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A FRACTAL IMAGE CODING METHOD COMBINED WITH COMPRESSED SENSING ALGORITHM

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МЕТОД ФРАКТАЛЬНОГО КОДУВАННЯ ЗОБРАЖЕНЬ, КОМБІНОВАНИЙ З АЛГОРИТМОМ СТИСЛИХ ВИМІРЮВАНЬ

Purpose. Since fractal image coding is time-consuming and is prone to causing "blocking artifact", the article aims to combine fractal image coding, wavelet transform and compressed sensing to put forward a method which can shorten the coding time effectively and improve the quality of a reconstructed image.

Methodology. The compressed sensing algorithm can quickly compress and highly restore sparse matrixes. The paper made use of this feature to conduct fractal coding for a low-frequency sub-image after wavelet transform, followed by recoding the samples of low-frequency differential sub-graphs and high-frequency sub-images by means of the compressed sensing algorithm for the purpose of compensating the quality of reconstructed images.

Findings. Compared to the traditional fractal coding method, the algorithm in the paper (hereinafter referred to as "this Algorithm") can shorten the time considerably and get a maximum speed-up ratio by up to 6.45 times. Compared to the compressed sensing coding method, the quality of the reconstructed images is improved significantly.

Originality. The innovation of the paper lies in applying the compressed sensing theory to the fractal coding algorithm to compensate the quality of the reconstructed images obtained by means of fractal coding based on wavelet transform.

Practical value. This Algorithm can shorten the coding time on the basis of ensuring the quality of a reconstructed image, and has certain significance for promoting the fractal coding method.

Keywords: *fractal image coding, wavelet transform, compressed sensing, reconstructed image, sparse matrixes, speed-up ratio*

Introduction. The method of fractal image coding has found wide application due to its characteristics of high compression ratio and fast decoding. However, being applied, this method has two drawbacks, namely, long encoding duration and blocking artifact. The long encoding duration is mainly attributed to the long traverse duration in the search of matching blocks. In order to solve this problem, Literature [1] proposes a fast encoding algorithm based on relevant information features: the sub-blocks are partitioned into two categories according to the relevant information features, so as to convert the issue of sub-block search into the issue of searching for the same type of neighbouring parent blocks based on the relevant information features, thereby accelerating the encoding process. Literature [2] realizes fuzzy clustering by using pixel value space and 1D-DCT vector, thus increasing the encoding speed by 40 times under the precondition of maintaining equal decoding quality. Literature [3] realizes neighbourhood search by taking advantage of the phenomenon that blocks with similar edge shapes tend to concentrate in certain specific areas. Works [4] propose neighbourhood search methods respectively based on the similarity ratio and relative error to substitute the global search method, thereby shortening the encoding duration. In addition, the fractal compression method divides the original image into regular blocks and encodes them separately, resulting in errors at the block boundaries, which cause the "blocking artifact". Studies have also been conducted to solve this problem. On the basis of the elaboration of how the length and distribution of characteristic track relate to encoding performance, literature [5] proposes a new sub-block characteristic function, and accordingly obtains better PSNR values under the precondition of maintaining the same encoding duration. By applying discrete cosine transform, literature [6] finds the best parent block and mapping through the adjustment of grayscale transformation, so as to lower the mean square error to below the allowable value, thus achieving the purpose of improving image quality and cutting down encoding duration. Literature [7] puts forward a fast fractal image coding algorithm based on structural information feature, presents the definition of structural information feature, conducts codebook classification and nearest neighbour search by using this feature as a feature quantity, matches sub-blocks in the neighbourhood given by the search results, and thus achieves the encoding. In light of the characteristics of local images, Literature [8] designs an image encoding algorithm by combining the self-adaptive partitioning method with a variety of block classification technologies for reducing encoding duration, thus significantly improving the visual effect of image encoding and increasing the encoding speed by thousands of times.

In order to overcome the two shortcomings of fractal coding described above, the hybrid encoding algorithm, which is a combination of factual algorithm and other algorithms, has become one of research topics nowadays. By combining fractal coding and compressed-sensing encoding in the wavelet domain, the paper attempts to utilize the compressed sensing approach to process sparse high-frequency sub-graphs so as to compensate for the distortion and detail loss occurring in the fractal coding of low-frequency sub-graphs. The encoding for compressed sensing is not a time-consuming process and therefore will not bring a large burden to the encoding end. Experimental results demonstrate that this Algorithm compensates to some extent for the image quality loss in fractal coding in the presence of certain requirements for compression ratio and duration.

The basic fractal image coding algorithm. Jacquin proposed the local iterated function system (LIFS), which is a fractal compression encoding system based on partition and works in the following way: partitioning the original image into non-overlapping range blocks and overlapping domain blocks, traversing the range block set to search for the best matching block for each domain block, saving the information on similar blocks, and eliminating the self-similarity of an image to achieve the goal of image compression. The basic steps of fractal image coding algorithm are as follows:

Step 1: Segment the original image with a size of $N \times N$ into non-overlapping $n \times n$ range blocks (R-blocks), and store them in the set R, $P = \bigcup_{i=1}^{N/n} R_i$; then, segment P into overlapping $2n \times 2n$ domain blocks (D-blocks), and store them into the set D, $P = \bigcup_{i=1}^{N/2n} D_i$.

Step 2: Conduct four-neighbourhood pixel averaging for D-blocks, make their sizes equal to those of R-blocks, before performing eight kinds of isometric transformation of D-blocks; denote the D-blocks that have gone through the isometric transformation by $w_j(D_i')$, where w_j is the type of isometric transformation and j = 1,2,..., 8. Subsequently, conduct brightness transforms shown in (1), where, s is the contrast factor, o is the brightness offset factor, l is the unit matrix, and D_{ij}' is the block resulting from the compressed mapping of D-block.

$$D_{ij}' = s(w_j(D_i')) + ol. \quad (1)$$

Step 3: Compare R-blocks with D_{ij}' to calculate the error between the two, as shown in (2). Traverse the set D_{ij}' to get D_{ij}' that the smallest error value $E(R_i,\ D_{ij}')$ corresponds to, that is, the best matching block for this R_i. Then, record the position and isometric transformation type of this D-block.

$$E(R_i, D_{ij}') = \frac{1}{\sqrt{n}} \left\| R_i - D_{ij}' \right\|_2 . \quad (2)$$

Step 4: Following the identification of the best matching block, compute according to (3), where $\overline{R}$ is the mean of R-blocks and $\overline{D}$ is the mean of D-blocks, to obtain the IFS code, which is composed of the best matching block position i, isometric transformation type w_j, contrast adjustment coefficient o_i and brightness adjustment coefficient s_i.

$$s = \frac{\left\langle R_i - \overline{R}_i l, w_j(D_i' - \overline{D}_i l) \right\rangle}{\left\| w_j(D_i') - \overline{D}_i l \right\|_2^2}, \quad o = \overline{R}_i - s \cdot \overline{D}_i. \quad (3)$$

Step 5: Repeat the above steps to obtain the fractal codes for all the R-blocks of the image, thereby constituting an IFS.

The compressed-sensing encoding algorithm. The traditional process of signal acquisition and processing mainly comprises of four parts, namely, sampling, compressing, transmitting and decoding. In order to acquire accurate reconstructed signal, the sampling process must satisfy the Nyquist–Shannon sampling theorem, that is to say, the sampling frequency should not be lower than twice as high as the highest frequency in the analog signal spectrum. In the process of signal compression, the signal is first diluted, and then a small number of coefficients with large absolute values in the signal are encoded, while the coefficients which are equal to or close to zero are removed. During data compression, the removal of most of the data acquired in sampling will not affect the recovery effect. For example, when photographing with a megapixel camera, only a small amount of useful information about the image will be stored and a huge amount of useless information will be removed, before reconstruction is performed based on the acquired data.

According to the compressed sensing theory, if there is an intrinsically sparse or compressible signal, the data following the compression may be exploited directly, with the purpose of avoiding the acquisition of a large amount of useless information. The advantage of compressed sensing is that the required amount of observation data in signal sampling is far smaller than the amount of data obtained with the traditional signal-sampling method, thus the restriction of the Nyquist–Shannon sampling theorem is overcome and the acquisition of high-resolution signals becomes a possibility.

The theoretical basis of compressed sensing is as follows: if the transformation coefficient Θ for a one-dimensional signal with a length of Nunder of orthogonal basis set ψ is sparse, then $x = \Psi\Theta$ or $x = \sum_{i=1}^{N} a_i \varphi_i$.

Thus, the coefficient vector $\Theta = \Psi^T x$ or $a_i = \langle x, \varphi_i \rangle$, and such Θ is called the sparse representation of the signal x. If an observation matrix Φ, that is unrelated to ψ, is found, linear transformation between this matrix and the coefficient vector is conducted to obtain the measured value

$$y = \Phi x = \Phi\Psi\Theta = A^{CS}\Theta. \quad (4)$$

In (4), Φ refers to a $M \times N$ matrix, $M = O(K \cdot \log(N/K))$, $M \ll N$, and $A^{CS} = \Phi\Psi$.

Subsequently, the measured value is applied to solve the following problem

$$\overline{\Theta} = \min \|\Theta'\|_{l_0} \quad s.t. \quad y = \Phi\Psi\Theta.$$

Thus, the transformation coefficient is obtained, and through high-probability reconstruction by inverse transformation, an image that approximates the original image is generated $x = \Psi\overline{\Theta}$.

The theoretical frame diagram of the traditional signal compression is presented in Fig. 1.

The theoretical frame diagram of compressed sensing is presented in Fig. 2.

Compressed sensing is characterized by:

1. The applicability of one observation matrix to different sparse matrices, since the observation is unrelated to the original matrix or the recovered matrix.

2. Short encoding duration: the sampling process can be completed only through obtaining the observed value with the formula $y = \Phi x$, thus, the difficulty in compressed sensing lies in the signal-reconstruction process.

3. Random data acquisition, since the data design for the observation matrix is random and independent from the original sparse matrix.

Therefore, the compressed sensing theory mainly involves the sparse representation of a signal, the design of observation matrix, and the signal reconstruction.

Signal diluting. In the study of signal compression, continuous efforts have been made to find a way of representing all information within a small amount of information, thereby, shortening the encoding duration and enhancing the compression ratio. Any signal can be represented by an orthogonal basis set, that is,

$$X = \sum_{i=0}^{N} a_i \Psi_i \quad \text{or} \quad X = \Psi\Theta,$$

where $\Theta = \{a_1, a_2, \ldots, a_N\}$. The signal can be considered sparse, if Θ only contains a small amount of data, or if Θ only contains a small amount of data with large absolute values and most of the data in it is close to zero. If a small amount of data with far above-zero absolute values is centrally distributed in a signal, this signal can be considered compressible, and the preservation and accurate recovery of such a signal can be realized by acquiring a small amount of data from the sparse signal. Ordinary signals, however, are not sparse, thus signal diluting has become an urgent research topic.

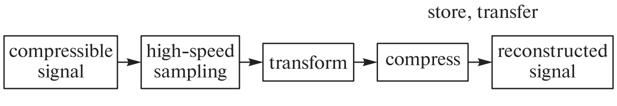

Fig. 1. The traditional process of signal acquisition

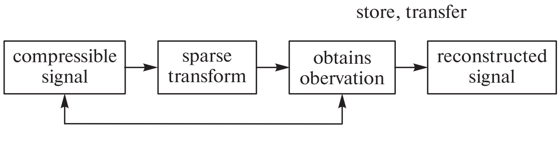

Fig. 2. The signal acquisition in compressed sensing

Sparse decomposition of a signal is usually conducted based on orthogonal basis. Usually, sparse transformation basis can be flexibly selected according to the characteristics of the signal itself, and the commonly used transformation bases include discrete cosine transform (DCT) basis, fast Fourier transform basis, Gabor basis and redundant dictionary.

The design of observation matrix. It is known that the process of compressed-sensing encoding is

$$y = \Phi x.$$

Hence, the design of an observation matrix is vital to guarantee the quality of the reconstructed signal, that is, to guarantee the validity of the measured value. In the design of the observation matrix, the projection matrix must satisfy the requirement of restricted isometry property (RIP) in order to ensure the retention of the original structure of the signal during the linear projection, before the measured value of the original signal in the linear projection is obtained by multiplying the original signal by the observation matrix.

For a signal vector υ with strict K sparsity and a length of N, Φ is an observation matrix with a size of $M \times N$, let a vector set $T \in \{1, 2, \ldots, N\}$ and $|T| < K$, and put the column vector, to which the elements of the set T selected from the set Φ correspond, into a new matrix Φ′; for example, $T = \{1, 2, 3\}$ means that Φ′ is composed of the 1st, 2nd and 3rd column matrices of the matrix Φ and that its size is $M \times |T|$.

If the matrix Φ′ satisfies the following formula, it means the matrix meets the K-order restricted isometry standard.

$$1 - \varepsilon_K \le \frac{\|\Phi'\upsilon\|}{\|\upsilon^2\|} \le 1 + \varepsilon_K, \quad 0 < \varepsilon < 1.$$

Signal reconstruction. In image decoding, signal reconstruction is generally conducted with the greedy algorithm, including the algorithms of orthogonal matching pursuit (OMP), matching pursuit (MP), weak matching pursuit (weak MP) and LS-OMP. When the number of columns in the observation matrix is smaller than that of its lines, the greedy algorithm is especially applicable to the reconstruction. Its basic idea is to choose the smallest number of lines out of the observation matrix to form an approximate representation of the observation matrix. As the most used kind of greedy algorithm, the OMP algorithm has a variety of types, such as an orthogonal type and a relaxation type. RIP matrix is one of the frequently applied matrices in compressed sensing, and when the original data matrix is a RIP matrix, the OMP algorithm is a good choice for encoding.

The implementation process of the OMP algorithm is as follows:

Input: The original image x, the observation matrix $\Phi = \{a_1, a_2, \ldots, a_N\}$, the measured value y, and the iteration number k;

Output: The reconstructed image $\bar{x}$;

Procedure of the algorithm:

Initialization: Reconstruction $x^0 = 0$; residual error $r^0 = y$, index set $\Gamma^0 = \varnothing$, and iteration number $n = 1$;

1. Compute the inner product of the margin and each column of the observation matrix Φ.

2. The element with the largest absolute value in g^n, $k = \arg\max_{i \in \{1,2,\ldots N\}} \left| g^n[i] \right|$.

3. Update the index set $\Gamma^n = \Gamma^n - 1 \cup \{k\}$ and the original sub-set $\Phi_{\Gamma^n} = \Phi_{\Gamma^{n-1}} \cup \{a_k\}$.

4. Compute the approximate solution by using the least square method $x^n = \left(\Phi^T_{\Gamma^n} \Phi_{\Gamma^n}\right)^{-1} \Phi^T_{\Gamma^n} y$.

5. Update the margin $r^n = y - \Phi \cdot x^n$.

6. If $n < k$, and r^n is greater than the limit, then $t = t + 1$, and return to Step 1); if $n > k$ or r^n.

Is smaller than the limit, then output $\bar{x} = x^n$.

This algorithm. Although the mere use of fractal compression can lead to a high compression ratio, long encoding duration and "blocking artifact" during decoding have restricted the application of the fractal compression. In order to solve these two problems, a variety of hybrid encoding methods emerge. The paper proposes the fractal coding algorithm combined with the compressed sensing algorithm, with the aim of compensating for the image quality loss in fractal image coding based on wavelet transform.

Wavelet transform and fractal coding are combined herein: the image first goes through wavelet decomposition before fractal coding of low-frequency sub-graphs is conducted. Through wavelet transform, the image is divided into sub-graphs with different frequencies in different directions, among which, the ones located in the upper left corner are low-frequency sub-graphs with about 99 % of the original image energy, and the other ones are collectively called high-frequency sub-graphs. Following wavelet decomposition, most of the information is preserved on the low-frequency sub-graphs, which resemble the original image, as shown in Fig. 3.

This Algorithm involves the combination of wavelet transform and fractal coding. Encoding only low-frequency sub-graphs will cause the loss of high-frequency sub-graph information; moreover, fractal image coding algorithm is a lossy coding algorithm, and part of the data regarding the original image will be missing on the reconstructed image (the lost data is the low-frequency differential sub-graph obtained by subtracting low-frequency sub-graphs from the reconstructed image). In order to improve the quality of the reconstructed image, the compressed sensing algorithm is combined with the fractal coding algorithm in this paper. The approach of compressed-sensing encoding is applied to the sparse matrix composed of the low-frequency differential sub-graph and the high-frequency sub-graphs, and then the reconstructed image resulting from that is

Fig. 3. Level-1 wavelet decomposition

fused with the reconstructed image acquired in fractal coding, so as to compensate for the image quality loss occurring during the image construction with the fractal coding method based on wavelet transform; in addition, the encoding for compressed sensing is fast and will not bring a significant effect on the encoding duration of the hybrid encoding algorithm.

The specific steps of this Algorithm are as follows:

Input: the original image P and the observation matrix Φ;

Output: The reconstruction image P_1.

Steps:

1. Perform Level-1Haar wavelet transform of P to obtain low-frequency sub-graphs LL and high-frequency sub-graphs LH, HL, HH.

2. Extract low-frequency sub-graphs for fractal compression processing to get the reconstructed image LL'.

3. Obtain low-frequency differential sub-graph through calculation $LL_1 = LL - LL'$.

4. Put together the differential sub-graph and the high-frequency sub-graphs to form a sparse data matrix $M = [LL_1, LH; HL, HH]$.

5. Perform compressed sensing of M, measure the matrix Φ to obtain the measured value $R = \Phi * M$, conduct compressed-sensing encoding of the measured value R, and obtain the image M_1through reconstruction.

6. Fuse M_1 with LL' to form the image $p = M_1 + LL'$.

7. Perform inverse wavelet transform of the image P to generate the reconstructed image P_1.

8. Compute the root-mean-square error (MSE) and peak signal-to-noise-ratio (PSNR), and then return to the reconstructed image P_1.

As a hybrid encoding algorithm, the fractal image compression method proposed herein involves both the wavelet transform algorithm and the compressed sensing algorithm, and has the following characteristics:

1. Through wavelet decomposition and Level-N wavelet transform of an image, the size of the low-frequency sub-graphs is only $\frac{1}{4^N}$ of that of the original image, and fractal compression of the low-frequency sub-graphs can lead to significantly shorter encoding duration.

2. Through wavelet decomposition of the image into low-frequency and high-frequency sub-graphs, no energy change occurs, and most of the energy is retained on the low-frequency sub-graphs; thus, a re-

constructed image that resembles the original image can be obtained through fractal coding of only low-frequency sub-graphs.

3. The high-frequency sub-graphs resulting from wavelet decomposition and the reconstructed low-frequency differential sub-graph feature little information and sparse distribution, which serve as the preconditions for encoding them by means of compressed sensing.

4. The sparse matrix composed of the low-frequency differential sub-graph and high-frequency sub-graphs are encoded by means of compressed sensing, before the reconstructed image is fused with that resulting from fractal coding, so as to compensate for the image quality loss occurring during image construction with the fractal coding method based on wavelet transform.

Experimental results. Based on MATLAB, the basic fractal coding algorithm, the compressed-sensing encoding algorithm and this Algorithm were separately applied to the experiment with five 256 × 256 images with 256 gray levels, namely, *Baboo*, *Boat*, *Goldhill*, *Lena* and *Peppers*. The R-block size for the basic fractal coding algorithm is 2 × 2, and Level-1 Haar wavelet transform and the fractal coding algorithm with 2 × 2 R-blocks are employed for this Algorithm. Fig. 4–5 show the comparisons among the reconstructed images respectively for *Lena* and *Boat*, resulting from encoding with the three algorithms.

According to Fig. 4–5, the mere use of the compressed sensing algorithm leads to slightly poorer quality of the reconstructed image than the other two algorithms, while the reconstructed image for this Algorithm appears identical to that for the basic fractal coding algorithm, which proves the feasibility of this

a b c

Fig. 4. Comparisons among the reconstructed image for Lena, resulting from encoding with the three algorithms:

a – the compressed sensing algorithm; b – the basic fractal coding algorithm; c – this Algorithm

a b c

Fig. 5. Comparisons among the reconstructed images for Boat, resulting from encoding with the three algorithms:

a – the compressed sensing algorithm; b – the basic fractal coding algorithm; c – this Algorithm

Algorithm. Table below shows the experiment data obtained when encoding the five images respectively by using the three algorithms: encoding duration T (unit: S) and PSNR (unit: dB).

According to Table, compared with the basic fractal coding algorithm, this Algorithm leads to slightly lower PSNR values yet significantly shorter encoding duration – the maximum speed-up ratio can increase by 6.45 times; compared with the compressed-sensing encoding algorithm, this Algorithm leads to slightly longer encoding duration yet obviously better quality of the reconstructed image. Based on comprehensive consideration of encoding duration and quality of the reconstructed image, this Algorithm is arguably an effective means.

Conclusion. In the paper, the compressed sensing theory is integrated into the fractal coding algorithm in an innovative way, so as to shorten the encoding duration without the loss of quality of the reconstructed image. In this Algorithm, an image is decomposed through wavelet transform into low-frequency and high-frequency sub-graphs, and despite the small amount of original-information content on the high-frequency sub-graphs, the removed information is encoded and reconstructed in order to improve the quality of the reconstructed image in the fractal compression algorithm. In the encoding of the coefficient matrix composed of the high-frequency sub-graphs and the low-frequency differential sub-graph, the compressed sensing algorithm is chosen owing to the sparsity of this coefficient matrix, which is in line with the precondition of compressed sensing; furthermore, considering the large speed of compressed-sensing encoding, the addition of the compressed sensing algorithm will not have a significant impact on the encoding duration in the hybrid coding algorithm.

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Table

The performance comparison among the three algorithms

Image	Performance parameter	The basic fractal coding algorithm	The Compressed sensing algorithm	This Algorithm
Baboo	*T/s*	872.68	46.72	148.76
	PSNR/db	30.70	20.55	25.93
Boat	*T/s*	903.68	46.16	146.98
	PSNR/db	37.50	26.58	35.70
Goldhill	*T/s*	899.09	45.83	146.24
	PSNR/db	42.72	25.88	34.59
Lena	*T/s*	901.38	45.94	139.64
	PSNR/db	41.63	30.93	36.51
Peppers	*T/s*	897.31	46.07	149.89
	PSNR/db	40.52	29.13	37.95

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Мета. Оскільки фрактальне кодування зображень займає багато часу та схильне до появи „блокуючих артефактів“, ця робота присвячена об’єднанню фрактального кодування зображень, вейвлет-перетворення й стислих вимірів так, щоб запропонувати метод, який дозволить ефективно скоротити час кодування та покращити якість реконструйованого зображення.

Методика. Алгоритм стислих вимірів може швидко стискувати й сильно відновлювати розріджені матриці. У даній роботі використана ця особливість для проведення фрактального кодування для низькочастотної компоненти зображення після вейвлет-перетворення, а потім перекодування виборок низькочастотних диференціальних суб-графів і високочастотних компонент зображень за допомогою алгоритму стислих вимірів, з метою компенсації якості відновлених зображень.

Результати. У порівнянні з традиційним методом фрактального кодування, алгоритм, запропонований у даній роботі (далі по тексту „Цей Алгоритм“), дозволяє значно скоротити час, і дістати максимальне прискорення продуктивності до 6,45 разів. У порівнянні з методом стислих вимірів, якість відновлених зображень значно покращується.

Наукова новизна. Полягає в тому, що вона пропонує застосування теорії стислих вимірів до фрактального алгоритму кодування аби компенсувати якість відновлених зображень, отриманих за допомогою фрактального кодування на основі вейвлет-перетворення.

Практична значимість. Цей Алгоритм дозволяє скоротити час кодування на основі забезпечення якості відновленого зображення та має велике значення для просування фрактального методу кодування.

Ключові слова: *фрактальне кодування зображень, вейвлет-перетворення, стислі виміри, реконструкція зображення, розріджені матриці, коефіцієнт прискорення*

Цель. Поскольку фрактальное кодирование изображений занимает много времени и подвержено появлению „блокирующих артефактов“, эта работа посвящена объединению фрактального кодирования изображений, вейвлет-преобразования и сжатых измерений таким образом, чтобы предложить метод, который позволит эффективно сократить время кодирования и улучшить качество реконструированного изображения.

Методика. Алгоритм сжатых измерений может быстро сжимать и сильно восстанавливать разреженные матрицы. В данной работе использована эта особенность для проведения фрактального кодирования для низкочастотной компоненты изображения после вейвлет-преобразования, а затем перекодирования выборок низкочастотных дифференциальных суб-графов и высокочастотных компонент изображений с помощью алгоритма сжатых измерений, с целью компенсации качества восстановленных изображений.

Результаты. По сравнению с традиционным методом фрактального кодирования, алгоритм, предложенный в данной работе (далее по тексту „Этот Алгоритм“), позволяет значительно сократить время, и получить максимальное ускорение производительности до 6,45 раз. По сравнению с методом сжатых измерений, качество восстановленных изображений значительно улучшается.

Научная новизна. Заключается в том, что она предлагает применение теории сжатых измерений к фрактальному алгоритму кодирования, чтобы компенсировать качество восстановленных изображений, полученных с помощью фрактального кодирования на основе вейвлет-преобразования.

Практическая значимость. Этот Алгоритм позволяет сократить время кодирования на основе обеспечения качества восстановленного изображения и имеет большое значение для продвижения фрактального метода кодирования.

Ключевые слова: *фрактальное кодирование изображений, вейвлет-преобразование, сжатые измерения, реконструкция изображения, разреженные матрицы, коэффициент ускорения*

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