A HYBRID COMPRESSION MODEL FOR CLUSTERS OF SIMILAR MEDICAL IMAGES

JIANN-DER LEE¹, SHU-YEN WAN² AND RUI-FENG WU¹

¹Department of Electrical Engineering,

²Graduate Institute of Information Engineering,
Chang Gung University, Tao-Yuan, Taiwan

ABSTRACT

In this paper, a new compression scheme called hybrid compression model (HCM) is proposed for compressing clusters of similar images. The HCM exploits region growing to segment the median image that created by a cluster of similar images; and further, it uses centroid method to predict the values of original images data. The difference between the predict values and original data is stored for later use of progressive transmission. The experimental results obtained on various images show that our method provides significant improvement in compression efficiency while compared to the traditional centroid method.

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1. INTRODUCTION

Compressing an image cluster with multiple slices is very important in a telemedicine system, especially radiology, because the most commonly used digital modalities, including magnetic resonance (MR), computed tomography (CT), positron emission tomography (PET), 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 cluster slice by slice, more efficient compression can be achieved by exploring the correlation between slices. Methods to remove slice correlation for clusters of similar images include three-dimension (3-D) transforms and prediction methods. In this paper, we will focus on the latter approach, i.e., prediction methods.

In general, there are two categories for image compression, i.e., lossless and lossy [1]. Lossless com-

pression is an error free compression. The decompressed image is all the same as the original image, on a pixel-by-pixel basis. In spite of this benefit, only a small amount of compression is possible and hence, the total compression ratio is low as expected. In general, for some applications, the lossless compression is the only acceptable method of image compression. These kinds of applications tolerate no loss in information. The typical examples consist of 1) the archival of medical images where the loss of any information is not tolerated because it may affect the accuracy of the diagnosis, 2) the archival of business document where losing information is illegal. It is known that lossless image compression can provide a compression ratio ranging between 2 and 10.

On the other hand, lossy compression method is a kind of irreversible compression. It is based on compressing the accuracy of the recovered image in exchange for more compression, and usually the reconstructed image contains the distortion, which may or may not be visually apparent. If this resulting degradation can be tolerated for some specific applications, the compression ratio can be significant improved with easy. To our knowledge, a lot of lossy compression approaches can often produce good recognizable images with compression ratios of 30 or higher.

In the past, several research efforts applied the prediction method to image compression [1-3].

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Correspondance: Jiann-Der Lee, Professor
Department of Electrical Engineering, Chang Gung
University, Tao-Yan, Taiwan.

Karadimitriou [4] proposes a similar images compression model called Enhanced Compression Model, which exploits centroid method to reduce cluster redundancy and improves performance even more. Moreover, progressive transmission [5,6] plays an important role in this field for its compression efficiency, speed and bit rate less than 1 bit per pixel (bpp). The nature of the 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.* [7] proposed a prediction/residual approach to form the variable resolution pyramid by subsampling. This kind of approach has been termed hierarchical interpolation (HINT).

In this paper, a new hybrid compression model (HCM) is proposed for compressing clusters of similar images such as 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 predict values and original data is stored for later use in the stage of progressive transmission. In additions, HINT is also used in progressive transmission procedure due to its excellent performance in hierarchical decomposition.

This paper is organized as follows. Section II gives a brief introduction on the similar images compression that includes cluster redundancy and centroid method. The proposed compression model is illustrated in Section III. Section IV presents experimental results and the conclusion is summarized in Section V.

2. THE PROPOSED HYBRID COMPRESSION MODEL

2.1 Centroid 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 [7] and adaptive DPCM are often used.

For a cluster 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 cluster of similar image and a correlation term can be expressed as below, i.e.,

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

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 from position i across all images. Eq. (1) is so called centroid method [4], and it can help to reduce inter-image redundancy and then improve compression efficiency. In this paper, the proposed scheme is based on similar concept of the centroid model, but takes the advantage of median model and image segmentation techniques, to reduce the cluster redundancy more efficiently. Using median value but average value can avoid the influence of the extreme pixel value due to the noise and reduce the diversion of a pixel cluster.

2.2 Region Growing Algorithm

In general, region growing techniques [8] are often used for object identification or features analysis. However, the main purpose of region growing in this approach is to group spatially connected pixels whose gray level are within a small dynamic range.

There are two criteria 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*:

$$\text{error level} = 2^{\text{error bits}-1} \quad (2)$$

where *error bits* is a preselected number.

During the 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

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).

$$e_j = x_j - x_i + \text{error level} \quad (3)$$

If only the first one of the two region growing criteria 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 ($N - \text{error bits}$) 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 decoding process. The criteria of region growing during decoding are that

Fig. 1 Lossless Predictive Coding System.

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 equal to zero. When the criteria 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):

$$x_j = x_i + e_j - \text{error level} \quad (4)$$

If only the first one of two criteria 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 the proposed HCM method. Assume that there is a cluster of similar images $X = \{x_1, x_2, \dots, x_N\}$ 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 cluster 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 clusters of corresponding error image data and high-bits seed data are created when region growing procedure is completed, and only one cluster of discontinuity index is stored.

Exploit region growing technique to analyze the content of the median image which is determined by a

cluster of similar images can group spatially connected pixels whose gray level are within a small dynamic 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.

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

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.

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

3. EXPERIMENTAL RESULTS

The main purpose of the proposed scheme (HCM) is to efficiently compress a cluster of similar images such as medical images by reducing the cluster redundancy further. In the following, three compression procedures are developed to evaluate the performance of our system. These three procedures include hybrid lossless compression process, hybrid lossy compression process, and progressive transmission process.

As described above, data compression technique is divided two parts: lossless compression technique and lossy compression technique. The lossless compression procedure mainly includes the stage of hybrid

Fig. 2 Enhanced Compression Model.

compression model (i.e., segmentation based centroid method) and the stage of entropy coding (i.e., LZW coding [9-10]). In the lossy compression procedure, here, besides the segmentation based centroid method and LZW coding techniques are used the same as lossless compression procedure, the wavelet transform and quantization technique are utilized for data reduction further.

Recently, encoder based on discrete wavelet transform become more and more popular in image compression due to its flexibility to nonstationary signals, the fast implementation, and the effective coding technique for wavelet coefficients. The principle behind wavelet transform is to represent a signal as a superposition of wavelets, which are formed by dilation and translation of a mother wavelet $\Psi(t)$, i.e.,

$$WT_x(a, \tau) = \frac{1}{\sqrt{a}} \int x(t) \Psi^* \left(\frac{t-\tau}{a} \right) dt = \langle x(t), \Psi_{a\tau}(t) \rangle \quad (7)$$

With good frequency selectivity at lower frequencies and good time selectivity at higher frequencies, wavelet transform gives a spatial and frequency representation of signal. According to the fast algorithm proposed by Mallat [11], discrete wavelet transform can be implemented by a filter bank as shown in Fig. 3. $h_0(n)$ and $h_1(n)$ are low-pass and high-pass analysis filters, and $g_0(n)$ and $g_1(n)$ are low-pass and high-pass synthesis filters, respectively. In order to implement perfect reconstruction, the filter coefficients should satisfy the criteria defined as Eq. (8).

$$\begin{aligned} g_1(n) &= (-1)^n h_0(-n+1) \\ g_0(n) &= (-1)^n h_1(-n+1) \end{aligned} \quad (8)$$

There are various extensions of the one-dimension (1-D) wavelet transform to higher dimensions. Fig. 4 presents one stage in a wavelet decomposition of an image.

In a conventional way of viewing an image, the content of the image cannot be revealed until the transmission is almost over. Using the progression transmission technique, however, the resolution of an image increases gradually according to the amount of data transmitted. That is, progressive transmission of an image permits the initial reconstruction of an approximation followed by a gradual improvement of quality in image reconstruction. When the speed of the transmission or the bandwidth of the communication channel is relatively high compared to the image data size, the conventional method of viewing the image is not a problem. However, when the amount of image data is very large, the progressive transmission plays an important role in viewing or browsing the image. Since the image can be viewed progressively, a high

Fig. 3. Two-Channel filter banks for wavelet transform.

Fig. 4. Filter banks of 2-D DWT.

degree of effective compression ratio can be achieved by not transmitting the rest of the data when the image turns out to be of no interest.

A spatial-based approach for progressive transmission generates a cluster of image frames at different resolutions by means of subsampling or averaging. The top level of the pyramid initiates the transmission and it can be expended as the lower level of the structure is transmitted. Conventional pyramidal structure required one-third more space to build the hierarchy as illustrated in Fig. 5.

For example, HINT (Hierarchical Interpolation) is a variable resolution pyramid based on the subsampling [6]. In HINT, a subsampled version of the original image consisting of the pixels (symbol "1" shown in Fig. 6) is transmitted first. Next, the intermediate pixel (symbol "2" shown in Fig. 6) was estimated by linear interpolation of the four surrounding pixels (symbol "1" shown in Fig. 6). The estimation was rounded to the nearest integer to ensure the reversibility. Then, the difference between the estimated value and the actual pixel value was coded using variable length coding, like Huffman coding.

In HINT, only the interpolated pixels needed a residual in order to be reconstructed exactly, since the subsampled pixels are already exact. As a result, the total number of values that must be stored is equal to the number of original pixels. Fig. 7 shows that the LENA image through the HINT progressive reconstruction for five different resolutions.

In the experiments, four groups of medical images have been established for the purpose of evaluat-

Fig. 5. Pyramidal structure.

1	5	3	5	1	5	3	5	1
5	4	5	4	5	4	5	4	5
3	5	2	5	5	5	2	5	3
5	4	5	4	5	4	5	4	5
1	5	3	5	1	5	3	5	1
5	4	5	4	5	4	5	4	5
3	5	2	5	3	5	2	5	3
5	4	5	4	5	4	5	4	5
1	5	3	5	1	5	3	5	1

1	Level 1
2	Level 2
3	Level 3
4	Level 4
5	Level 5

Fig. 6. HINT pyramid.

ing the system performance. Some of these images are shown in Fig. 8. Their content is summarized as below.

1. Brain CT images $\times 11, 512 \times 512$ pixels, 8 bits/pixel gray scale
2. Chest CT images $\times 15, 256 \times 256$ pixels, 8 bits/pixel gray scale
3. Ultrasound images $\times 15, 256 \times 256$ pixels, 8 bits/pixel gray scale
4. Brain MRI T1 images $\times 15, 256 \times 256$ pixels, 8 bits/pixel gray scale

Various tests are conducted to compare the efficiency of the proposed HCM model and traditional centroid method in compression ratio and peak-signal-noise-ratio (PSNR). Details of the comparison are described as below.

3.1 Performance Comparison of the HCM and Centroid Method

Clusters of similar medical image compressed by various error bit are tabulated in Table 1. According to different organization, texture etc., region growing technique analyze the content of image data and clas-

Fig. 7 HINT reconstructed image (a) level 1 (b) level 2 (c) level 3 (d) level 4 (e) level 5.

sify 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 following experiment will use the value 5 be the error bit.

Performance comparison results between HCM and centroid method are tabulated in Table 2. It shows that the performances using HCM are all better than centroid method. The improvement between traditional centroid method and HCM is 5.6% to 134.9%.

3.2 Performance Comparison for Compression Ratio and PSNR Using Wavelet Transform

Five different wavelet mother functions [12] are used in the experiments. To compare with different qualities of images, quantization threshold value T is set in the range of 5~50. Table 3 is the results for brain CT images. It shows that the performances are the best using wavelet mother function HAAR for brain CT image. However, in other experiments [13], using HAAR function are the worst results relatively for

Fig. 8. Experimental image data set (a) One of brain CT images $\times 11, 512 \times 512$ pixels, 8 bits/pixel gray scale (b) One of chest CT images $\times 15, 256 \times 256$ pixels, 8 bits/pixel gray scale (c) One of ultrasound images $\times 15, 256 \times 256$ pixels, 8 bits/pixel gray scale (d) One of brain MRI T1 images $\times 15, 256 \times 256$ pixels, 8 bits/pixel gray scale.

chest CT images. In other words, the key point to obtain the best compression ratio is not the kind of the wavelet mother function. The critical point should be the image features such as contents, organization and texture etc. Reconstructed brain CT images using various wavelet mother functions is illustrated in Fig. 9. The result shows that the image quality is very close original ones

3.3 Performance Comparison between Bit Rate and PSNR Using HINT

HINT is a progressive transmission technique in spatial domain, and a set of brain CT images (i.e., 11 slices) is used as an example to illustrate the system performance. These images are decomposed and reconstructed with five different resolution levels. From the experimental results, we observe that the content of reconstructed image can be distinguished clearly with the progressive data part of level 1. Table 4 shows the comparison between bit rate and PSNR under different levels. The result shows that the progressive transmission using hybrid compression model through HINT can get good performance in low bit rate.

Fig. 9. Reconstructed brain CT image data using various wavelet mother function, $T=5$ (a) BIOR3.7 (b) COIF (c) DB4 (d) HAAR (e) SYM4.

4. CONCLUSION

In this paper, a new compression scheme (HCM) is proposed for compressing clusters of similar images. Compared with traditional still image compression technique whose goal is to reduce the three redundancies, similar images compression can decrease cluster 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 network and achieve low bit rate.

Table 1. Performance 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 x15	3.262	3.341	3.340	3.214	3.199
256X256Brain MR T1 image x15	1.646	1.677	1.679	1.675	1.637
512X512Brain CT image x11	17.078	17.213	18.346	17.165	17.155

Table 2. Performance comparison between HCM and Centroid method.

Image data set	Correlation coefficient	Centroid Method	HCM
		Compression Ratio	Compression Ratio
256X256 Chest CT image x15	0.9411	2.321	3.341
256X256 Brain MR T1 image x15	0.4770	1.588	1.677
512X512 Brain CT image x11	0.999	7.350	17.213

Table 3. Performance comparison between compression ratio (CR) and PSNR using various wavelet 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
SYM 4	CR	17.390	24.721	35.012	42.969	48.043	51.989	54.571	57.346	57.834	59.460
	PSNR	84.835	79.758	78.689	77.953	75.190	74.947	74.651	73.811	73.676	72.632

Table 4. Performance 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

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