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An Improved Image Sparse Decomposition Algorithm

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ABSTRACT

Sparse decomposition is developed in recent years, the signal and image processing tools, signals and images can be decomposed into a very simple form of expression. Image compression technology in the image processing has an important role, is widely used in various fields of image processing. At present, commonly used image compression techniques are usually based on orthogonal transformation, but in low bit rate conditions, this approach often cannot get the desired recovery effect. In order to solve this problem, this paper proposes a particle swarm optimization (PSO) algorithm to improve the speed of image sparse decomposition by selecting suboptimal atoms instead of the best atoms from the complete library.

1. INTRODUCTION

In the field of signal processing, in order to be able to represent more complex signals, as well as to improve their representation accuracy, also need more redundant waveform library. And in a single base on the linear expansion, whether it is Fourier, or wavelet, or other base, are not flexible enough, Fourier Foundation cannot be a good representation of the time domain local signal, and wavelet base cannot So that the use of such a base to express the signal will cause the loss of information, such a signal decomposition as if the use of less vocabulary to write the same article, although these vocabulary enough to express all the meaning, but the There may be a need to replace a word with no words. In order to make the signal representation more flexible and concise.

Sparse decomposition is Mallat and Zhang in 1993 proposed the signal in the over-complete atomic pool decomposition of the idea. Mallat and Zhang put forward the idea of decomposing the signal over the complete atomic library. In order to obtain a more sparse representation of the signal, it is necessary to make the construction of the base sufficiently close in the signal space, so that the orthogonality of the base cannot be ensured This base is no longer the traditional sense of the base and renamed the atom. Mallat et al. (1994) proposed a Matching Pursuit (MP) algorithm, which extends the one-dimensional signal to the image representation as a two-dimensional signal. At present, image sparse decomposition has also been successfully applied to many aspects of image processing, such as image compression, image denoising and image recognition. Commonly used image compression standard JPEG and JPEG2000, these two standards is based on the idea of transform domain coding, JPEG is the use of DCT, and JPEG2000 is the use of DWT} 39}. These transformations convert the coordinates from the standard Euclidean coordinate system to the other coordinate system, just to get a more sparse representation. The use of DCT media content will generally have such a feature: the beginning of a few transform coefficients larger, and the latter part of the conversion coefficient is very small, so the smaller size of the latter will be ignored as 0, only a large number of quantitative Encoding to produce an approximate representation of the original data, so that the original data can be stored with relatively few bits. And the inverse of these coefficient sequences can be reconstructed to reconstruct the contents of the original medium. The use of DWT media will have some different characteristics: the latter part of the transformation may also be a small amount of relatively large coefficient. DWT's excellent performance in image coding has benefited from its ability to sparse image content. JPEG2000 performance for many types of image content will be better than JPEG: to meet the requirements of the accuracy and error can use less bits, which is mainly due to DWT representation than the DCT representation is more sparse.

2. Organization of the Text Image sparse decomposition

2.1 Image signal

The image is a two-dimensional signal, so the sparse decomposition of the image is similar to the sparse decomposition of the one-dimensional signal. The image contains some complex structures, such as textures and edges, which require a flexible image representation. Although the characteristics of the image are entirely determined by its decomposition on the orthogonal basis, such bases are not sufficient to effectively represent all potential useful structures. The representation of some of the components on the basis of the image is very lengthy, so it may be difficult to analyze the signal from the base representation, as if it were a dictionary with a small vocabulary. In order to provide an accurate representation of the important local features in the image, a set of waveform functions is selected from the complete atomic library to represent the image, so that the signal is not decomposed on the entire base, but rather the least suitable The waveform approximates the image.

2.2 Image sparse decomposition core idea

Let the study image f, its size $M \times N$, M and N, respectively, the length and width of the image. The image is sparse and decomposed by the complete atomic library of $D = \{g_\gamma\}_{\gamma \in \Gamma}$, where g_γ is the matching atom, $\|g_\gamma\| = 1$, and Γ is the set of γ.

The MP algorithm decomposes the image process as follows:

First, from the complete atomic library selected with the image to be decomposed to best match the atomic $g_{\gamma 0}$ meet the following conditions

$$\left|\left\langle f, g_{r_0} \right\rangle\right| = \sup_{\gamma \in \Gamma} \left|\left\langle f, g_r \right\rangle\right| \qquad (1)$$

In this way, the image can be decomposed into two parts on the best atom $g_{\gamma 0}$ and the residual information

$$f = R^0 f = \left\langle f, g_{\gamma 0} \right\rangle g_{\gamma 0} + R^1 f \qquad (2)$$

Where $\left\langle f, g_{\gamma 0} \right\rangle g_{\gamma 0}$ denotes the projection component of the image f on the atom $R^1 f$, and $g_{\gamma 0}$ denotes the residual amount after the matching of the original two pairs of images. In the equation (2), it is known that $g_{\gamma 0}$ and $R^1 f$ are orthogonal,

$$\|f\|^2 = \left|\left\langle f, g_{r_0} \right\rangle\right|^2 + \left\|R^1 f\right\|^2 \qquad (3)$$

In order to minimize the energy of the residual amount $R^1 f$, the projection component $\left|\left\langle f, g_{r_0} \right\rangle\right|$ is required to be maximized, then $g_{\gamma k}$ satisfies:

$$\left|\left\langle R^K f, g_{r_K} \right\rangle\right| = \sup_{\gamma \in \Gamma} \left|\left\langle R^K f, g_{r_K} \right\rangle\right| \qquad (4)$$

After the same amount of the residual amount is *n* times above

$$f = \sum_{k=0}^{n-1} \left\langle R^k f, g_{y_k} \right\rangle g_{y_k} + R^n f \qquad (5)$$

Where $\left\|R^n f\right\|$ decreases exponentially with *n*., So with a small number of atoms and image size compared to the image can be expressed as the main component, that image can be expressed as:

$$f \approx \sum_{k=0}^{n-1} \left\langle R^k f, g_{y_k} \right\rangle g_{y_k} \qquad (6)$$

3. Particle swarm optimization algorithm model

Although image sparse decomposition has been successfully applied to many aspects of image processing, but at present, image sparse decomposition is difficult in the practical application of image processing and industrialization. One of the key factors is the computational complexity of image sparse decomposition. In order to solve this problem, this paper proposes a particle swarm optimization (PSO) algorithm to improve the speed of image sparse decomposition by selecting suboptimal atoms instead of the best atoms from the complete library. Particle Swarm Optimization (PSO) is an evolutionary harmonic technique with a new global evolutionary evolutionary algorithm developed by Dr. Eberhart and Dr. Kennedy. From the behavior of the predation of birds. PSO is similar to genetic algorithm and is an iterative optimization tool. The system is initialized as a set of random solutions, and the optimal values are searched by iterations. In this paper, we introduce particle swarm optimization (PSO) algorithm to image sparse decomposition. In this paper, we use particle swarm optimization (PSO) to quickly select sub-optimal atoms from over-complete library for each iteration of sparse decomposition. The best atom, thus to a certain extent, to avoid the huge amount of image sparse decomposition. Particle swarm optimization algorithm flow chart shown in Figure 1.

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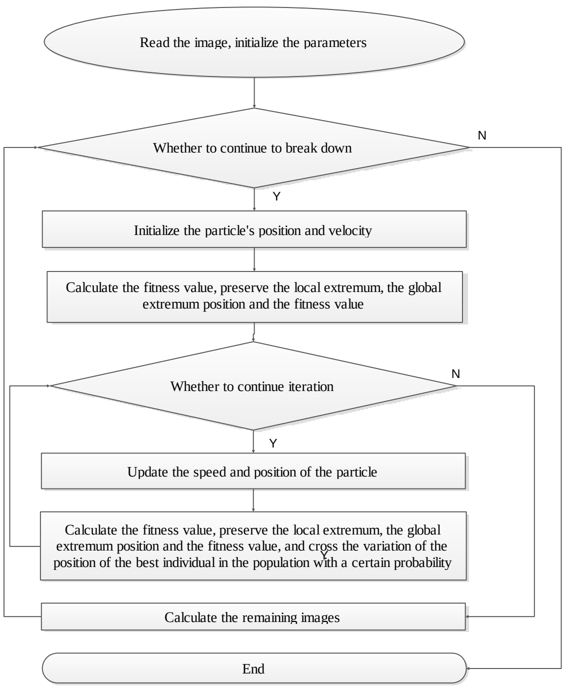

Figure 1. Particle Swarm Optimization Algorithm

In the D-dimensional search space, the total number of particles is n and the position of the I the particle is $x_i = \left[x_{i1}, x_{i2}, x_{ij} \cdots x_{iD}\right]$. The optimal position of the *I* the particle in the iteration process is $p_i = \left[p_{i1}, p_{i2}, p_{ij} \cdots p_{iD}\right]$. The velocity of the i-the particle is $v_i = \left[v_{i1}, v_{i2}, v_{ij} \cdots v_{iD}\right]$. So far, the optimal position of the whole population is P_g. When the kth iteration is carried out, the update rate and position of the particle are:

$$v_{ij}^{k+1} = w \times v_{ij}^{k} + c_1 \times rand_1() \times (\mathrm{p}_{ij} - \mathrm{x}_{ij}^{k}) + c_2 \times rand_2() \times (\mathrm{p}_{gj} - \mathrm{x}_{ij}^{k}) \tag{7}$$

$$v_{ij} = \begin{cases} v_j^{\max}, v_{ij} > V_j^{\max} \\ v_{ij}, -v_j^{\max} \le v_{ij} \le v_j^{\max} \\ -v_j^{\max}, v_{ij} \le -V_j^{\max} \end{cases} \tag{8}$$

$$x_{ij}^{k+1} = x_{ij}^{k} + x_{ij}^{k+1} \tag{9}$$

$$x_{ij} = \begin{cases} X_j^{\max}, x_{ij} > X_j^{\max} \\ x_{ij}, X_j^{\min} \le x_{ij} \le X_j^{\max} \qquad 1 \le i \le n \qquad 1 \le j \le D \\ X_j^{\max}, x_{ij} \le X_j^{\min} \end{cases} \tag{10}$$

The iteration steps are as follows:

Step 1: Read the image and set the particle swarm parameter.

Step 2: Initialize the location and velocity of the particle group.

The position and velocity of the particle group are initialized within the allowable range, the position of the particle swarm is rounded, the fitness value $\left|\left\langle R^K f, g_{r_K}\right\rangle\right|$ of each particle is calculated, the position of each particle is the initial value of the local extremum P, the fitness value in *P* The maximum position is set to the initial value of the global extremum P_g.

Step 3: Update the particle's position and velocity according to the above formula.

Step 4: Evaluate the particle swarm.

Calculate the fitness value $\left|\left\langle R^K f, g_{r_K}\right\rangle\right|$ for each particle, If the fitness value of the particle is superior to the fitness value of *P*, the position *P* and the fitness value of the local extremum are updated with the current position and the fitness value. If the maximum fitness value in the local extremum is superior to the fitness value of the global extremum, the fitness value and the position P_g of the global extremum are updated with the maximum fitness value and the corresponding position in the local extremum.

Step 5: Cross

The position of the two optimal individuals in the particle group is cross-mutated with a certain probability.

Step 6: Determine whether it is necessary to continue iterating, and if so, turn to step 3, otherwise output the fitness value and position P_g of the global extremum, calculate the residual image according to the following formula and judge whether it is necessary to continue to decompose the image, Step 2, look for the next best match atom of the residual image, otherwise, end.

$$R^{k+1} f = R^k f - \left\langle R^k f, g_{r_k}\right\rangle g_{r_k} \tag{11}$$

4. Analysis of results

The experiment uses a standard Lena image of 128 * 128 size. In this paper, a large variation factor is used in the early stage of particle swarm optimization (PSO), and with the increase of evolutionary algebra, the variance factor is linearly reduced. The peak signal-to-noise ratio PSNR is used to measure the quality of reconstructed image.

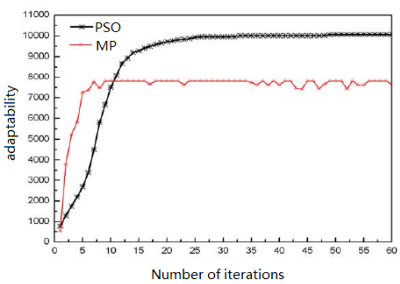

Figure 2 Convergence comparison

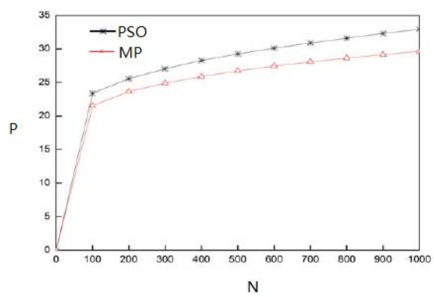

Figure 3 Reconstruction of image quality contrast

It can be seen from the simulation diagram that Figure 2 shows the average fitness change curve of the population based on the PSO algorithm and the MP algorithm in the first best atomic process. It can be seen that the search ability of the algorithm is strong and the evolutionary convergence of the population is more stable The Figure 3 shows the quality comparison of sparse reconstructed images based on PSO algorithm and MP algorithm. It is shown that the peak signal-to-noise ratio of the image obtained by this algorithm is always larger than that of MP-based algorithm.

5. Conclusions

Image compression has an important position in image processing technology. So far, researchers have put forward a variety of image compression ideas and programs, but also developed a series of international standards for image compression, and has been widely used, but the image sparse The huge amount of decomposition. This paper presents a fast image sparse decomposition algorithm - particle swarm optimization algorithm, the paper illustrates the principle of the method and gives the specific implementation steps, through experiments show that the reconstruction of the image quality is better than the MP algorithm decomposition method.

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