

MEDICAL IMAGE COMPRESSION BASED ON REGION OF INTEREST, WITH APPLICATION TO COLON CT IMAGES

Salih Burak Gokturk¹ Carlo Tomasi² Bernd Girod¹ Chris Beaulieu³

{¹Electrical Engineering, ²Computer Science, ³Radiology } Department, Stanford University
{gokturkb,tomasi,bgirod,beaulieu}@Stanford.edu

Abstract- CT or MRI Medical imaging produce human body pictures in digital form. Since these imaging techniques produce prohibitive amounts of data, compression is necessary for storage and communication purposes. Many current compression schemes provide a very high compression rate but with considerable loss of quality. On the other hand, in some areas in medicine, it may be sufficient to maintain high image quality only in the region of interest, i.e., in diagnostically important regions. This paper discusses a hybrid model of lossless compression in the region of interest, with high-rate, motion-compensated, lossy compression in other regions. We evaluate our method on medical CT images, and show that it outperforms other common compression schemes, such as discrete cosine transform, vector quantization, and principal component analysis. In our experiments, we emphasize CT imaging of the human colon.

Keywords - motion compensated coding, compression, region of interest, colonoscopy

I. INTRODUCTION

Medical imaging has had a great impact on the diagnosis of diseases and surgical planning. However, imaging devices continue to generate more data per patient, often 1000 images or ~500 MB. These data need long-term storage and efficient transmission.

Current compression schemes produce high compression rates if loss of quality is affordable. However, medicine cannot afford any deficiency in diagnostically important regions (*Region of Interest, ROI*). An approach that brings a high compression rate with good quality 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 allowing lossily encoding the other regions. The main reason for preserving regions other than ROI is to let the viewer more easily locate the position of the critical regions in the original image, and to evaluate possible interactions with surrounding organs.

In this study, we put special emphasis on the human colon wall. Colon cancer is the second leading cause of cancer deaths in the USA. American adults have 1/20 chance of developing and 1/40 chance of dying from this disease[19]. To our knowledge, however, this is one of the first studies concerned with the compression of human colon CT data. The main research in this area is on graphical visualization of the colon and automatic colon cancer detection [11][12]. The development of compression technology will also allow for efficient use of visualization and automatic detection techniques in human colon analysis.

After the evolution of digital imaging techniques, many researchers have attempted to apply compression methods to medical data. The initial emphasis was on information preserving methods. Scan pixel difference was researched by Takaya *et al* in [1]. Assche *et al* exploit the inter-frame redundancy in [2]. Linear predictive coding schemes were

investigated in [3]. The lossless compression studies have all resulted in low compression rate. Transform coding schemes such as Principal Component Analysis (PCA) and Discrete Cosine Transform (DCT) were applied in [4],[8] and [9] to get better rates. In order to achieve higher compression rates without detracting from quality, region of interest based methods were investigated in the subsequent years. In [4], an ROI-DCT algorithm that uses more DCT coefficients in ROI, was proposed. Cosman *et al.* used a subband compression scheme in [5] and [6] for application to mammography. In [7], 3-D wavelet compression was investigated.

A 3D medical data set is a collection of 2D images, henceforth called *slices*. The most important drawback of 3D based approaches in ROI based compression is twofold. First, the image quality along the three principal 3D axes is not uniform, i.e. the resolution between the slices is much less than the resolution within each slice. Second, the ROI does not necessarily lie in a 3D primitive shape such as a cube. As a consequence, a primitive 3D ROI would occupy a big portion of the data, thereby deviating from our initial objective of high compression rate. To address these problems, a 2D ROI based scheme is explored in this paper.

On the other hand, there is a considerable amount of correlation between consecutive slices. We propose to exploit the consequent redundancy by using motion compensated coding. We compare the performance of motion compensated coding scheme with a number of lossy compression schemes including DCT, PCA, and blockwise Vector Quantization (VQ). Our results suggest that motion compensated coding is more suitable than other methods for the compression of CT abdomen images.

We propose a complete hybrid coder that uses a motion compensated coder in the overall image and an entropy minimizing, lossless coder for coding the error in the ROI region. The first step of an ROI based system is segmentation. In our application, the colon wall is segmented through a sequence of 3-D morphological image processing techniques. Next, 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.

The paper continues as follows: Section II describes our proposed hybrid solution. In Section III, a description of investigated lossy and lossless compression schemes is given, and the results are compared to our approach. Section IV gives our conclusions and discusses possible future work.

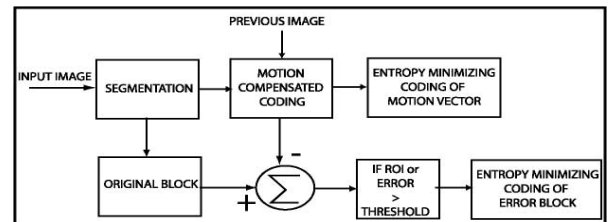


Fig. 1. Flow diagram for ROI Compression

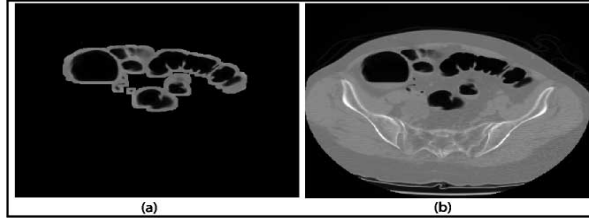


Fig. 2. (a) ROI alone (b) ROI together with the other organs

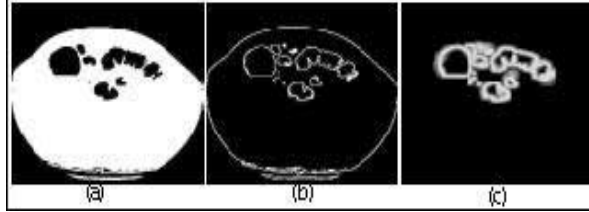


Fig. 3. (a) Air segmented (b) Colon wall segmented (c) ROI

II. ROI BASED SYSTEM

This section describes a hybrid compression system for lossless compression of ROI in CT abdomen images. The overall flow of the system is given in Figure 1. The colon wall is chosen as the region of interest. The first stage is the segmentation of ROI. Here, we propose an automated segmentation method that utilizes a series of 3-D morphological operations as described in section A. Once the ROI is segmented, the entire image is first coded by motion compensated compression. The output of the motion compensated coding acts as an initial approximation for ROI areas. In ROI, an entropy minimizing, lossless coder encodes the residual between this approximation and the original image. The details of this compression stage are described in section B. In this study, we have chosen not to discard the non-ROI, but rather to highly compress it by motion compensated coding. This helps the viewer locate the human colon in the image since the shape of the colon is constrained by the surrounding organs in the body. Figure 2(a) illustrates the ROI alone, while Figure 2(b) shows ROI in the entire image. In the latter case, the radiologist can more easily identify the portions of the colon looking at the nearby organs in the image.

A. Segmentation of ROI

Diagnostically critical region is given as about 5 pixels inside and outside of the colon wall in typical CT scans. We would like to add practical value to our system by automatically segmenting this critical region. Our segmentation algorithm relies on a 3-D extension of *mathematical morphology*, a branch of science that is built upon set theory with many application areas in image processing. It 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 consists of three steps:

- The air is separated away from the tissue by intensity thresholding.
- The colon wall that surrounds the air is extracted by a

3D extension of Sobel's derivative operation. [21]

- A morphological 3-D grassfire operation determines the colon-wall region within the 5-pixel margin mentioned above. This algorithm finds points that are at equal distance from a layer of points.

The outputs of the three stages of segmentation are depicted in figure 3. Each pixel in the segmented ROI is coded in a lossless manner, while the rest is lossily compressed. Figure 3(c) includes only a little portion of the complete image in Figure 3(a), and this brings a considerable amount of compression efficiency.

B. ROI Based Compression Scheme

Once the ROI is segmented in each slice, a hybrid compression scheme is used for coding the images. The first slice of the volume is compressed with a lossless coder. Each slice is then coded by motion compensated coding, which also acts as a prediction filter for ROI. Finally, the difference between the real-image ROI block and the predicted-image ROI block is coded by an entropy minimizing lossless coder, e.g. Huffman coder[20].

Motion-compensated coding interprets the smooth changes from one slice to the next as motion, and uses displaced versions of blocks in one slice as approximations for blocks in the next slice. More specifically, each slice is first partitioned into uniform square blocks. Next, a motion vector is determined for each block using the previous image as a reference. In other words, for each block in the current image, the most similar, nearby block from the previous image is computed, and the difference in coordinates between the two blocks is recorded as a translation vector with two components: translation in x (d_x) and translation in y (d_y), where x and y denote the two principal axes of the image. In this research, we used the Lucas-Tomasi-Kanade optical flow tracker [10]. This is an accurate method to track points from one image to the other. It determines block motion by minimizing the sum of pixel-wise squared differences between a given block in the current image and neighboring blocks in the previous image. Since there is a high correlation between consecutive slices, the motion vectors are usually very small, and can therefore be coded efficiently. The estimation precision of the vectors d_x and d_y was 0.1 pixels. Using a small accuracy assures that the difference between the real and the estimated block has a lower energy. Indeed, the better the accuracy of the algorithm, the better is the estimation image, but the more complex is the encoder. Once the translation vector is calculated, it is recorded to represent the particular block. During this process, the motion vectors are coded with an entropy minimizing lossless coder in order to occupy fewer bits.

After the motion vector is predicted for every block in the image, the root mean squared error (rmse) between the original image block and the motion estimated block is obtained. If the block contains pixels belonging to ROI or if the rmse is higher than a threshold, then the difference block is encoded with an additional entropy minimizing, lossless coder. The theoretical entropy of the difference blocks was calculated as 4.38 bpp (bits per pixel), which is better than the theoretical entropy values of spatial or temporal

prediction filters, as described in Section 3. The efficiency of the method is inversely proportional to the portion of ROI in the image. The smaller the portion of ROI in the image, the better is the resulting compression rate. In addition to its remarkable compression gain, the algorithm is accurate, since there is no degradation of diagnostic quality in ROI.

III. EXPERIMENTS

Before we give our results on the ROI based scheme, we present a comparison study on different compression schemes for exploiting the temporal and spatial redundancy in CT abdomen images. This redundancy includes correlation between and within slices of a CT volume.

First, we investigate theoretical entropy values for various lossless prediction filters. Next, we compare the results for the following lossy compression methods: Discrete Cosine Transform (DCT), Principal Component Analysis (PCA), blockwise Vector Quantization (VQ), and Motion Compensated Coding. All of the experiments for these four methods are performed on 20 CT abdomen slices of size 512 by 512 and with an original bit rate of 16 bpp. Figure 6 shows the output image for each of these methods.

First, we would like to give theoretical bit rates for lossless schemes. The entropy is computed as the expected value of information in the image, viewed as a stream of statistically uncorrelated pixel values. The theoretical entropy of the intensity values of the CT abdomen images was found to be 7.93 bpp. However, the assumption of statistical uncorrelatedness inherent in the definition of entropy is obviously false, since neighboring pixels within and across slices are statistically correlated. First, to exploit the intra-slice redundancy, a coding scheme that predicts the current pixel as a linear combination of the west, north and northwest pixels in the same image is used. With this scheme, the entropy of the error falls to 5.9 bpp. Second, in order to get even higher compression rates, the inter-slice, or temporal, statistical dependency of the pixel values is considered. Specifically, each image pixel value is predicted to be the same pixel value as in the previous image, in which case the entropy of the prediction error reduces further to 5.76 bpp. This result shows that there is only slightly more temporal redundancy than the spatial redundancy in CT abdomen images. As discussed in Section 2, motion compensated coding works as a better prediction scheme for temporal redundancy avoidance, *i.e.*, the entropy of the error image reduces by a considerable amount to 4.38 bpp.

Next we evaluated three lossy compression schemes and compared with motion compensated coding: The Discrete Cosine Transform (DCT), Principal Component Analysis (PCA) and Blockwise Vector Quantization. For DCT, we applied 8x8 DCT matrix followed by uniform quantization of transformed components[21]. We applied PCA by extracting the principal modes of 8x8 image patches[8]. Finally, we applied vector quantization on the intensity values of centroids of 8x8 or 16x16 blocks[18].

In order to judge the performances of the methods better, we zoom into non-ROI portions of the image in Figure 4. It is intuitive to observe that blockwise vector quantization results in smoother images (Figures 4(e)). Although PCA

compression yields much worse rmse than DCT, the image quality looks nearly as pleasing with DCT. Finally, Figures 4(f) show the sub-window resulting from motion compensated coding. In this example, motion compensated coding is coded with 25 times more coding efficiency than DCT and PCA coding, yet the image quality looks as pleasing.

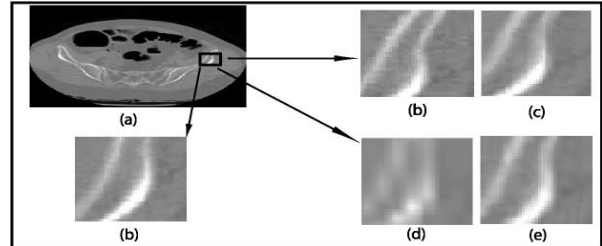


Fig.4 (a) The main image. (b) original detail region (c-f) Analysis of a small ROI region with different methods, specifically: (c) DCT with quantization size 128. (d) PCA (e) Blockwise vector quantization (f) Motion estimated coding.

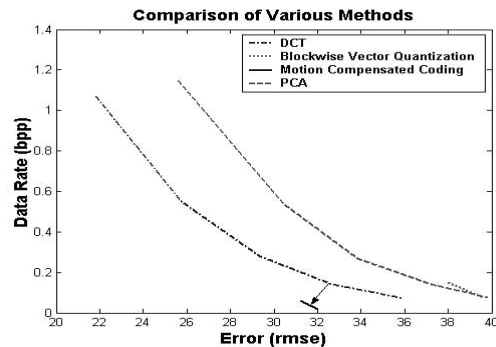


Fig.5 Comparison of the methods.

TABLE I

Results of ROI Scheme		
Experiment	Rate(bpp)	RMSE(dB)
ROI, Blocksize 8x8 –Dataset 1	0.41	30.8
ROI, Blocksize 16x16–Dataset 1	0.56	31.4
ROI, Blocksize 8x8 –Dataset 2	0.47	30.8
ROI, Blocksize 16x16–Dataset 2	0.63	31.0
ROI, Blocksize 8x8 –Dataset 3	0.52	32.0
ROI, Blocksize 16x16–Dataset 3	0.59	32.0

Motion compensated hybrid coding is the core of our ROI based compression system. Figure 5 clearly demonstrates that motion compensated coding outperforms the other methods at the same rmse, and produces a bit rate as low as 0.018 bpp for an acceptable error level for coding the non-ROI regions. This high performance let us choose motion compensated coding as the prediction scheme in our system design.

We applied our ROI based hybrid compression method to three datasets of 20 slices each. 8 by 8 and 16 by 16 block sizes were used in the experiments, and the results are summarized in Table 1. Observe that ROI compression with 8

by 8 blocks produces not only a better rmse, but also better compression rate compared to ROI compression with 16 by 16 blocks. This is mainly due to diminishing ratio of ROI blocks when using 8 by 8 block-size. Figures 6(g) and (h) show the reconstructed images for both blocksize. The ROI based method with 8 by 8 blocks results in a compression rate of 2.5% without any loss of image quality in ROI.

IV. CONCLUSION

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 the region of interest, and very high-rate, lossy compression in the other regions. There are two main contributions of the paper: First, we have designed a compression scheme that automatically segments and utilizes ROI in order to get efficient and accurate results. Second, common compression schemes have been applied to CT abdomen images and the performances are compared. After surveying common compression schemes, we have chosen motion-estimating coding as a prediction scheme for each medical abdomen slice. The difference between the ROI blocks and the prediction is coded separately with an entropy minimizing coder. We have applied our experiments on CT abdomen images with the colon wall as ROI. The results show that a compression rate of 2.5% can be obtained by our approach.

There are many possible directions for future investigation. In order to obtain better compression rates, ROI can be lossily encoded, *i.e.*, by DCT compression. Future study will include the design of lossy compression schemes in ROI and a clinical case study with radiologists to observe the effect of lossy compression on diagnostic performance.

REFERENCES

- [1] K. Takaya, and C.G. Tannous, "Information preserved guided scan pixel difference coding for medical images," *WESCANEX 95. Communications, Power, and Computing. Conference Proceedings.*, IEEE Volume: 1, 1995, Page(s): 238 -243.
- [2] S.Van Assche., D. De Rycke, W. Philips, and I. Lemahieu, "Exploiting interframe redundancies in the lossless compression of 3D medical images," *Data Compression Conference*, 2000, Page(s): 575.
- [3] Jian-Hong Hu, Yao Wang, and P.T. Cahill, "Multispectral code excited linear prediction coding and its application in magnetic resonance images," *IEEE Transactions on Image Processing*, Volume: 6 11, Nov. 1997, Page(s): 1555 -1566.
- [4] A.Vlaciui, S. Lungu, N. Crisan, and S.Persa. "New compression techniques for storage and transmission of 2-D and 3-D medical images," *In Advanced Image and Video Communications and Storage Technologies*, volume 2451, pages 370-7, Amsterdam, Netherlands, March 1995..
- [5] R.M. Gray, R.A. Olshen, D. Ikeda, P.C. Cosman, S. Perlmuter, C. Nash, and K. Perlmuter, "Evaluating quality and utility in digital mammography," *Proceedings of International Conference on Image Processing*, Volume: 2, 1995, Page(s): 5 -8.
- [6] P.C. Cosman, R.M. Gray, and R.A. Olshen, "Evaluating quality of compressed medical images: SNR, subjective rating, and diagnostic accuracy," *Proceedings of the IEEE*, Volume: 82 6, June 1994, Page(s): 919 -932.
- [7] A. Baskurt, F. Peyrin, H. Benoit-Cattin, and R. Goutte, "Coding of medical images using 3D wavelet decompositions," *IEEE International Conference on Acoustics, Speech, and Signal Processing*, ICASSP-93, Volume: 5, 1993, Page(s): 562 -565 vol.5.
- [8] J.S. Taur, and C.W. Tao, "Medical Image Compression using Principal Component Anlysis," *International Conference on Image Processing*, Volume: 1, 1996, Page(s): 903 -906 vol.2.

- [9] M. Yoshioka, and S. Omatu, "Image Compression by nonlinear principal component analysis," *IEEE Conference on Emerging Technologies and Factory Automation*, EFTA '96, Volume: 2, 1996, Page(s): 704 -706 vol.2.
- [10] J. Shi, and C. Tomasi, "Good features to track," *International conference on computer vision and pattern recognition*, CVPR 1994, Page(s): 593 -600.
- [11] S.B. Gokturk, and C. Tomasi, "A graph method for the conservative detection of the polyps in the colon," *International Symposium on virtual colonoscopy*, Boston, October 2000.
- [12] D.S. Paik, C.F. Beaulieu, R.B. Jeffrey, Jr., C.A. Karadi, S. Napel, "Detection of Polyps in CT Colonography: A Comparison of a Computer-Aided Detection Algorithm to 3D Visualization Methods," *Radiological Society of North America 85th Scientific Sessions*, Chicago, November 1999.
- [13] R.Vogt, "Precise Extration of Bones from CT Scans," *Advances in Mathematical Morphology*, Volume 2.
- [14] J.Serra, *Image Analysis and Mathematical Morphology*, Academic Press, New York, N.Y., 1982.
- [15] J.Storer, *Data Compression*, Rockville, MD: Computer Science Press, 1988.
- [16] G. Wallace, "The JPEG still picture compression standard," *Communications of the ACM*, vol.34, pp. 30-44, April 1991.
- [17] M. Turk and A. Pentland, "Eigenfaces for recognition," *Journal of Cognitive Neuroscience*, 1991.
- [18] T. Senoo and B. Girod, "Vector quantization for entropy coding image subbands," *IEEE Transactions on Image Processing*, 1(4):526-533, Oct. 1992.
- [19] Wingo P.J., Cancer Statistics, *Ca Cancer Journal*, 1995;45:8-30.
- [20] A. Gersho and R.M. Gray, *Vector Quantization and Signal Compression*, Kluwer Academic Press, 1992.
- [21] R. Gonzalez and R. Woods, *Digital Image Processing*, Addison-Wesley, 1993.

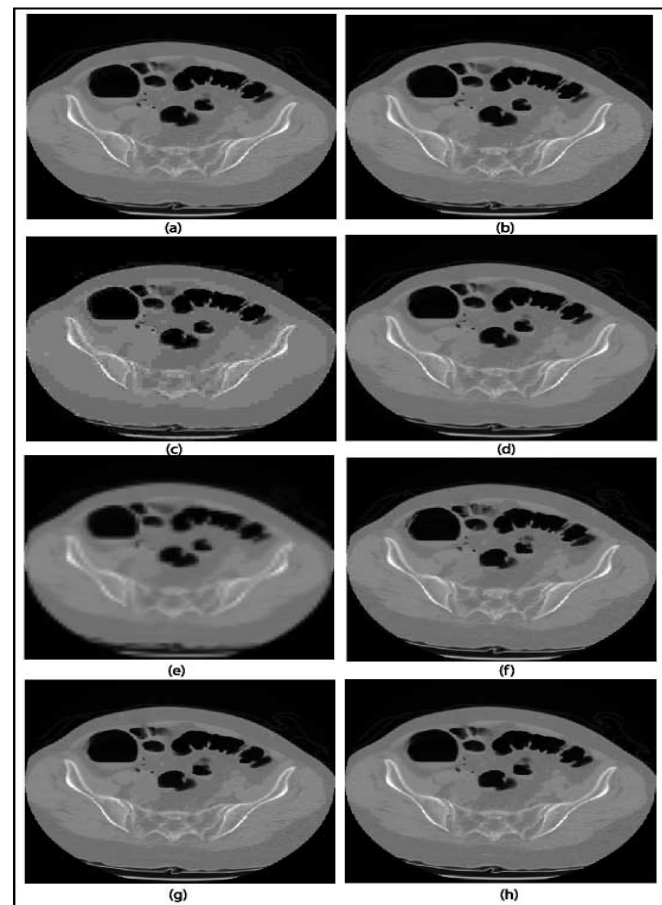


Fig. 6. (a) Original image (b) DCT with quantization step size=128 (c) DCT with quantization step size=1024 (d) PCA (e) Vector Quantization with 7 by 7 blocks (f) Motion Compensation Coding (g) ROI with 8 by 8 Blocks (h) ROI with 16 by 16 blocks