ISBN: 978-1-948012-05-8

Contents List available at VOLKSON PRESS

Intelligent Computing and Information Engineering (ICIE)

DOI : http://doi.org/10.26480/icie.01.2017.174.176

Journal Homepage: : https://www.intelcomp-design.com/

Image Compression Based on Sparse Decomposition

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ARTICLE DETAILS

Article History:

Received 12 May2017
Accepted 12 July 2017
Available online 14 September 2017

Keywords:

Sparse decomposition; image compression; data transmission; data storage.

ABSTRACT

With the development of social information and the progress of science and technology, digital cameras, camcorders, scanners, printers and other image devices gradually popular, making the image information is everywhere. But the current use of storage devices and network bandwidth can not support the amount of data on such a large amount of storage and transmission requirements, in order to achieve the effective storage of images and fast transmission, its compression is particularly important. This paper focuses on the image compression technology based on sparse decomposition, and the compressed image has significant advantages in the process of data storage and transmission. Therefore, the image compression technology has become an important part of the field of multimedia communications.

1. INTRODUCTION

Image compression is realized by image quantization, transformation and coding. Among them, the image transformation is the image transformation. From the point of view of the decomposition result, the image transformation can be divided into two types: orthogonal decomposition and sparse decomposition. The orthogonal decomposition method of image occupies an important position on the stage of history, and has greatly promoted the progress of image compression technology. However, with the view that the subjective visual effect of image is taken into account after the compression field, the advantage of sparse decomposition method It will gradually highlight the use of sparse decomposition of the image transformation, you can better meet the physiological characteristics of the human eye, with a better subjective visual experience. Although the image sparse decomposition in image compression research is successful, but because of its own large amount of computing characteristics, resulting in its development has been seriously hampered. As a result, digital image processing technology has been paid more and more attention. Today, digital image processing technology has become an independent discipline, widely used in scientific research, military, public security, education, economy and other fields, for contemporary society Activities in all aspects of service. In general, the image has not yet compressed, its representation requires a considerable amount of data, a 512x1212 size static true color image, each pixel accounted for 3 bytes of storage, the amount of data is 2MB, Assuming that the film consists of 25 frames (PAL) images per image, each image is a true color image of 352 x 288 size, then the amount of data for a second movie is about 7. 2MB, and the amount of data for one hour is 2. 6G. Commonly used storage devices and network bandwidth can not support the data storage and transmission of such a large amount of requirements, in order to achieve the effective storage of images and fast transmission, it is particularly important to compress. The compressed image has a significant advantage in the process of data storage and transmission. Therefore, the image compression technology has become an important part of the field of multimedia communications.

Generally, the compression of the signal is called coding, and the process of reconstructing the original image becomes decoded. Image compression is generally divided into lossless compression (no distortion coding) and lossy compression (with distortion coding) two categories, which is based on whether the loss of image information to divide. The method based on dictionary technology and the method based on statistical probability belong to lossless compression. The principle of the former is that a particular sequence in the original file is represented by each code. In the method based on the statistical probability, the symbols with small probability are represented by longer codes, and the symbols with large probability are represented by relatively short codes. Image lossy compression coding is not the same as lossless compression coding, which improves the image compression capability, but the quality of the reconstructed image is not necessarily good. If the distortion is not affected by the quality of the reconstructed image, then this method can be used. The traditional method of compressing the image is shown in Figure 1 below:

Figure 1. Method for compressing an image

2. Sparse decomposition theory

With the continuous development of signal and image processing technology, how to use the signal and image components to express the signal and image has become the focus of attention. Assuming that the signal to be processed is sparse, it can be transformed into the transform domain by a suitable transformation, sparsely changing, and then multiplying the sparse matrices with a sparse matrix that is not associated with the sparse base. With a suitable reconstruction algorithm to restore the original image, that is, to solve a problem of optimal solution. The above method can be proved theoretically, that is, the sparse coefficients after the multiplication of the observation matrix can reconstruct the original image. Mathematically, a two-dimensional matrix is used to represent the sampled and quantized analog image,

$$F = \begin{bmatrix} f(0,0) & f(0,1) & \cdots & f(0, N-1) \\ f(1,0) & f(1,1) & \cdots & f(1, N-1) \\ \vdots & \vdots & & \vdots \\ f(M-1,0) & f(M-1,1) & \cdots & F(M-1.N-1) \end{bmatrix} \quad (1)$$

An element in the matrix represents a point in the image, and each element is called a pixel. A pixel consists of coordinates and grayscale, and the coordinates of the pixels in the plane image are a two-dimensional point. The value *F* (*m, n*) of the image F at the point where the coordinates are (*m, n*) is called the gray scale of the point.

A finite length of the one-dimensional signal can be regarded as an *N × 1* dimensional column vector f of the R^N space, the elements are *F [n], n = 1, 2, 3, ... N.* For each signal in the *R* space, it is linearly expressed by a set of *N × 1* dimensional basis vectors $\{\psi_i\}_i^N$ of numbers N, that is, $f = \sum_{i=1}^{N} \theta_i \Psi_i$: where θ_i is the coefficient of the corresponding vector. If the vector $\{\psi_i\}_i^N$ is regarded as the base matrix S of the *N × N* order, then the signal f can be expressed as $\Psi = [\Psi_1, \Psi_2, \cdots \Psi_N]$, where Θ denotes the N × 1-dimensional column vector of the coefficient $f = \Psi\Theta$, and each row corresponds to a base vector. Thus, f and Θ can be understood as different manifestations of the same signal: f is the original signal expressed in the time domain; Θ is the embodiment of the original signal after a linear combination. The larger the absolute value of the element in the coefficient vector Θ obtained after the linear combination, the more the signal is similar to the base. If there are few elements in the coefficient vector Θ that are not zero and most of the elements are zero, we say that the signal has sparsity in the base Ψ linear representation, or that the signal is sparse under the Ψ domain.

3. Sparse decomposition of the classical algorithm

At present, the sparse decomposition of the signal has developed a variety of algorithms, such as matching tracking algorithm (MP), basic tracking algorithm (BP), frame method (MOF) and best orthogonal basis method (BOB). The algorithm is easy to understand, and the computational complexity of the algorithm is the lowest among all sparse decomposition algorithms. Therefore, the most widely used sparse decomposition method is the most widely used algorithm. This paper also uses the matching tracking algorithm to achieve the signal and image sparse decomposition. MP ideas and algorithms to attract more and more researchers involved in the main applications are:

(1) Video coding and video compression, in particular the estimation and compensation of moving images. Many scholars have proposed many new dictionaries and dictionary search algorithms for video compression and coding, and have achieved more successful application in low bit rate video coding compression. This is also the MP algorithm formed shortly after the practical application of the field.

(2) Image representation, analysis and coding.

(3)) Medical signal processing field. Medical signal analysis and processing has always been a very active area of signal processing, MP is applied to them, such as EEG signal time-frequency analysis and compression, breathing and heart rate analysis and detection.

(4) Voice and audio signal processing. MP thought first appeared in the field of statistical data processing and speech signal processing, and in its perfect process is also a speech signal as a research example, such as high-resolution sound signal analysis, adaptive audio decomposition.

Matching algorithm (MP), the algorithm is through the complete dictionary in the gradual selection of the signal closest to the base to achieve the purpose of sparse. Given a signal $f \in R^N$, dictionary $D = \{g_y\}_{y=1}^{\Gamma}$, where g_y is normalized, is $\|g_y\|_2^2 = 1$. Matching the tracking algorithm. The sparse decomposition of the signal f is as follows:

Initialize $R^1 f = f$, the first decomposition signal is

$$R^1 f = \langle g_{y_1}, R^1 f \rangle g_{y_1} + R^2 f \quad (1)$$

Where g_{y_1} is the atomic selected from the dictionary *D* that matches the signal *f*, and the selected residuals of the residual residual $R^2 f$ are the least. So we can see g_{y_1} and $R^2 f$ are orthogonal. therefore:

$$\|R^1 f\|^2 = |\langle g_{y_1}, R^1 f \rangle|^2 + \|R^2 f\|^2 \quad (2)$$

In order for the remaining residuals $R^2 f$ to have the minimum energy, the atoms g_{y_1} selected in the dictionary *D* should satisfy:

$$|\langle R^1 f, g_{y_1} \rangle| = \max_{y \in (1,2,\cdots\Gamma)} |\langle R^1 f, g_y \rangle| \quad (3)$$

From the second decomposition, the process continues to repeat the above. After n iterations, you can get:

$$R^n f = \langle g_{y_n}, R^n f \rangle g_{y_n} + R^{n+1} f \quad (4)$$

At this point, the signal can be expressed as:

$$f = \sum_{k=1}^{n} \left\langle g_{y_k}, R^k f \right\rangle g_{y_k} + R^{n+1} f \tag{5}$$

which is:

$$\|f\|^2 = \sum_{k=1}^{n} \left| \left\langle g_{y_k}, R^k f \right\rangle \right|^2 + \left\| R^{n+1} f \right\|^2 \tag{6}$$

The analysis of the above iterative process shows that the nth iteration can be obtained from the complete dictionary selected from the most approximate signal base, and can be used (5) the sparse representation of the signal. The convergence analysis of (6) shows that this algorithm only converges under finite dimensional conditions. And even if some specific dictionaries are selected, the solution obtained by the MP algorithm can only be suboptimal for the signal due to the completeness of the dictionary.

4. Simulation and testing

With the MP iterative process, the meaningful content of the signal is gradually reduced, so the value of < $R^2 f$, g_y > should be gradually reduced with the iterative process. In the iterative process, the first capture of the contour information, after the capture of detailed information, so the expansion factor, with the iteration should be a decline in the distribution. as shown in Figure 2.

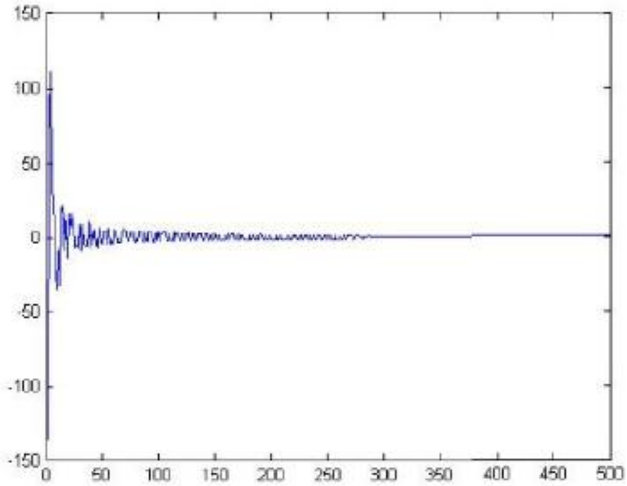

Figure 2. After the iteration of the< $R^2 f$, g_y >component value

5. Conclusions

Image compression is an important research direction in the field of image processing. It mainly studies the decomposition of a natural image into multiple components, each containing specific information. In accordance with the actual needs, people can extract the specified ingredients and processing. As the different components have different properties, respectively, different components of compression, recovery identification, classification and other post-processing will greatly improve performance and reduce the burden of data storage and computing.

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