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RESEARCH ARTICLE

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Medical image lossless compression based on combining an integer wavelet transform with DPCM

Abstract To improve the classical lossless compression of low efficiency, a method of image lossless compression with high efficiency is presented. Its theory and the algorithm implementation are introduced. The basic approach of medical image lossless compression is then briefly described. After analyzing and implementing differential plus code modulation (DPCM) in lossless compression, a new method of combining an integer wavelet transform with DPCM to compress medical images is discussed. The analysis and simulation results show that this new method is simpler and useful. Moreover, it has high compression ratio in medical image lossless compression.

Keywords medical image, integer wavelet transform, differential plus code modulation (DPCM), lossless compression

1 Introduction

Medical image compression is important in the field of medical image databases such as long-distance medical diagnosis systems and medical image storage transmission systems. The purpose of medical image compression is to express images with less data to save storage space and transmission time, based on the premise that true information in the original image shall be preserved [1].

Lossy compression possibly destroys pivotal information such as image information on pathological body changes, which is harmful to subsequent processing and application. Thus, lossless compression is widely used in medical image storage and transmission. Classical lossless compression methods, such as Huffman coding, arithmetic coding and differential plus code modulation (DPCM), are of lower compression efficiency. For this reason, it is important and meaningful to improve and optimize classical lossless compression coding [2]. A new lossless compression method combining integer wavelet transforms with DPCM is presented. Experimental results show that the method uses simple arithmetic and offers a higher compression ratio.

2 Basic steps of medical image lossless compression

The redundancy of image sources consists in their correlation. Based on the information theory, image lossless compression coding is separated into two parts: transforming and coding.

1) Transforming (also called de-correlation) is used for reducing the image dynamic range and removing redundant information.

2) Coding applies the entropy encoder to encode the transformed image coefficient matrix.

At present, entropy coding technology is close to image information entropy. Lossless compression arithmetic has already combined model de-correlation with entropy coding [3]. The process of lossless compression is shown in Fig. 1.

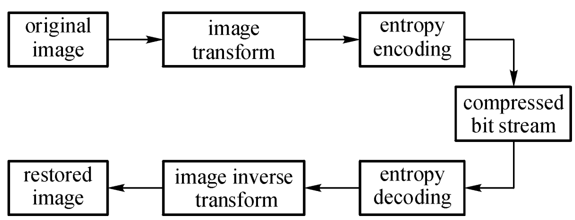

Fig. 1 Flowchart of lossless compression of an image

3 DPCM prediction in lossless compression

The method in which an original image is compressed by entropy coding is not of perfect compression efficiency due to correlations in the original image. Prediction coding is a

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simple and useful intra-de-correlation method for medical image lossless compression.

DPCM prediction is nonlinear [1,2]. Its basic idea is to predict the information in every image pixel and make the predicted image entropy less than the original image entropy. Because there is strong correlation among adjacent pixels, current pixel values are predicted by pixel knowledge [4].

3.1 DPCM prediction model and realization

In this article, the prediction model for medical image lossless compression is as follows:

$$X = \frac{1}{2}A + \frac{1}{4}B + \frac{1}{4}C, \tag{1}$$

where X, A, B and C respectively represent the corresponding pixel values in Fig. 2.

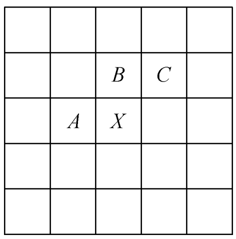

Fig. 2 Prediction model of DPCM system

X is a pixel value to be predicted. When it comes to the image boundary, one or two values among A, B and C do not exist. The prediction model then becomes:

$X = A$ (B and C do not exist),

$X = \frac{3}{4}B + \frac{1}{4}C$ (A does not exist),

$X = \frac{1}{2}A + \frac{1}{2}B$ (C does not exist).

For the first pixel in the upper left corner, all of the three values do not exist. Thus, this pixel is not predicted and its value is saved in the header information of the output code stream.

The original position method is used in this algorithm, i.e., the prediction value is subtracted from the current value and the resulting prediction error is saved in the current position:

$$X' = X - \mathrm{int}\left(\frac{1}{2}A + \frac{1}{4}B + \frac{1}{4}C\right). \tag{2}$$

3.2 Experimental results

In the experiment, two standard test images, Barbara and Lena, as well as two medical images are used to test compression performance. Experimental results are shown in Table 1.

Table 1 Entropy and compression ratio of DPCM

image	entropy		compression ratio
	original image	DPCM prediction	DPCM + Huffman
Barbara	7.47	5.65	5.672
Lena	7.45	4.54	4.580
brain CT	4.84	2.23	2.275
chest X ray	6.46	3.75	3.820

The results show that the entropy of the new image produced by DPCM prediction is much less than that of the original image, with an average decrease in image entropy of up to 40%. After the subsequent entropy coding, a higher lossless compression ratio is obtained. Partly for this reason, DPCM is widely used in medical image lossless compression. However, DPCM de-correlates pixels only in a space domain. After the DPCM transform, image energy distribution is not centralized. Hence, there is correlation among different frequency components.

4 Lossless compression method combining DPCM with integer wavelet transform

Integer wavelet transform (IWT) can decompose the image into different sub-bands based on frequency, and implement a wavelet reversible transform. This makes medical image wavelet lossless compression possible [5,6].

4.1 Arithmetic and its realization

A medical image, such as a CT, MRI and US, has higher spatial correlation. Its correlation value is far higher than the standard test image. Thus, it is necessary to perform prediction coding in medical image lossless compression. If only DPCM prediction is applied, it is difficult to resolve the storage and fast transmission of medical image despite perfect compression performance. In this case, a new medical image lossless compression method is introduced based on combining DPCM with IWT. First, the original image data are predicted by DPCM to remove the most redundancy. Second, a reversible integer wavelet transform is executed to separate high frequency components and low frequency components. This step makes the energy more centralized and image data more compact. Finally, the image data are encoded by Huffman coding [7,8]. The structure of the encoder and decoder is shown in Fig. 3.

In Fig. 3, the integer wavelet transform applies a 5/3 reversible integer wavelet. Its transform is described as

$s_{1,l}^{0} := s_{0,2l}$

$d_{1,l}^{0} := s_{0,2l+1}$

for $i = 1$ to M

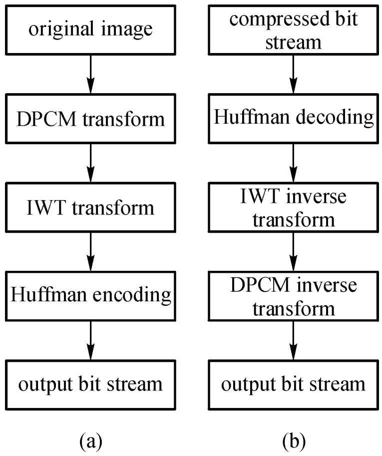

Fig. 3 Flowchart of encoder/decoder. (a) Encoder; (b) decoder

$$\forall l : d_{1,l}^{i} = d_{1,l}^{i-1} + \left\lfloor \tau(s_{1,l}^{i} + s_{1,l+1}^{i-1}) + \frac{1}{2} \right\rfloor$$

$$\forall l : s_{1,l}^{i} = s_{1,l}^{i-1} + \left\lfloor \upsilon(d_{1,l}^{i} + d_{1,l-1}^{i}) + \frac{1}{2} \right\rfloor$$

end

The inverse transform is described as

for $i = M$ to 1

$$\forall l : s_{1,l}^{i-1} = s_{1,l}^{i} - \left\lfloor \upsilon(d_{1,l}^{i} + d_{1,l-1}^{i}) + \frac{1}{2} \right\rfloor$$

$$\forall l : d_{1,l}^{i-1} = d_{1,l}^{i} + \left\lfloor \tau(s_{1,l}^{i} + s_{1,l+1}^{i-1}) + \frac{1}{2} \right\rfloor$$

end

$s_{0,2l+1} := d_{1,l}^{0}$

$s_{0,2l} := s_{1,l}^{0}$

where $\tau = -0.5$, $\upsilon = 0.25$, $\omega = \sqrt{2}$.

4.2 Boundary processing of a wavelet

A wavelet transform can decompose the image into a set of multi-scale sub-band images. The decomposed sub-band images are comparatively stable and easy to encode. However, since the image is a finite length signal, the signal boundary extends during sub-band decomposition. To meet the perfect reconstruction condition, the number of samples of strict re-sampling sub-band signals should be increased, which will lead to low efficiency. To resolve this problem, the signal boundary must be properly extended. The signal then becomes of infinite length and meets the perfect reconstruction requirement without increasing the number of samples. However, it should be noted that the extension method must avoid importing new distortion or influencing compression results. Common boundary processing methods include zero extension, periodic extension, periodic symmetry extension and smooth constant extension.

For ordinary wavelet transform arithmetic, every extension method has different effects on signal reconstruction. Only periodic extension can effectively reconstruct signals, but also lead to a discontinuous boundary and poor low bit rate. If periodic symmetry extension is performed, signals can be perfectly reconstructed if filters have a symmetrical structure. The periodic symmetry extension is used in JPEG2000 for boundary processing of wavelet transforms. In this article, boundary processing of integer wavelet transforms uses the same extension method. Supposing the row sequences and line sequences are $s_0, s_1, s_2, \ldots, s_{n-1}$, the signal that is periodically extended is

$$\ldots, s_{n-1}, \ldots, s_2, s_1, s_0, s_1, s_2, \ldots, s_{n-1}, \ldots.$$

For linear phase filters, such as a 5/3 wavelet, the periodic symmetry extension method not only implements perfect reconstruction, but also increases no data. When the arithmetic is realized, it decides whether the boundary components need to be extended. If extension is necessary, the corresponding extension components are immediately obtained. Thus, the calculation efficiency is improved [9].

5 Experimental results

In the experiments, two standard test images, Barbara and Lena, and two medical images are losslessly compressed. The image size is $512 \times 12 \times 8$ bits. The wavelet transform is a 5/3 integer wavelet transform, while decomposition level is 6. Experimental results of four images in Fig. 4 are compared in Tables 2, 3 and 4.

Table 2 shows that Huffman coding is very simple and useful. However, just using this method results in lower image lossless compression efficiency. This happens because the lowest bit ratio of image lossless compression coding is limited by image information entropy based on Shannon information theory, i.e., the bit ratio of image lossless compression is not less than information entropy.

Table 2 also shows that when the DPCM prediction or wavelet transform is completed, the entropy of new images is significantly less than the original entropy. After the DPCM transform or integer wavelet transform, the average decrease of image entropy is more than 30%. This makes further entropy coding possible and improves the compression efficiency. Table 3 shows that the method combining DPCM with integer wavelet transform has excellent compression performance. The average increase of compression ratio is between 6% and 9%, compared with that for DPCM or integer wavelet transform alone. In addition, its compression ratio is increased by 43% compared with that using only Huffman encoding. At the same time, its operation time is less than DPCM and IWT.

The method combining DPCM with IWT is effective in practice. Its lossless compression ratio is perfect for

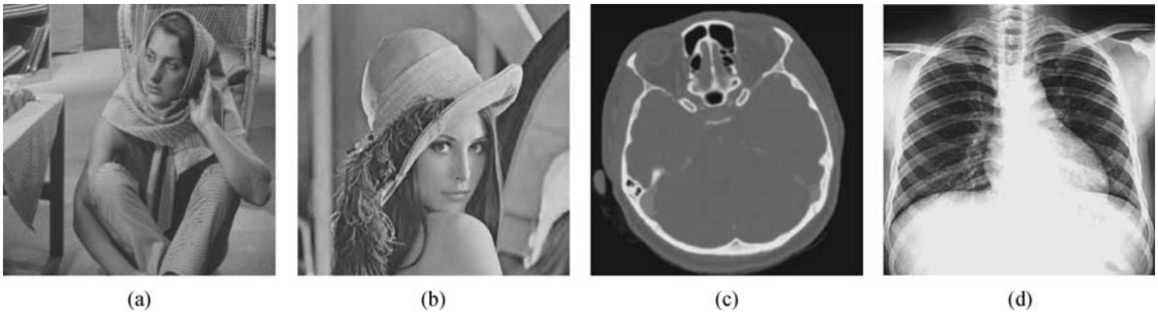

Fig. 4 Images tested in experiments. (a) Barbara; (b) Lena; (c) brain CT; (d) chest X ray

Table 2 Comparison of lossless compression entropy

test images	entropy/Shannon			
	original images	DPCM	IWT	DPCM + IWT
Barbara	7.47	5.65	5.57	5.14
Lena	7.45	4.54	4.42	4.42
brain CT	4.84	2.23	2.53	1.99
chest X ray	6.46	3.75	4.02	3.66

Table 3 Compare in lossless compression ratio

test images	compression ratio/bpp			
	Huffman	DPCM + Huffman	IWT + Huffman	DPCM + IWT + Huffman
Barbara	7.496	5.682	5.583	5.187
Lena	7.476	4.580	4.461	4.455
brain CT	4.881	2.275	2.590	2.007
chest X ray	6.498	3.820	4.059	3.738

Table 4 Compare in lossless compression time

test images	encoding time/s			decoding time/s		
	DPCM	IWT	DPCM + IWT	DPCM	IWT	DPCM + IWT
Barbara	0.41	0.54	0.63	0.24	0.34	0.38
Lena	0.36	0.53	0.61	0.22	0.32	0.36
brain CT	0.23	0.43	0.51	0.19	0.30	0.35
chest X ray	0.34	0.51	0.56	0.20	0.33	0.36

medical images. The new method resolves the problem of deficient image storage space to a certain extent. Because DPCM and IWT only need addition, subtraction and shift operations, this method is used for real-time processing. Moreover, it is implemented using simple hardware.

6 Conclusions

This article presented a method of improving medical image lossless compression efficiency and introduced the theory and arithmetic realization in detail. The classical Huffman method was discussed. Furthermore, Huffman encoding was improved. The function of DPCM in medical image lossless compression was analyzed. On the basis of these conditions, the method combining integer wavelet transform with DPCM was developed for medical image lossless compression. The experimental results show its concision, high compression ratio and practicability.

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