Discrete Cosine Transform Optimization in Image Compression Based on Genetic Algorithm

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Abstract—***Based on the basic principles and characteristics of discrete cosine transform (DCT), we propose a DCT optimization method using genetic algorithm in order to improve the efficiency of image compression. First, we calculate the error between the reconstructed image and its original one. Then, in order to optimize DCT transform matrix coefficients, we use genetic algorithm to find optimal solution by minimizing the mean square error. Finally, we use the optimized transform kernel to process images. Experimental results indicate that the PSNR of the reconstructed images has been improved using the proposed optimization DCT in both cases of image block 4×4 and 8×8.***

Keywords-DCT optimization; Genetic algorithm; Image compression; Mean square error

I. INTRODUCTION

With the rapid progress of modern science and technology, image information is widely used in computer systems and multimedia communications. Accordingly, the requirements of data processing are getting higher and higher. Image information, especially high-definition image is carrying huge amount of information, however, the storage and processing of images for communication devices are under tremendous pressure. A large number of requirements for real-time transmission of multimedia information in various communication networks are also a great challenge even under the existing high communication transmission rate. Therefore, efficient image compression plays a crucial role in such cases.

At present, the most-widely-used method of image compression is based on discrete cosine transform (DCT) [1] [2]. Original image has strong correlation. Therefore, most energy will concentrate on a few coefficients after performing DCT on the image [3]. We can achieve the goal of image compression by keeping the significant coefficients of main energy. And in some new image or video coding methods the integer transform form of DCT [4] is adopted, which use similar transformation coefficients.

In order to get higher compression ratio, some DCT coefficients will not be recovered in the decoder, therefore, the reconstructed image is often different from the original image. Subjectively, we hope the difference or distortion is smaller. A genetic algorithm in processing of image compression is proposed in [5] and [6], which is based on the premise that the approximate extent is the maximum between reconstructed and original images. We put forward an optimization DCT method of image compression based on genetic algorithms, which adopts adaptive optimized correction by applying genetic algorithms to the traditional DCT coefficient regarding image features such as texture and edge information. Our method breaks the unified bondage of the traditional DCT matrix coefficient, achieves the goal of improving the effect of image compression.

II. TRADITIONAL DCT ALGORITHM

Two-dimensional discrete cosine transform [7] is

$$F(u,v)=\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\alpha(u)\alpha(v)\cos(\frac{u\pi(2x+1)}{2N})\cos(\frac{v\pi(2x+1)}{2N}) \quad (1)$$

where

$$\alpha(u),\alpha(v)=\begin{cases}\frac{1}{\sqrt{N}} & u,v=0\\ \sqrt{\frac{2}{N}} & u.v=1,2,...,N-1\end{cases}$$

Traditional image compression method is as follows: Let original image matrix is f , DCT matrix is C , reserved coefficient matrix is M , the transformed coefficient matrix is obtained by

$$F=C\cdot f\cdot C^{-1} \quad (2)$$

The coefficient matrix L after stripping off insignificant coefficients is given by

$$L=F\cdot M \quad (3)$$

In the decoder, the reconstructed image matrix f' is obtained by

$$f'=C^{-1}\cdot L\cdot C \quad (4)$$

This processing is simple and general, however the transform effect depends on transform matrix and the reserved coefficient matrix. The retention of the coefficient is certain in most practical applications, so the whole processing performance will be determined by the transform matrix. According to (1), if the size of the transform block N is known, the transform matrix C is constant. There is larger distortion between the reconstructed image and its corresponding original one due to the process of transformation, compression and inverse transform. The reason is that the transform blocks are definite and the transform matrix is kept constant. In other words, no matter what images are processed, the same transform matrix is used, which means image characteristics are not fully considered. Therefore, we need to optimize the traditional DCT method to minimize the difference between the reconstructed image and the original image.

III. OPTIMAL DCT ALGORITHM

In the proposed method, the least square method is used to optimize DCT matrix. The error caused by image compression is

$$E\left[\|e(n)\|^2\right] = E\left[\|f'-f\|^2\right] = E\left[\left|C^{-1}\cdot L\cdot C - f\right|^2\right] \qquad (5)$$

To minimize the mean square error[8], we have

$$\frac{\partial E\left[\left\|e(n)^2\right|\right]}{\partial C} = 0 \qquad (6)$$

Because C is a matrix, (6) becomes to take the derivative of each element in the matrix is as follows.

$$\frac{\partial E\left[\left\|e(n)^2\right|\right]}{\partial c_{ij}} = 0 \qquad (7)$$

The optimized DCT matrix C_{OPT} can be worked out using (7). The optimized discrete cosine transform is referred to as ODCT in this paper. Replacing C with C_{OPT} , and then repeating the original traditional DCT process to complete the image compression based on ODCT. The whole transform process is shown in Figure 1.

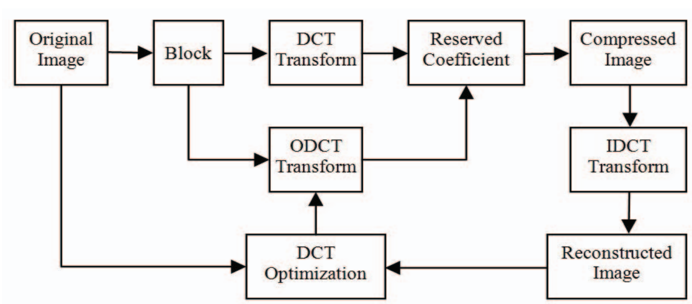

Figure1. Block diagram of ODCT algorithm

It needs to be noted that ODCT matrix is determined by approximation degree of the original image and the reconstruction image. So the optimal results can be obtained by the method of multiple approximate optimizations.

IV. GENETIC ALGORITHM FOR THE OPTIMAL SOLUTION

We propose to perform traditional DCT optimization by minimizing the mean square error between the original image and the reconstructed image. However, (6) is actually the process of solving the optimal solution with simultaneous equations for each pixel of image blocks. This process has two characteristics: First, the optimal solution is the solutions of equations, which is not a single solution and requires the simultaneous processing of multiple information in parallel. Second, the adjacent pixels in image blocks are related, the optimization process is not deterministic, and we know exactly what the optimal solution appears near the DCT coefficients. Accordingly we need to adopt certain rules to guide the solutions. Thus, we use the optimal solution method based on genetic algorithm to search [9].

A. Encoding

First, the image information data is expressed as the genotype string structure data of the genetic space. These different combinations of string structure data constitute different points. We adopt binary encoding. Assume the value ranges from a to b, then the coding accuracy is calculated as follows.

$$x = \frac{b-a}{2^l - 1} \qquad (8)$$

where l is the string length of the string structure data, then the i -th test data decoding is

$$X_i = a + \sum_{i=1}^{l} b_i \times 2^{(i-1)} \times \frac{(b-a)}{2^l - l_i} \qquad (9)$$

The larger the value interval selected, the greater we may select the optimal value, the better image effect is.

B. Generation of the initial population

There are M numbers of randomly generated initial string structure data, each string structure data is an individual, which constitute a population. These M numbers of string structure data are the initial point of iterations, which denotes the number of individuals in the population. In order to avoid premature or inefficiency and other phenomena caused by inappropriate values, M takes the range from 20 to 100 in our method.

C. Assessment test of adaptive values

Adaptive function indicates the unique merits, which follows the principle of simplification, and it is designed to reduce the complexity of algorithm to accelerate the speed of obtaining the optimal value. In the proposed method, the adaptive function is the error function of image compression [10] as in (5).

D. Selection

The purpose of selection is to select superior individuals from the current population and give them the opportunity for the next generation of breeding offspring. This paper adopts "roulette wheel" selection method [11] and selects the next generation of individual based on the principle of survival of the fittest. Given the objective function, $f(b_i)$ is called the fitness of individual b_i. The number of selected individuals P for the next generation is given by

$$P\{b_i is\ \text{selected}\} = \frac{f(b_i)}{\sum_{j=1}^{n} f(b_j)} \cdot n \tag{10}$$

Obviously, the higher the fitness of individuals is, the larger the number of breeding in the next generation is, on the contrary, a smaller number of breeding the next generation is, or even to be eliminated. This produces descendants who have strong abilities to adapt the environment. From the perspective of getting the optimization solution, it is a process of choosing the solution which is closer to the optimal one.

E. Crossover

Crossover operation is the most important genetic manipulation in genetic algorithms. We can get a new generation of individuals through crossover operation, and the new individuals contain individual characteristics of their parents.

F. Mutation

We select an individual randomly in the population. For the selected individuals, the values of a string structure of data in the string are changed randomly with a certain probability. Like in the biological community, the probability of occurrence mutation is really low in the encoding. It is usually ranging from 0.001 to 0.01. Mutation provided an opportunity for the new generation. Mutation will affect the population fitness again.

The optimal matrix ODCT is obtained by the above steps, and the process of repeating conventional DCT is solved. As shown in Figure 1, the optimized ODCT image compression is accomplished.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. Parameter settings

In the optimization process, ODCT matrix results depend on parameters of genetic optimization algorithm. The effect of image compression varies with the experimental parameters, which is shown from Figure 2 to Figure 5.

1) Population size

As can be seen from Figure 2, for 4x4 and 8x8 image blocks, the PSNR of reconstructed images is essentially unchanged when ODCT populations change from 40 to 60. This indicates the number of populations has reached saturation point basically and that is enough for carrying out genetic algorithm optimization. Therefore, the optimal population size is 40 for 4×4 image block, and 60 for 8×8 image block. It is worthy of mention that in the case of 8×8 image block, when the number of population size is 10 and the PSNRs of the reconstructed images using ODCT and DCT are equal, which indicates that the population size 10 is not sufficient to process genetic optimization algorithm, resulting in a "premature" phenomenon which should be avoided in the genetic optimization algorithm.

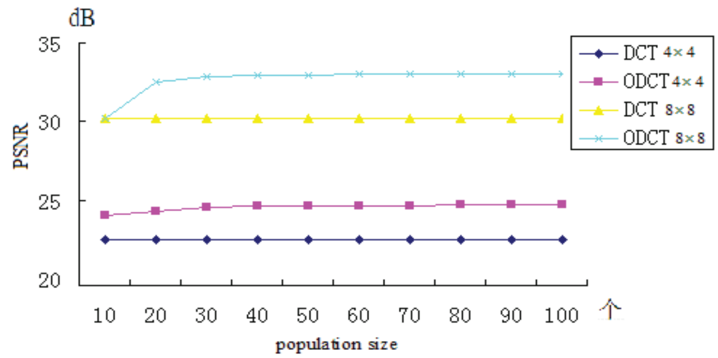

Figure2. PSNR comparison results with different block sizes using DCT and ODCT for varing population size

2) String size

The results of using different string size are shown in Figure 3. It can be seen that the quality of the reconstructed image for both cases are stable when the string size is larger than 8. And the curve of 8×8 block is relatively flatter than that of 4×4 block. It illustrates that larger blocks are not sensitive to the change of string size, which results in the relatively small perturbation of the algorithm. Therefore the optimal string size of the proposed method is 8.

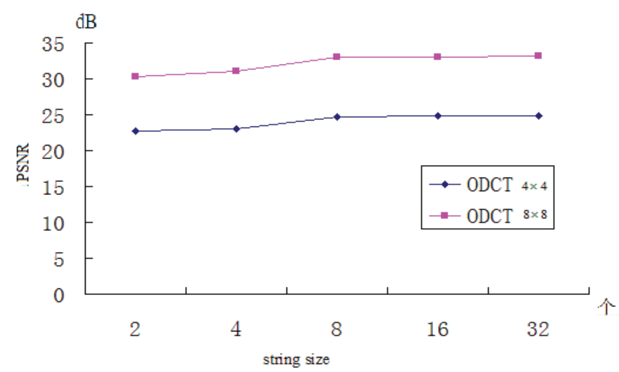

Figure3. PSNR comparison results with different block sizes using ODCT for varing string size

3) Crossover probability

The performance of the proposed method using different crossover probability is shown in Figure 4. The curves show that the crossover probability is 0.7 for 4×4 block and 0.8 for 8×8 blocks. The reconstructed image effect in different cases are basically stable, so the smaller the image blocks, the less the required crossover probability. We select 0.8 as the crossover probability in our method.

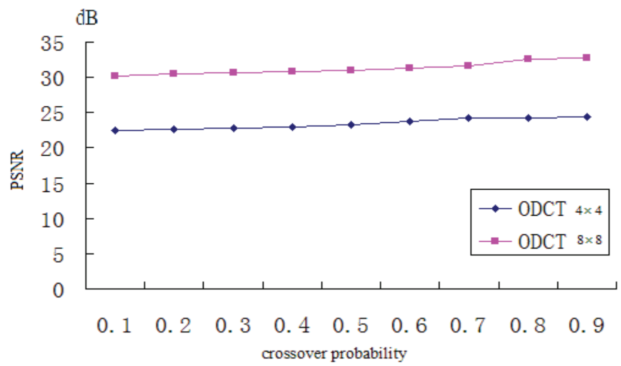

Figure 4. PSNR comparison results with different block sizes using ODCT for varing crossover probability

4) Mutation probability

Figure 5 presents the PSNR results of image compression using ODCT with different mutation probability. It shows that the reconstructed image effects are basically stable, when mutation probability is 0.007 for 4×4 blocks and 0.008 for 8×8 blocks. Consequently, the smaller the image block is, the less the required stable mutation probability is.

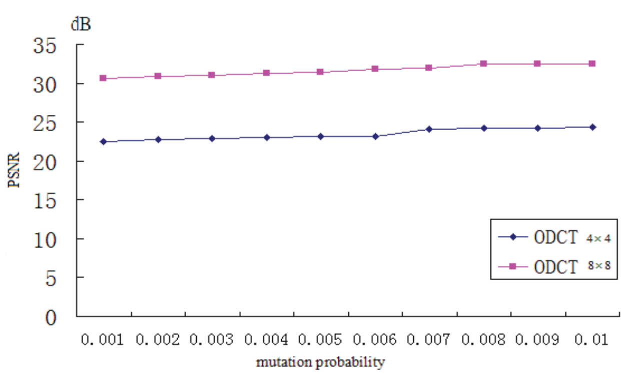

Figure5. PSNR comparison results with different block sizes using ODCT for varing mutation probability

B. Experimental comparison results

In order to compare the performance of the proposed ODCT method with the traditional DCT method, *Lenna* image is used in our experiments for image compression. The parameters used in our method are: the population size is 40, the length of individual and chromosome is 8, crossover probability is 0.8, variation probability is 0.01 and the number of iterations is 20. The results of experiments with different block sizes are shown in Figure 6 and Table 1.

（a）The reconstructed image of 4x4 block using DCT
（b）The reconstructed image of 4x4 block using ODCT
（c）The reconstructed image of 8×8 block using DCT
（d）The reconstructed image of 8×8 block using ODCT

Figure6. Comparison results of reconstructed *Lenna* image using DCT and ODCT

TABLE I. COMPARISON RESULTS OF PSNR USING DCT AND ODCT

Block size	**DCT**		**ODCT**	
	PSNR	***Compression ratio（%）***	***PSNR***	***Compression ratio（%）***
4×4	35.1450	81.5	36.4994	80.7
8×8	31.1835	38.3	33.2907	35．9

Experimental results in Table 1 show that compression performance using the proposed ODCT is better than that of using DCT obviously. Comparing cases of 4×4 and 8×8 blocks in Table 1, the larger the blocks size are, the better the performance is. The reason is that the optimization process for larger blocks are more comprehensive for finding ODCT transform matrix coefficients.

We use different types of images in our experiments for further comparison of the proposed method with the corresponding state of art methods based on DCT. The images we use here are *Stonebird*, *Riverstreet*, *Raingutter* and *Cameraman*. The comparison results of using DCT, the proposed ODCT and ADCT[12] are shown in Table 2. Table 2 shows that the ODCT method has a better compression effect.

TABLE II. COMPARISON RESULTS OF PSNR USING DIFFERENT MATHODS

Images	DCT	ADCT [12]	ODCT
Stonebird	28.9113	29.765	30.3325
Riverstreet	29.025	32.3281	33.657
Raingutter	24.4659	25.57	26.0132
Cameraman	24.1228	25.812	26.6328

VI. CONCLUSION

In this paper, aiming at the improving discrete cosine transform (DCT) matrix in image compression, the genetic algorithm is used to optimize the traditional DCT. By testing with different image blocks and parameter optimization, the ideal setting of optimization parameters and blocks are determined. Experimental results show that for the images with line edge and texture feature, our DCT optimization method based on genetic algorithm for image compression can reach the best effects when small block processing is used, the number of population is from 40 to 60, the length of the string is 8, the crossover probability is from 0.7 to 0.8, and the mutation probability is from 0.007 to 0.008.

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REFERENCE

[1] Feifei Zhang, Wei Xie, Guorui Ma. “High dynamic range compression and detail enhancement of infrared images in the gradient domain”.Infrared Physics & Technology. Vol. 67, November 2014, pp. 441-454.

[2] Jie Wei. “Image segmentation based on situational DCT descriptors”.Pattern Recognition Letters, Vol. 23, Issues 1–3, January 2002, pp. 295-302.

[3] Dae-Yeon Kim, Yung-Lyul Lee. “A fast intra prediction mode decision using DCT and quantization for H.264/AVCOriginal”.Signal Processing: Image Communication, Vol. 26, Issues 8–9, October 2011, pp. 455-465.

[4] D.J. Duh, J.H. Jeng, S.Y. Chen. “DCT based simple classification scheme for fractal image compression”.Image and Vision Computing. vol. 23, Issues 13,November 2005, pp. 1115-1121.

[5] TIAN Ying, YUAN Wei-qi. “Application of the Genetic Algorithms in Image Processing”.Journal of Image and Graphics. Vol. 12, Issues 3, March 2007, pp. 389-396.

[6] Snehamoy Chatterjee, Ashis Bhattacherjee. “Genetic algorithms for feature selection of image analysis-based quality monitoring model: An application to an iron mine”. Engineering Applications of Artificial Intelligence. Vol. 24, Issues 5,August 2011,pp.786-795.

[7] Rafael C.Gonzalez,Richard E.Woods,Steven L.Eddins. “Digital Image Processing Using MATLAB”. Publishing House of Electronics Industry.Beijing.pp.239-251.

[8] CAO Ji-hua, WANG Zhao-hua. “The Interpolation Algorithms of Picture Error Conceal Ment Based on Minimum Mean Square Error”.Journal on Communications .Vol.21,Issues12,December 2000, pp.1-4.

[9] Ek Peng Chew, Chong Jin Ong, Kim Hee Lim. “Variable period adaptive genetic algorithm”.Computers & Industrial Engineering, Vol.42,Issuse 2-4,April 2002,pp. 353-360.

[10] U.M. Al-Saggaf, M. Moinuddin, M. Arif, A. Zerguine. “The q-Least Mean Squares algorithm.Signal Processing”.Available online 3 December 2014. In Press.

[11] XIA Gui-mei, ZENG Jian-chao. “A Stochastic Particle Swarm Optimization Algorithm Based on the Genetic Algorithm of Roulette Wheel Selection”.Computer Engineering and Science.Vol.29,Issuse 6,June,2007, pp.51-54.

[12] K.Saraswathy, D.Vaithiyanathan and R.Seshasayanan. “A DCT Approximation with Low Complexity for Image Compression”. International conference on Communication and Signal Processing, India.2013,pp.465-468.