A Lossless Compression Method of Medical Images based on the Local Texture Feature

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***Abstract* -- As for a kind of medical images with clear texture feature, a new lossless compressive method is presented in this paper. With two main steps, the method firstly sets up the predictive model of the current pixel with its surrounding texture features, including its four color change gradients; and then measures the similarity of all pixels within the image with their predictive models so that the redundancy brought about by the similarity is removed and a higher compression ratio is obtained. The following simulation results show that the new method is much more efficient than JPEG-LS algorithm in the compression of such kinds of medical images.**

I. INTRODUCTION

In estimating the effectiveness of a lossless compression way, the bit/pixel ratio after compression is always considered to be very important. For the reason that no data of the images are allowed to loss during the compression, its efficiency is difficult to improve. However, in some special application areas, such as medical images process, there is an increasing conflict between the increasing number of the digital images and limited storage space and transportation bandwidth, so high efficient lossless compression methods are urgently needed[1].

JPEG-LS standard[2], published in 1998 by ISO/ITU-T, is an international standard for still images lossless/near lossless compression, whose core algorithm is LOCO-I (LOw COmplexity LOssless COmpression for Images)[3]. In fact, LOCO-I algorithm is radically a single-pixel processing method[4], paying no attention to the local area's texture feature that may exist, so its efficiency and real-time performance is not so good as expected.

However, in a kind of medical images, there are texture similarities and continuity among several or more local areas, such as endoscope images. So a new lossless compression method is put forward in this paper, where the current pixel is predicted by its local area's texture feature. Compared with JPEG-LS algorithm, the compression ratio of the new method is improved in compressing several kinds of medical images, while the compression time doesn't increase more, for the low-complexity of JPEG-LS is maintained.

II. THE CONTEXT PREDICTOR OF THE LOCO-I ALGORITHM

The context predictor of the LOCO-I algorithm uses the neighboring area of the current pixel x, as shown in Fig.1.

	c	b	d	
	a	x		

Fig.1 The Context Predictor of LOCO-I Algorithm

Where, x, the current pixel
a,b,c,d, the pixels in the neighboring area of the x.

The x is predicted according to the following formula,

$$x = \begin{cases} \min(a,b) & c \ge \max(a,b) \\ \max(a,b) & c \le \min(a,b) \\ a+b-c & \text{else} \end{cases} \tag{1}$$

The prediction process is divided into 2 steps[5]: Firstly, boundary detection. Suppose that there is a horizontal boundary up to the x, then the value of b and c are both big or small, and x can be represented by a; or suppose the boundary is vertical and left to the x, at the time a and c are both big or small, then b is selected as x. Secondly, if no boundary is detected, then the value of c is between that of a and b, then x is predicted as $a+b-c$, whose geometrical meaning is to put x at the plane made up of by its context so that the value change of the neighboring area of the x is continuous to some degree.

III. THE LOCAL AREA'S TEXTURE FEATURE PREDICTOR PRESENTED IN THIS PAPER

A. The Local Area's Texture Feature of the Medical Images and its Predictive Model

Some medical images, such as endoscope images, taking pictures of the biological organ or viscera, have similar content and color, and their texture changes regularly and continuously. For example, the pictures of two different parts of a rectum are shown in Fig.2, showing that their texture feature is almost the same,

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Fig.2 Two Parts with Similar Local Area's Texture Taken from a Rectum's Endoscope Image

In processing color-images with clear local texture feature like above, the single-pixel processing method of JPEG-LS seems likely not so effective and considerate. Efficiently removing the redundancy brought about by this similarity of the local texture is the key to raise the compression bit/pixel ratio and then an improved efficiency is obtained.

Consider a 3×3 neighboring area around the current pixel, as shown in Fig.3.

I(x-1,y-1)	*I(x,y-1)*	*I(x+1,y-1)*
I(x-1,y)	*P(x,y)*	*I(x+1,y)*
I(x-1,y+1)	*I(x,y+1)*	*I(x+1,y+1)*

Fig.3 a 3×3 Neighboring Area of the Current Pixel (x,y)

Where, $P(x,y)$ — the predictive value of the current pixel (x,y).

Define (a,b) as the pixel in the neighboring area of the current pixel (x,y). So

$$(a,b) = \{x-1 \le a \le x+1, y-1 \le b \le y+1, \text{ and } a \ne x, b \ne y\} \quad (2)$$

Equation (2) represents a set of all the pixels in the neighboring area. So $I(a,b)$ represents the color value of the pixel (a,b).

Local area's texture feature around the current pixel (x,y) can be described by the following four gradients formulas, from (3) to (6).

$$D_1(x,y) = I(x-1,y) - I(x+1,y) \quad (3)$$
$$D_2(x,y) = I(x-1,y-1) - I(x+1,y+1) \quad (4)$$
$$D_3(x,y) = I(x,y-1) - I(x,y+1) \quad (5)$$
$$D_4(x,y) = I(x+1,y-1) - I(x-1,y+1) \quad (6)$$

D_1 to D_4 depict the color change of the pixel (x,y)'s 3×3 neighboring area in horizontal, 135°angle, vertical and 45° angle direction, respectively, and by the way represent the texture feature of the local area of the pixel (x,y).

In a decomposed color-image, which is now a gray image, the absolute value of the four gradients is limited to no much than 255. To be standardized, each of them is divide by 255, so that it ranges from –1 to +1. Use the following matrix to represent the local area's texture feature and the predictive value of the pixel (x,y),

$$P(x,y) = \begin{bmatrix} D_1 & D_2 \\ D_4 & D_3 \end{bmatrix} \quad (7)$$

Where, D_1 -D_4 is defined as (3)-(6), and the change range of them is [-1,1]. In general, the above matrix describes the local texture change of the pixel (x,y).

B. The Similarity Measurement of the Texture Feature Based on Vision Consistency

According to the definition of the texture feature mentioned above, the same local texture feature has the same color change gradients in four directions. Exceptionally, even the gradients are not the same, the texture feature is still possibly to be the same according to the human's vision habit. That occurs with the images that have local symmetrical characteristic, such as the pairs shown in Fig.4. Although they have different $P(x,y)$, the texture feature of two images should be considered the same, according to the vision consistency theory.

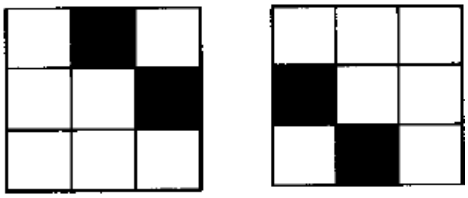

Fig.4 Two Local Symmetrical Images, whose Texture are considered to be the Same According to the Vision Consistency Theory

In Fig.4, the image on the right can be obtained by rotating the one on the left 180° clockwise. So their texture expression matrixes are linearly correlated, which is described as the following,

$$P_r(x,y) = \begin{pmatrix} -1 & 0 \\ 0 & -1 \end{pmatrix} P_l(x,y) \quad (8)$$

Where, $P_r(x,y)$, $P_l(x,y)$ —represent the local texture feature matrix of the right and left image in Fig.4, respectively. While

$\begin{pmatrix} -1 & 0 \\ 0 & -1 \end{pmatrix}$ is a rotating operator of clockwise 180°.

Orderly, other three rotating operators of clockwise 0°, 90° and 270° are also deducted, and listed below, respectively.

$$0° \text{ operator, } \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \quad (9)$$

$$90° \text{ operator, } \begin{pmatrix} 0 & -1 \\ -1 & 0 \end{pmatrix} \quad (10)$$

$$270° \text{ operator, } \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \quad (11)$$

With the four rotating operators described above, the similarity of the texture feature between different local areas can be measured.

C. Removing the Redundancy Caused by the Similarity in the Local Texture

When each pixel of the image is predicted and the similarity among them is measured as the steps describe above, there is another important work to do in the lossless compression of images, that is to remove the redundancy of the images and then encode all of the predictive errors of each pixel into compressed data under the frame of JPEG-LS standard.

According to the algorithm in this paper, the pixel on the four borders of the image is not predicted, and then the prediction starts from the first pixel on the second line.

--Firstly, mark off a 3×3 neighboring area for each pixel as mentioned above, and then calculate the four gradients to set up its local texture predictive model.

--Secondly, measure the similarity among each pixel's predictive model with the four rotating operators and a proportional parameter one by one, and record the measurement results as each pixel's new predictive value.

--Finally, according to the measurement results, the coding work is divided into three parts:

1) Texture Continue Run Length Coding. As for the pixels with the same local texture feature, the coding mode is set to texture continue run length coding mode, and only the run length of the pixels with the same local texture feature needs to be coded.

2) Texture Change Run Length Coding. As for the pixels with the similar local texture feature, including those ones with the texture matrix rotating and needing a proportional parameter, the coding mode is set to texture change length coding mode, and only the number of the rotating operator and the proportional parameter are coded.

3) Normal Coding. If a pixel is not similar or the same with other pixels, that is said its local texture feature is unique in the image, the coding mode is then set to normal coding mode, and the pixel is coded with its predictive value as the following,

$$P(x, y) = D_i / 2 + I(a,b) \tag{12}$$

Where D_i is the smallest one among the D_1-D_4 gradients, representing the most smoothly changing direction.

$I(a,b)$ is the color value of the pixel in the D_i direction.

The flow chart of the above steps is shown in Fig.5.

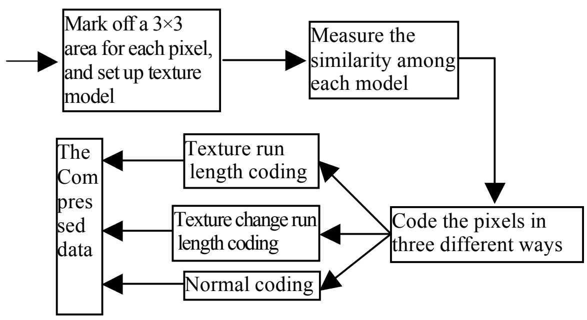

Fig.5 The Flow Chart of the Local Texture Compression Method

IV. SIMULATION AND RESULTS

The compression simulation experiments are conducted with the LOCO-I algorithm and the one presented in this paper as well. The devices configuration for simulation includes Intel P4 2.8G CPU, 512M RAM, and Visual C++ language under the platform of Windows 2000 system for programming.

The images for simulation experiments come from the Medical Image Gallery and Internet. In order to test the new algorithm thoroughly, six kinds medical color-images with different local texture features (listed in TABLE 1), each kind including ten images are chosen out for the comparison of the performance by two compression methods.

TABLE 1
THE IMAGE GROUPS USED FOR COMPRESSION SIMULATION

The Kind Number	The Semantic Meaning of the Images
1	Endoscope images
2	Cell micro-images
3	Tongue-coating images for Chinese Traditional Clinic Diagnosis
4	Skin Disease Diagnostic Images
5	Color Doppler Echocardiography

During the experiments, each image mentioned above is compressed with the two different methods. Firstly use the LOCO-I algorithm to predict the current pixel and code the predictive error in Glomb code, and then use the method presented in this paper to catch the local texture similarity in the image and code it with length adjustable Huffman code.

After all, the comparison of the compression results and the time taken during the compression are shown in TABLE 2, where the compression results are given as the average bit ratio after compression.

TABLE 2
THE COMPARISON RESULTSS OF THE COMPRESSION EXPERIMENTS WITH TWO METHODS

Number	Average Compression Ratio / bit/pixel		Average Time Taken / s	
	LOCO-I algorithm	This paper's algorithm	LOCO-I algorithm	This paper's algorithm
1	4.44	3.54	1.67	0.94
2	5.01	5.17	2.38	2.84
3	4.62	3.81	10.41	8.87
4	4.56	3.61	5.83	4.94
5	4.29	4.36	0.81	0.88

From the TABLE 2, it is shown that when the local texture features of the medical images are clear and continuous in color space, such as endoscope images, tongue-coating images and skin images, the efficiency of the method presented in this paper is much higher than that of the LOCO-I algorithm, while the local texture feature is not so clear or obvious, the compression efficiency by the method presented in this paper is almost the same as by the LOCO-I algorithm. Statistically, in the first instance mentioned above, the average compression ratio by the new method is raised to be 15%-20% higher than that by the LOCO-I algorithm. The reason is possibly the new method sufficiently removes the similarity of the local texture features so that a high compression ratio can be obtained.

From the comparison results of the time used in the compression by two methods, it is found that the time used by the new method is a little shorter than the other used by the LOCO-I algorithm, showing that the real-time performance of the new method is a little improved than before.

V. CONCLUSION

By the construction of the local texture predictive model, a new color-images lossless compression method is presented in this paper. The model utilizes four color-change gradients of the current pixel to represent its local texture feature, which is easy to calculate and understand, and has a good performance in vision consistency.

Furthermore, the similarity of the local area's texture feature, which brings about the redundancy of the medical images, is easy to measure and define by using this model. The measurement of this similarity is important to efficiently decrease the redundancy information in the color spectrum space. The compression simulation experiments on several kind medical images show that, for a kind of medical images with clear local texture features, the predictive model set up in this paper performs rather well in catching the feature of the pixels, and it is could be said it would do better with the combining use of it in multi-dimension space. The further research will be on that as mentioned above.

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