Compressing Sets of Similar Images Using Hybrid Compression Model

Jiann-Der Lee*, Shu-Yen Wan*, Cherng-Min Ma** and Rui-Feng Wu***
*Graduate Institute of Information Engineering,
*Department of Computer Science and Information Management
***Graduate Institute of Electrical Engineering
Chang Gung University
Tao-Yuan, Taiwan 333, ROC

Abstract

A new compression scheme called hybrid compression model (HCM) is proposed for compressing sets of similar images[1]. The HCM employs the region growing technique to partition the median image of a set of similar images; and furthermore, it uses the centroid method to characterize the original image data. The differences between the predicted and the original image data are stored and encoded for later use. The efficacy of its application on progressive transmission of similar images over the networks is also studied. The experimental results on various images show that our method provides significant improvement in compression efficiency, ranging from 5.6% to 134.9% in comparison with traditional centroid methods.

1. Introduction

Compressing an image set with multiple slices is very important in a modern telemedicine system, because the most commonly used digital modalities, such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET), can generate multiple slices in a single examination. Multiple slices generated this way are normally anatomically or physiologically correlated to each other. In other words, there are some image structure similarities between adjacent slices. Although it is possible to compress an image set slice by slice, more efficient compression can be achieved by exploring the correlation between slices. Methods to remove slice correlation for sets of similar images include three-dimension (3-D) transforms and prediction methods. In this paper, we will focus on the latter approach.

In the past, several research efforts applied the prediction method to image compression [1-2]. Karadimitriou *et al.* proposed a similar images compression model, called Enhanced Compression Model, which exploits centroid method to reduce set redundancy and improves performance even more [3].

Moreover, efficient transmission over the networks, such as progressive transmission, raises a peripheral aspect and has introduced significant impact on how the images are compressed [4-5]. The nature of the previously proposed pyramid structure is ideal for progressive transmission. The pyramid decomposition of an image consists of an original image and successively lower resolution images. Roos *et al.* proposed a prediction/residual approach to form the variable resolution pyramid by sub-sampling [6]. This kind of approach has otherwise been termed as hierarchical interpolation (HINT).

In this paper, a new hybrid compression model (HCM) is proposed for compressing sets of similar images such as a stack of two-dimensional (2-D) medical images. HCM is a segmentation based prediction method. It combines region growing and centroid method to predict the values of original images data, and the difference between the predicted values and original data is stored for later use in the stage of progressive transmission. In additions, HINT is also used in the proposed progressive transmission procedure.

2. The proposed hybrid compression model

2.1Centroid method

Predictive decorrelation is an important technique for medical image compression. In predictive decorrelation, an estimate of the image based on previously encoded pixels or on a statistical model of the image is subtracted from the original image. The recorded differences will be small when the estimate agrees well with the original image. A differential image containing mostly small values can be efficiently coded by a variable-length code. Several methods such as DPCM and adaptive DPCM are often used.

For a set of K images with N pixels per image, the formula for predicting the value of a pixel using the average value of the same position across the set of similar image and a correlation term can be expressed as below, i.e.,

$$\begin{aligned} C_{i+1,j} &= m_{i+1} + e_{i,j} \\ e_{i,j} &= x_{i,j} - m_i \end{aligned} \qquad (1)$$

where $C_{i+1,j}$ is an estimate at position i+1 in image j, $x_{i,j}$ is the pixel at position i in image j, and m_i is the average value form position i across all images. Eq.(1) is

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so called centroid method, and it can help to reduce inter-image redundancy and improve compression efficiency [3]. In this paper, the proposed scheme is based on a similar concept of the centroid model, but takes advantages of the median model and image segmentation techniques, to reduce the set redundancy more efficiently. Using median value, instead of the average valuem can avoid the influence of the extreme pixel value due to the noise and reduce the diversion of a pixel set.

2.2 Region Growing Algorithm

In general, region growing techniques are often used for object identification or features analysis [7]. However, the main purpose of region growing in this approach is to group spatially connected pixels lying within a small dynamic gray level range.

There are two conditions required for consideration while applying region growing procedure. The first one is that the neighbor pixel is not a member of any regions already grown, and the other one is the absolute difference between the neighbor pixel and the corresponding center pixel is less than *error level*:

$$ereror\ level = 2^{error\ bits-1} \qquad (2)$$

where *error bits* is a pre-selected number.

During region growing process, an image data will be decomposed three data parts:

(1) corresponding error image data part
(2) corresponding discontinuity index image data part
(3) high-bits seed data part

Examples to illustrate this concept can be found in ref. [7]. When a new (neighbor) pixel x_j is included in the region being grown, its difference e_j with respect to its center pixel x_i is stored as the pixel's "error" value using the Eq. (3).

$$e_j = x_j - x_i + error\ \ level \qquad (3)$$

If only the first of the two region growing conditions is satisfied, the discontinuity index of the pixel is incremented.

The error value of the seed pixel of each region is defined as the value of its low (*error bits*) bits; the value of high (*N- error bits*) bits of the pixel is stored in a "high-bits seed data part," where N is the number of the b/pixel in the original image data.

The above three data parts are used to fully recover the original image during the decode process. The region growing conditions during decoding are that a neighbor pixel under consideration to be included in a specific region must be not in any of the previously grown regions, and its discontinuity index equals to zero. When the conditions are satisfied for a pixel, its pixel value is restored as the sum of its error value e_j and its center pixel value x_i using Eq. (4):

$$x_j = x_i + e_j - error\ level \qquad (4)$$

If only the first of two conditions is satisfied, the discontinuity index of that pixel is decremented. And the "high-bits seed data part" is combined with the "error image data part" to recover the seed pixel value of each region.

2.3 Segmentation based Compression Model

The segmentation technique – region growing is the first step for HCM method. Assume that there is a set of similar images $X = \{x_1, x_2, ..., x_N\}$ that we want to process. The corresponding median image m is determined and treated as the input of region growing procedure. For a pixel m_i, its neighbor pixel is checked with the region growing conditions. The neighbor pixel m_{i+1} is included in the region, if the conditions are satisfied. Furthermore, corresponding pixel is also included in the same region in each image that belong image set X. In other words, the pixel $x_{i,1}$ and $x_{i+1,1}$ in the first image, $x_{i,2}$ and $x_{i+1,2}$ in the second image, and $x_{i,N}$ and $x_{i+1,N}$ in the last image are processed at one time. *N* sets of corresponding error image data and high-bits seed data are created when region growing procedure is completed, and only one set of discontinuity index is stored.

We exploit region growing technique to analyze the content of the median image which is determined by a set of similar images can group spatially connected pixels lying within a small dynamic gray level range. The next stage is to use centroid method to predict the estimates of the corresponding error image data and the difference between predict values and original data is then determined and stored. Eq. (5) is the modified centroid method formula.

$$\begin{aligned} C_{e_{x_{i+1,k}}} &= e_{m_{i+1}} + r_{e_{x_{i,k}}} \\ r_{e_{x_{i,k}}} &= e_{x_{i,k}} - e_{m_i} \end{aligned} \qquad (5)$$

where $C_{e_{x_{i+1,k}}}$ is the estimate of the corresponding error image data at position *i*+1 in image *k*, $e_{m_{i+1}}$ is the corresponding error image data at position *i*+1 in the median image, and $e_{x_{i,k}}$ is the corresponding error image data at position *i*+1 in image *k*. The difference value at position *i*+1 in image *k* is shown as following.

$$D_{x_{i+1,k}} = e_{x_{i+1,k}} - C_{e_{x_{i+1,k}}} \qquad (6)$$

3. Experimental Results

In the experiments, five groups of medical images are used. Some of these images are shown in Fig.1. Their content is summarized as below.

1. Brian CT images ×11, 512×512, 8 bits/pixel gray scale
2. Chest CT images ×15, 256×256, 8 bits/pixel gray scale
3. Ultrasound images ×15, 256×256, 8 bits/pixel gray scale
4. Brain MR T1 image×15, 256x256, 8 bits/pixel

3.1 Comparison between HCM and centroid method

Sets of similar medical image compressed by various error bit are tabulated in Table I. According to different organization, texture etc., region growing technique analyze the content of image data and classify it become various region we expect. So there are different optimal values for different error bits that are the variables in region growing process. The follow experiment will use the value 5 be the error bit.

Comparison results between HCM and centroid method are tabulated in Table II. It shows that the performances using HCM are all better than centroid method. The improvement range between traditional centroid method and HCM is 5.6% to 134.9%.

3.2 Comparison between compression ratio and PSNR using wavelet transform

Five different wavelet mother functions are used in experiment [8]. For compare with different qualities of images, quantization threshold value T is set in range 5~50. Table III and IV are the results for brain CT images and Chest CT images, respectively. It shows that the performances are the best using wavelet mother function HAAR for brain CT image. But there are the worst results relatively for chest CT images. In other words, the key point is not the wavelet mother function. The critical point should be the image features such as contents, organization and texture etc.

3.3 Bit rate vs. PSNR Comparison using HINT

HINT is a progressive transmission technique in spatial domain, and brain CT images ×11 (set 1) are used to decompose five different resolution levels. Table V shows the comparison between bit rate and PSNR. The result shows that the progressive transmission using hybrid compression model through HINT can get good performance in low bit rate.

4. Conclusions

In this paper, a novel compression scheme (HCM) is proposed for compressing sets of similar images. While Compared with traditional still image compression technique whose goal is to reduce the three redundancies, similar images compression can decrease set redundancy further and thus improve the overall performance of the system. That is, the cooperation between HCM and progressive transmission technique can let similar images, especially medical images that have large amount data, transmission efficiently over the networks and achieve low bit rate.

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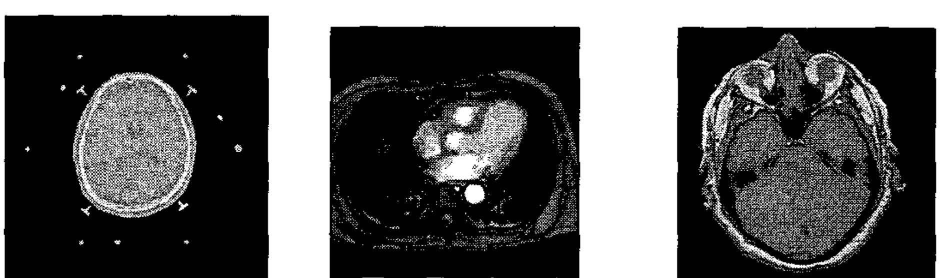

(a) (b) (c)

Fig. 1:Experimental image data set (a) One of brain CT images ×11, 512 ×512 pixels, 8 bits/pixel gray scale (b) One of chest CT images ×15, 256 ×256 pixels, 8 bits/pixel gray scale (c) One of brain MRI T1 images ×15, 256 ×256 pixels, 8 bits/pixel gray scale.

Table I. Comparison between error bit and compression ratio

	Compression Ratio				
	error bit = 6	error bit = 5	error bit = 4	error bit = 3	error bit = 2
256X256Chest CT image × 15	**3.262**	**3.341**	**3.340**	**3.214**	**3.199**
256X256Brain MR T1image × 15	**1.646**	**1.677**	**1.679**	**1.675**	**1.637**
512X512Brain CT image × 11	**17.078**	**17.213**	**18.346**	**17.165**	**17.155**

Table II. Comparison between HCM and Centroid method

Image data set	Correlation coefficient	Centroid Method	HCM
		Compression Ratio	Compression Ratio
256X256 Chest CT image × 15	**0.9411**	**2.321**	**3.341**
256X256 Brain MR T1 image × 15	**0.4770**	**1.588**	**1.677**
512X512 Brain CT image × 11	**0.999**	**7.350**	**17.213**

Table III. Comparison between (CR) and PSNR using various wavelets functions for brain CT images

	T	05	10	15	20	25	30	35	40	45	50
BIOR 3.7	CR	**17.349**	**21.76**	**28.033**	**33.124**	**36.265**	**39.330**	**42.449**	**44.326**	**45.783**	**47.669**
	PSNR	**83.639**	**79.010**	**76.031**	**74.098**	**74.056**	**74.029**	**73.280**	**73.469**	**73.091**	**72.650**
COIF 3	CR	**17.194**	**24.222**	**33.355**	**40.197**	**44.243**	**46.971**	**49.575**	**51.248**	**53.169**	**56.797**
	PSNR	**86.599**	**82.795**	**79.859**	**78.164**	**75.367**	**74.067**	**72.578**	**72.495**	**71.588**	**71.118**
DB 4	CR	**17.542**	**25.613**	**35.762**	**42.731**	**47.179**	**51.437**	**55.117**	**57.885**	**60.447**	**62.999**
	PSNR	**85.190**	**80.623**	**78.028**	**76.138**	**75.290**	**73.809**	**73.587**	**73.507**	**73.361**	**72.972**
HAAR	CR	**20.424**	**30.302**	**34.766**	**48.962**	**52.778**	**55.880**	**58.831**	**60.952**	**63.404**	**68.207**
	PSNR	**87.525**	**84.853**	**83.095**	**80.387**	**78.218**	**74.969**	**74.615**	**73.433**	**72.124**	**71.544**

Table IV. Comparison between (CR) and PSNR using various wavelet functions for chest CT images

	T	05	10	15	20	25	30	35	40	45	50
BIOR 3.7	CR	**9.075**	**12.738**	**17.083**	**21.262**	**23.061**	**25.500**	**30.529**	**33.138**	**33.138**	**38.071**
	PSNR	**78.655**	**75.455**	**74.572**	**73.403**	**72.579**	**72.153**	**71.743**	**71.433**	**71.065**	**70.684**
COIF 3	CR	**8.941**	**13.259**	**19.608**	**26.517**	**32.769**	**38.903**	**43.870**	**49.210**	**53.492**	**58.836**
	PSNR	**80.664**	**77.000**	**74.893**	**73.020**	**72.159**	**72.118**	**71.467**	**70.646**	**70.351**	**69.952**
DB 4	CR	**7.875**	**11.628**	**17.096**	**22.918**	**30.253**	**36.752**	**42.413**	**47.702**	**52.988**	**59.029**
	PSNR	**79.992**	**76.081**	**74.592**	**73.611**	**72.812**	**72.117**	**71.703**	**71.304**	**70.991**	**70.755**
HAAR	CR	**7.306**	**10.170**	**10.689**	**21.156**	**22.587**	**22.599**	**28.907**	**34.692**	**37.957**	**44.102**
	PSNR	**81.935**	**78.185**	**75.835**	**72.649**	**71.977**	**71.478**	**70.985**	**70.756**	**70.110**	**69.703**

Table V. Comparison between PSNR and bit rate using HINT progressive transmission technique and HCM

	Level 1	Level 2	Level 3	Level 4	Level 5
PSNR	79.4705	80.2836	81.2625	85.520	-----
Bit rate	0.0414	0.1332	0.2951	0.5499	1.0229