannot be viewed as a rigid body. This can be seen in Fig.1, where the short axis (the left) and long axis (the right) ultrasound wave-line directions (broken lines), and the actual motion orientation (real lines) of cardiac structure are illustrated.

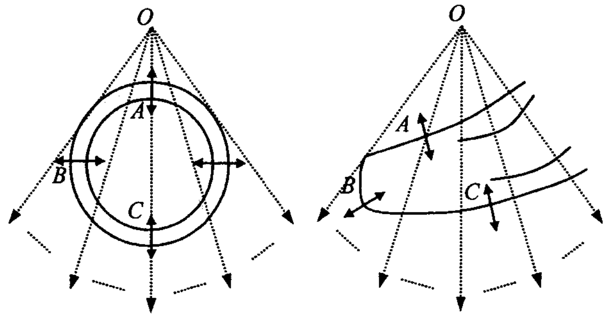

Fig. 1. The motion orientation of cardiac structure

As seen in Fig.1, the motion of the cardiac structure is a kind of contract-expand movement companied with slight translations caused by the strike of blood. However, between these two kinds of movement, its contract-expand movement is the most essential. As a consequence□ in ultrasound images, motion vectors of different parts in the heart are varied with time and parts.

In our research, a method based on the 3-D DPCM lossless image compression followed by Embedded Zerotree Wavelet (EZW) is proposed, which catches the interframe redundancies.

C. WAVELET-BASED ROI LOSSLESS COMPRESSION

Recently, the wavelet transform has emerged as a cutting edge technology, within the field of image compression research. With the multiresolution character, the wavelet decomposition leads to superior energy compaction and perceptual quality of the decompressed image. However, the different wavelet functions make different trade-off between how compactly the basis functions are localized in space and how smooth they are. Y. Low and R. Besar [7] investigated the impact and quality of orthogonal wavelet filter for EZW and looked into the effect of the level of wavelet decomposition towards compression efficiency using Haar and Daubechies wavelet filters. The result showed, that Haar wavelet performed a competitive result for Ultrasound images. In this research, we use the Haar wavelet filter for EZW.

The EZW coder is the first algorithm to show the full power of wavelet-based image compression efficiency, proposed by Shapiro in [8]. It is based on a wavelet decomposition followed by a successive approximation quantization procedure that predicts the insignificant information across scales with zerotrees of wavelet coefficients. The EZW algorithm has shown excellent performance in compressing natural images. It generally outperforms JPEG for most images.

On the other hand, image compression techniques that support the ROI coding have received much attention [6,9,10]. JPEG-2000 provides two ROI encoding schemes [11-13]. H. Tai et al. [14] proposed a ROI coding scheme that not only retain advantages, but also alleviate the drawbacks of ROI coding schemes in JPEG-2000. In this research, for the compression of ROI region in single frame, we use this compression scheme.

III. ROI-BASED COMPRESSION SYSTEM

This section describes a hybrid compression system for lossless compression of ROI region in ultrasound sequential images. In this research, the region of ultrasound is chosen as the region of interest. The first stage is the segmentation of ROI. Here, we propose a simple segmentation method as described in Section A. Once the ROI is segmented, the ROI region is first coded by lossless interframe compression via 3-D DPCM. And then, a wavelet-based lossless coder encodes the output image. The details of this compression stage are described in Section D. In this study, we choose not to discard the non-ROI, but rather to highly compress it as described in Section B and C.

A. SEGMENTATION OF ULTRASOUND IMAGES

Object-related applications require a prior segmentation of the scene into regions of interest. In general, these regions are of arbitrary shapes. For ultrasound images, the ROI is not rectangular-shaped. For the application of object-related compression, a shape adaptive decomposition using nonlinear decompositions (SAND) was developed [15]. In this context, we apply lossless coding scheme only to the ROI, whereas the rest of the image is processed in different channels. Obviously, compressing the regions of interest and background separately leads to a better coding performance than compressing the whole image in one bit stream. Notice that no shape information is taken into account assuming that such segmentation would be fixed for this application. Indeed, the ROI is for all the ultrasound images coming from the same machine at exactly the same location and thus, has not been sent with the coded image.

A typical ultrasound image is shown in Fig. 2. It can be seen that the echocardiography image can be divided into three regions as shown in Fig. 3. The division is based on the image spatial characteristics at various locations of the images. Generally, the medical information coming from the ultrasound is the central fan-shaped region. Let us call it the ROI. Clearly, this region should be compressed losslessly for many clinical applications. The ECG below the ultrasound information contains also medical information that should not be distorted. The rest of the image, however, contains no medical information. Some regions contain text, and other regions are part of the black background. Different algorithms can be used to remove redundancy of the images in each region depending on their local characteristic.

In our research, we identify three regions, as shown in Fig. 3, namely:

a. Region 1: light gray regions composed of text and gray level palette region and the white region corresponds to the black background. The content in this region does not change with time throughout the whole image sequence. As a consequence, it is possible to code this region by just coding the first frame with some kind of highly compression ratio methods.

b. Region 2: the dark gray pixels including time information that changes from frame to frame and the ECG waveform that changes with the heartbeat of the patients. However, this region basically consists of white lines on black background, and hence may be treated as binary image. A 2-level image compression algorithm is used for this region.

c. Region 3: the black region corresponds to the ROI. This is the fan-shaped ultrasonic scanned image region. It contains the visual information a physical requires to know about the internals of the patient's body. It is updated every frame for a real-time echocardiography system. Obviously, a lossless compression algorithm is required to maintain absolute fidelity of the reconstructed image.

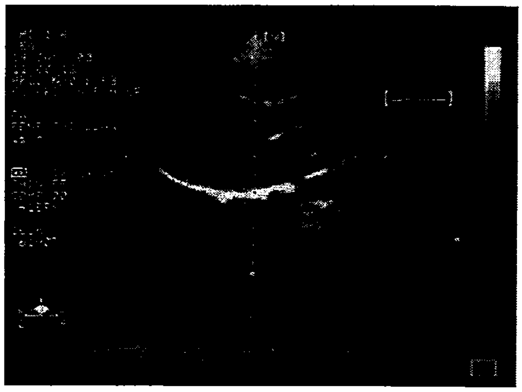

Fig.2. A typical ultrasound image

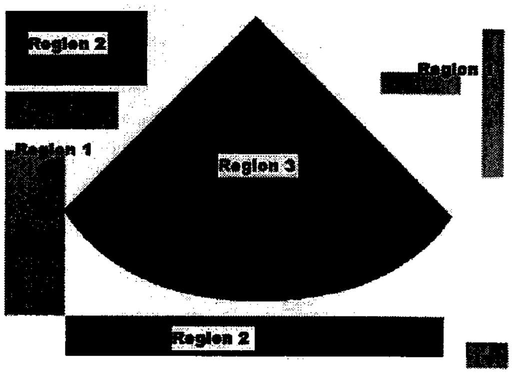

Fig. 3. Segmentation of Ultrasound Images

Once the ROI is segmented in each frame, a hybrid compression scheme is used for coding the images. For each region, the segmented images are first processed to remove any redundancy followed by arithmetic encoding to produce the final compressed data. This approach is illustrated in Fig. 4.

Intraframe coding is required for the first frame as there is no prior information to facilitate more efficient redundancy removal. The first image frame is similarly divided into regions as shown in Fig. 3, and its treatment is described in the following sections.

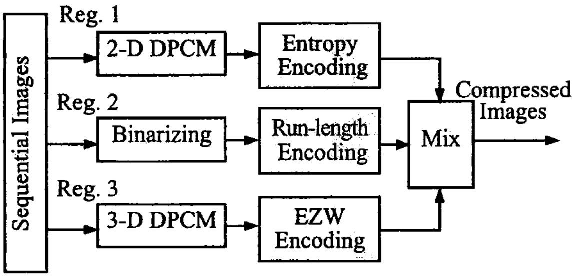

Fig. 4. ROI based compression system

B. REGION 1

Only the first frame of the whole sequences is coded using 2-D DPCM [16]. For the subsequent frames, there is no additional coding as information in this region is static.

For a given pixel $x(m,n)$ on the mth row and nth column, its predicted value is

$$\hat{x}(m,n) = \sum_{(i,j)\in ROS}\sum a(i,j)x(m-i,n-j) \tag{2}$$

where $a(i,j)$ are the prediction coefficients, and the region of summation (ROS) is chosen such that it only consists of those pixels whose values are already known prior to the coding of the current pixel. The error of the prediction is given by

$$e_{2D}(m,n) = x(m,n) - \hat{x}(m,n) \tag{3}$$

and the mean squared prediction error is

$$\varepsilon_{2D}^2 = E\{e_{2D}^2(m,n)\} \tag{4}$$

where the subscript 2D denoted 2-D prediction. The optimal prediction coefficients that minimize the mean squared prediction may be obtained by solving the Yule-Walker equations in 2-dimensions,

$$r(u,v) - \sum_{(i,j)\in ROS}\sum a(i,j)r(u-i,v-j) = \varepsilon_{2D}^2\delta(u,v) \tag{5}$$

where $r(u,v)$ is the 2-D covariance function of $x(m,n)$, and the Dirac delta function is demoted by δ. A solution of these equations can be obtained by assuming that the image is a homogenous random field with zero mean and an exponentially decaying autocovariance function. We implement a 3-point DPCM predictor, where

$$\begin{aligned}\hat{x}(m,n) &= a(-1,0)x(m-1,n)\\ &+ a(0,-1)x(m,n-1)\\ &+ a(-1,-1)x(m-1,n-1)\end{aligned} \tag{6}$$

In general, the set of predictor coefficients may be fixed for all images (global prediction), or may be varied from image to image (local prediction), or may even vary within an image to accommodate the local changes in image statistics (adaptive prediction). If an image is characterized as a stationary random field, a set of local predictor coefficients can be derived for each image that minimizes the mean squared prediction error. In our case we implemented a frame-adaptive set of coefficients that are obtained by solving

$$\begin{aligned}r(-1,0) &= a(-1,0)r(0,0) + a(0,-1)r(-1,1) + a(-1,-1)r(0,1)\\ r(0,-1) &= a(-1,0)r(1,-1) + a(0,-1)r(0,0) + a(-1,-1)r(1,0)\\ r(-1,-1) &= a(-1,0)r(0,-1) + a(0,-1)r(-1,0) + a(-1,-1)r(0,0)\end{aligned} \tag{7}$$

Note that the covariance function is given by

$$r(u,v) = \frac{\sum_{(m,n)\in S_x}\sum [x(m,n)-\bar{x}][x(m+u,n+v)-\bar{x}]}{Number\ of\ pixels\ in\ S_x} \tag{8}$$

where

$$\bar{x} = \frac{\sum_{(m,n)\in S_x}\sum x(m,n)}{Number\ of\ pixels\ in\ S_x} \tag{9}$$

and S_x is the region of interest.

The prediction error $e(m,n)$ is then arithmetic coded.

C. REGION 2

This region comprises the text and ECG waveform. The pixels in this region are first thresholded to produce a 2-level binary image represented by '1's and '0's. An optimum threshold can be got based on minimal-error segmentation between background and object in local region. In our experiment, the resulted threshold occurs at the gray level of 50 or so for this region.

A run length coding algorithm is then used to compress these binary images. For the first frame, the binary image is coded directly. For subsequent frames the run length coding is done on the difference binary image, which is obtained by pixel-XOR operation of the corresponding regions in two consecutive frames. In so doing we exploit the temporal correlation inherent in this region. The result is that because most parts of the image remain unchanged, the difference image has pixel values that are mostly '0's.

The run length coded data is then further compressed using standard arithmetic coding algorithm. The result is that we achieve an average CR of about 63 for the intraframe-coded regions, and about 98 for the interframe-coded regions. Clearly, this represents a significant compression performance achieved by using this approach.

D. REGION 3 (ROI REGION)

The fan-shaped ultrasonic scanned image is located in Region 3. As illustrated above, a lossless compression algorithm is required here. The motion in this region consists of abrupt motion from frame-to-frame. So, the first frame is coded using wavelet-based EZW algorithm, and for the subsequent frames, a 3-D DPCM algorithm is investigated to exploit the temporal correlation between consecutive frames, and then wavelet-based EZW algorithm is used to compress the difference image.

1) 3-D DPCM ALGORITHM

3-D DPCM algorithm is an extension of the 2-D DPCM into the third temporal dimension. The predicted pixel value is now given by

$$\begin{aligned}\hat{x}(m,n,p) &= a(-1,0,0)x(m-1,n,p)\\ &+ a(0,-1,0)x(m,n-1,p)\\ &+ a(-1,-1,0)x(m-1,n-1,p)\\ &+ a(0,0,-1)x(m,n,p-1)\end{aligned} \tag{10}$$

where p is the frame count index. Similarly, the predictor coefficients are obtained by solving

$$
\begin{aligned}
r(-1,0,0) &= a(-1,0,0)r(0,0,0) + a(0,-1,0)r(-1,1,0) \\
&\quad + a(-1,-1,0)r(0,1,0) + a(0,0,-1)r(-1,0,1) \\
r(0,-1,0) &= a(-1,0,0)r(1,-1,0) + a(0,-1,0)r(0,0,0) \\
&\quad + a(-1,-1,0)r(1,0,0) + a(0,0,-1)r(0,-1,1) \\
r(-1,-1,0) &= a(-1,0,0)r(0,-1,0) + a(0,-1,0)r(-1,0,0) \\
&\quad + a(-1,-1,0)r(0,0,0) + a(0,0,-1)r(-1,-1,1) \\
r(0,0,-1) &= a(-1,0,0)r(1,0,-1) + a(0,-1,0)r(0,1,-1) \\
&\quad + a(-1,-1,0)r(1,1,-1) + a(0,0,-1)r(0,0,0)
\end{aligned}
\tag{11}
$$

where $r(.,.,.)$ are the 3-D covariance coefficients given by

$$
r(u,v,w) = \frac{\sum\sum\sum_{(m,n,p)\in S_x}[x(m,n,p)-\bar{x}][x(m+u,n+v,p+w)-\bar{x}]}{Number\ of\ pixels\ in\ S_x} \tag{12}
$$

and

$$
\bar{x} = \frac{\sum\sum\sum_{(m,n,p)\in S_x} x(m,n,p)}{Number\ of\ pixels\ in\ S_x} \tag{13}
$$

where S_x comprises Region 3 from consecutive frames.

The error signal derived from the difference between the actual pixel value and the predicted value is then encoded using the wavelet-based EZW algorithm.

2) WAVELET-BASED ROI COMPRESSION

The ROI coding method proposed by H. Tai et al. in [14] retained advantages, while alleviates the drawbacks of JPEG-2000 methods by lowering the background quality appropriately in order to improve ROI rate distortion performance. This is achieved by truncating certain least significant bits of the background indices in the ROI code block. The coding method they proposed utilizes the block coding to assign a higher priority to ROI code blocks, which increases the ROI to background ratio in the ROI code blocks so that more ROI and less background information can be included in the bit-stream at the same compression rate.

The procedure for the proposed ROI encoding process is as follows:

1) Perform integer wavelet transform
2) Generate ROI mask
3) Truncate the k least significant bits of the background coefficients (set them as zeros) in the ROI code block
4) Entropy bit-plane coding (assign a large weight to distortion metric of ROI code blocks to increase their priority)
5) Construct the embedded bit-stream by rate control algorithm

Since no coefficients scaling is involved, it has relatively low implementation and computational complexity compared to the maxshift method.

IV. OVERALL PERFORMANCE

Generally, peak signal to noise ratio (PSNR) of reconstructed image is often cited to evaluate the image quality. In this research, however, it is insignificant to evaluate the image quality by PSNR since ROI has high quality of image and the quality in the other region is degraded on purpose.

On the other hand, we can determine the overall performance of the segmented image compression scheme from the point of CR. Using the combined algorithms, we obtain an average CR of 6.8.

V. CONCLUSIONS

This paper proposed a hybrid ultrasound sequential images compression scheme, which incorporates wavelet-based EZW algorithm, DPCM, run length coding and entropy coding for the compression of different regions in images. The principal advantage of the proposed approach is that for the very specific kind of ultrasound sequential images (echocardiography sequence) it first uses a simple segmentation scheme to partition an image into parts, and secondly uses different compression schemes to compress different parts. For the compression of ROI region in a single frame, it uses wavelet-based lossless compression, while for other non-ROI regions it uses simple linear prediction followed by entropy minimizing encoding methods and run length encoding. To reduce the correlation between temporal consecutive frames, a 3-D DPCM followed by wavelet-based EZW algorithm is used for the ROI region, and a 2-D DPCM followed by entropy minimizing encoding for non-ROI regions. The largest compression efficiency is obtained in the binary image Region 2 giving a CR in the range of 63 to 98 for intra- and interframe encoding separately. Overall, the overall CR of our test echocardiographic images is about 7.2.

ACKNOWLEDGMENT

This work is greatly supported by Fujian Province Hospital, who provides us with the original ultrasound sequential images. Moreover, the authors would like to thank the reviewers for their valuable comments and suggestions that helped enhance the quality of the paper.

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