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Hierarchical Oriented Predictions for Resolution Scalable Lossless and Near-Lossless Compression of CT and MRI Biomedical Images

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***Abstract*- CT or MRI Medical imaging produces digital form of human body pictures. There exists a need for compression of these images for storage and communication purposes. Current compression schemes provide a very high compression rate with a considerable loss of quality. In medicine, it is necessary to have high image quality in region of interest, i.e. diagnostically important regions. This paper discusses a hybrid model of lossless compression in region of interest with high compression rate lossy compression in other regions. The hybrid technique provides efficient and accurate coding of the medical images. We first survey a number of lossless and lossy compression schemes for the hybrid coder. An application to abdomen CT imaging with the special interest on human colon is presented.**

I. Introduction

Medical imaging has a great impact on diagnosis of diseases and preparation to surgery. On the other hand, the storage and transmission is an important dilemma due to enormous size of medical image data. For example, each slice of CT abdomen images is 512 by 512 of 16 bits, and the data set consists of 200 to 400 images leading to 150 MB of data in average. An efficient compression of the medical data can solve the storage and transmission problem. Current compression schemes bring great compression rates if loss of quality is affordable. Medicine can not afford deficiency in diagnostically important regions ('Region of Interest'). An approach that brings high compression rate with good quality in region of interest (ROI) is required. A hybrid coding scheme seems to be the only solution to this twofold problem. In other words, two different compression schemes should be used for ROI and non-ROI. The general theme is to preserve quality in diagnostically critical regions, while encoding the other regions so that the viewer can observe the position of the critical regions in the original image. Therefore, a very lossy compression scheme is suitable in non-ROI regions to give a global picture to the user while a lossless compression scheme is necessary for ROI regions.

CT images can be considered as many 2-D images (slices) traveling in the human body. In some sense, they are images from a movie of very smooth but everywhere transitions. For high quality, lossless compression purposes, we exploit two types of redundancy: Spatial redundancy, i.e. in each slice of the data set and temporal redundancy, i.e. between consecutive slices in the data set. It has been shown that, the temporal redundancy reduction results with a slightly better entropy rate. We surveyed a number of lossy compression schemes for non-ROI. In section 2, we present the results of DCT based, principal component analysis based, blockwise vector quantization based, and motion coding compression schemes. In our experiments, motion compansated coding scheme resulted with the best compression rate for non-ROI regions.

The overall goal of this research, is to represent the images with the smallest possible number of bits and with no loss in ROI. For this purpose, a complete hybrid coder that uses motion compensated coder in the overall image and entropy minimizing lossless coder for coding the error in the ROI region is implemented. The experiments are applied on CT abdomen images with the special concern on human colon. The first step of a ROI based system is segmentation. In our application, the colon wall is segmented through a sequence of 3-D morphological image processing techniques.

Colon cancer is the second leading cause of cancer deaths in USA. To our knowledge, however, this is one of the first work concerning on compression of human colon CT data. The main research in this area is on graphical visualization of the colon and automatic colon cancer detection[12][13]. However, that research suffers from lack of data, mainly due to storage and communication problems. The development of compression technology would allow for efficient use of visualization and automatic detection techniques in human colon analysis.

The paper goes on as follows: In section 1.1, the previous work is explored. In section 2, a description of the lossy and lossless compression schemes is given, and the results for abdomen CT image compression are compared. Section 3 describes our proposed hybrid model solution and summarizes the results. Section 4 gives our conclusions and discusses the possible future work.

II. RELATED WORKS

Since the evolution of digital medical imaging techniques, many researchers have attempted to apply compression methods. The initial concern was information preserving methods with the highest possible compression rate. Scan pixel difference was researched by Takaya et al in [1]. Assche et al exploits the interframe redundancies in [2]. Linear predictive coding schemes were investigated in [3]. One of the main observations in all of these studies was the low compression rate.

In terms of transform coding, Principal component analysis was given as a better alternative to DCT based compression schemes in [8] and [9]. The main assumption for this is the statistical similarity that the medical images would exhibit. However, we achieved better compression rates with DCT compared to principal component analysis in our experiments.

In order to achieve hgher compression rates without paying off from quality, region of interest based methods were investigated in the following years. In [4], a ROI-DCT algorithm that uses more DCT coefficients in ROI, was proposed. A subband compression scheme was used by Cosman et al. in [5]and [6]. In [7], 3-D wavelet compression is investigated. The most important drawback of 3-D based approaches in ROI based compression is twofold: First, the resolution between the slices is much less than the resolution in the image plane. Second, the ROI does not necessarily lie in a 3-D primitive shape such as a cube. Due to these reasons, 2-D ROI based scheme is explored in this paper.

2. A comparison study of compression schemes applied to CT abdomen images

In this section, we describe and evaluate the following compression schemes: 1- Lossless Compression Schemes, 2- DCT based compression scheme 3- Principal Component Analysis based Compression Schemes 4- Blockwise Vector Quantization 5- Motion compansated compression schemes. The optimal of the above methods, i.e. motion compensated coding, is proposed in a ROI based hybrid compression scheme in section 3. It has to be noted that, for all of the CT images used in experiments, the uncompressed data rate is 16 bpp.

2.1. Entropy minimizing Lossless Coding

The entropy is referred as the minimal number of bits to represent the information. The formulation is given as follows:

where pk is the probability of a particular intensity. The variable length coding schemes such as Huffman Coding or arithmetic coding approximates the theoretical entropy. The theoretical entropy of the intensity values of the CT abdomen images is found as 7.93 bits. However, there is statistical dependency between the values of neighbor pixels in the images and should be exploited.

An example of two consecutive CT abdomen images and their difference is given in figure 1. To exploit the redundancies in inter-slices, a coding scheme that predicts the current pixel as a linear combination of the west, north and north-west pixels is used. The prediction function and the error function is given as follows: where Ip is the predicted image and e is the error image. The entropy of the error vanishes to 5.9 bits. To achieve bigger compression rates, the temporal statistical dependency of the pixel values is considered. In other words, each image pixel value is predicted as the same pixel value in the previous image such as:

where the superscript t denotes the slice number (time). The predictive error entropy reduces to 5.76 bits. This result also suggests that there is more temporal redundancy than the spatial redundancy in CT abdomen images. However, when we look at the difference images, we observe that more of the information is included in the ROI area.

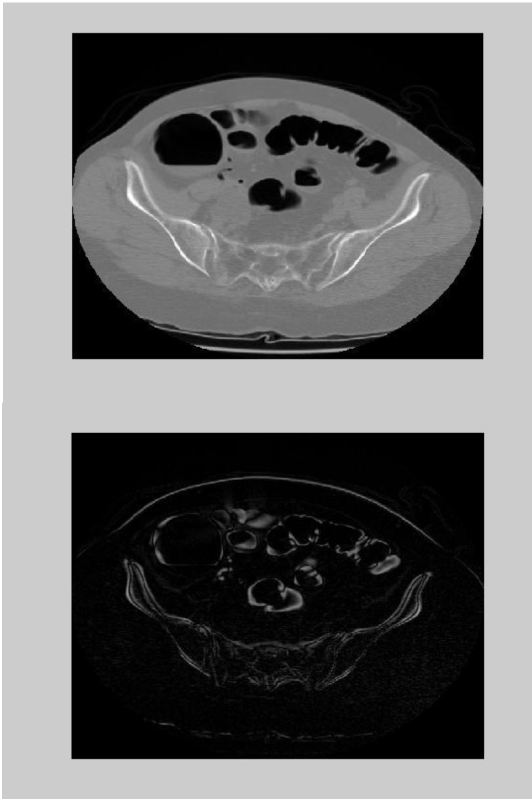

Figure 1. Two consecutive CT abdomen images and their difference image

2.2. DCT based Compression

Discrete Cosine Transformation (DCT) is a powerful mathematical tool that took its place in many compression standarts such as JPEG and MPEG. In the most general form, DCT can be expressed as matrix multiplication. The mathematical definition of 8 by 8 DCT matrix is given as follows:

Once the average is extracted for each block, Lloyd Max quantizer is executed. In our experiments, the centroid of each quantization level was found by the K-means algorithm with K=32. The theoretical entropy of these 32 levels of quantization was found to be 3.69. We experimented the setup with M=5 and M=7. The corresponding rates are 0.14 and 0.075 for M=5 and M=7 respectively. The reconstructed images for each case are presented in figure 7. The mean squared error for these images are 38 dB and 39 dB. Although the mean squared errors are much worse compared to DCT, the global view is still comprehensible. The main advantage of this approach is the simplicity of the decoder, since the decoder is composed only of a linear interpolation engine (at most four multiplications per pixel.)

3. Segmentation using morphology

Mathematical morphology is a branch of science which is built upon set theory and has many application areas in image processing. This approach includes generation of mappings for each pixel according to the pixel's local neighborhood. Many researchers have used this technique to segment biomedical images[14][15]. Segmenting the colon from the CT data set is composed of three steps:

- First, the air is segmented from the tissue. This is a thresholding operation, and the result of this step is shown at image 10(a). Air is shown in black in this image.
- Next, the colon wall that surrounds the air is extracted. A derivative operation is suitable for this task. We used a 3D version of Sobel derivative operator. The gradient magnitude is shown in figure 10(b). The derivative is shown in white. The region of interest is given as 5 pixels inside and outside of the colon wall. A morphological 3D grassfire operation is suitable. This algorithm, finds points that are equal distance from a layer of points. In other words it is composed of a series of dilation operations. The final segmented image, that contains 5 pixels of ROI around colon wall is given in figure 10(c). The image brightness is max at the colon wall and decreases as it departs from the colon wall.

4. Region of Interest(ROI) Based Compression System

Once the ROI is segmented from each slice, a hybrid compression scheme is used for coding each slice. The flow diagram of the encoder is given in figure 11. First, the image is compressed by motion compensated coding. We also assume that the initial slice of the volume is compressed in a lossless manner. Next the following algorithm is applied for each block:

- The mse between the original image block and the motion estimated block is found.
- if mse is lower than high threshold and the block does not contain any ROI, or mse is lower than the low threshold and the block contains ROI than only the motion vectors are used for that block else if block contains ROI and mse is higher than the low-threshold or block does not contain ROI but mse is higher than the high-threshold, additional entropy minimized lossless coding of the block is required. We have chosen to take the motion estimated block as the initial guess, and coded only the difference between the original block and the motion estimated block. This way, the theoretical entropy of the difference blocks was calculated as 4.38, which is better than the value obtained in section 2.1.

III. Conclusion and Future Work

In this study, we present a hybrid scheme that is appropriate for efficient and accurate compression of 3D medical images. The model uses lossless compression in region of interest, and very high rate compression in the other areas. After surveying through common compression schemes, we have chosen motion estimated coding as a prediction scheme for each medical slice. The difference of the ROI blocks and the prediction is coded separately with an entropy minimizing coder. We applied our experiments on CT abdomen images with the colon wall as ROI. The results show that a compression rate of %2.3 can be obtained by the ROI based compressor.

There are many possible directions of future investigations. We would like to evaluate the performance of affine tracker in stead of translational tracker. In order to get better compression rate, ROI can be lossy encoded. Future study will include a case study with the radiologists to observe the effect of lossy compression in ROI on diagnosis performance of the user.

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