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Research on Sensing Compression Method in Image Denoising

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Abstract

This paper mainly studies a kind of different from the traditional signal processing theory, compressed sensing. The theory in the process of data transmission greatly save the space and the cost of storage and transmission is a new breakthrough in the data mining technology. Application of compressed sensing principle, the discrete tracking algorithm combined with matrix learning algorithm, to deal with the noise of original image. Through a large number of experiments show that the fusion algorithm is better than other similar algorithms in terms of denoising, is a better image denoising technique.

Keywords: *compressed sensing, discrete tracking algorithm, matrix learning algorithm, image denoising*

1. Introduction

Image is the main source of access to information, and the image processing is one of the important works of information processing technology. At the same time, People got the image information and the clarity of image is becoming more and more demanding. And image in the process of gathering and compression transmission, inevitably will be affected by other factors such as noise pollution and interference, resulting in a decline in image quality and cover the important information of source image, cannot meet the requirements of image information [1-2]. This needs to choose a kind of effective method, the image to do the necessary processing, such as fuzzy, denoising, restore and enhance operation, will have the appearance of the damaged image restoration to the original or more clearly.

Based on the above problems and needs, based on the Nyquist sampling theorem developed a new data processing method of signal sampling, compression and transmission is an important problem of further development of information field. Compressed sensing theory arises at the historic moment, the theory realized at the same time is compressed in the process of signal sampling steps, successfully overcome the large amount of sampling data to a physical device and data storage transport waste storage problem. If you want to very small amounts of data, and want to unzip from these data through the original data, using compressed sensing sampling method, requirements: (1) these little signal contains enough can fully express the original signal data; (2) There is a kind of get the recovery of original signal algorithm so that this can be a small amount of data processing to extract [3-4]. The theory shows that the sparse signal or in the field of a sparse signal after transformation, compressed, by choosing appropriate reconstruction algorithms, can get the exact signal recovery.

Compressed sensing theory is different from the traditional sampling theory framework. Compressed sensing signal is sparse or compressible required, for the most part in the real world signal can be compressed. Such as a picture without any processing of natural images, contains only a small number of pixel value is zero point, is to transform to the wavelet domain, it most of the absolute value of coefficient is very small, almost zero, contains only a small number of numerical larger non-zero value, and these values contains all information of

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image reconstruction [5]. Now assume a length of N in an orthogonal basis or tight framework on bits of sparse or compressible signal $X_n(n=1,2,3.....N)$, its projection to the orthogonal transformation matrix, obtained the projection values of the absolute value of the coefficient (*i.e.*,) are small, only a handful of the absolute value of the coefficient is larger, the absolute value of coefficient of larger one vector $S(n)$, the vector is sparse, and can be used to represent the original signal. Vector $S(n)$ contains all the information in the original signal, by choosing appropriate reconstruction algorithm, to recover from the coefficient of the original signal [6].

2. Related Works

Based on compressed sensing theory, the discrete tracking algorithm combined with matrix learning algorithm is applied to image denoising, whether from the intuitive visual effects, or objective data, the denoising effect is better than other similar algorithms.

2.1. Discrete Tracking Algorithm

Discrete tracking algorithm thought is will be Gramm-Schmidt each column of the matrix orthogonal; get an orthogonal matrix, a multi-dimensional orthogonal space. Next, the original signal in the orthogonal space decomposition, get the original signal and approximate signal of residual error, and the decomposition of residual signal using the same method, ensure the approximation error after a limited number of iterations can decay to zero[7]. Here, a simple sum up the steps of orthogonal matching pursuit algorithm.

2.1.1. The Initialization: initialize sparse vector $x=0$, residual signal is initialized as $r_0=x$, the choice of the set of atom the number of columns in the matrix is initialized to the empty set, the number of iterations counter $t=1$, the maximum number of iterations for K.

2.1.2. Select the Atom: choose an atom, make the atoms and the previous step iterative calculation to get the best residual signals

Match that of the selected atoms

$$i_t = \arg\max_i \left|\langle g_j, r_{t-1}\rangle\right| \tag{1}$$

2.1.3. To Update the Selected Atoms and Index Set: a collection of serial number for the selected atoms $\Lambda_t = \Lambda_{t-1} \cup \{i_t\}$ .Reconstruction of atomic collection from the sensing matrix for $\Phi_t = [\Phi_{t-1} g_{i_t}]$.

2.1.4. Update the Sparse Vector: by the least squares method:

$$\hat{x}_t = \arg\min \left\| x - \Phi_t \hat{x} \right\|_2 \tag{2}$$

2.1.5. Update Residuals and Iteration Counter Plus 1:

$$r_t = x - \Phi_t \hat{x}_t, t = t+1 \tag{3}$$

2.1.6. Iterations: determine whether reached the maximum number of iterations, namely $t<K$, if satisfied, and continued to perform cycle, if not satisfied, and then stop the iteration.

Discrete tracking algorithm in each iteration step produced by the residual error and the selected atoms are orthogonal, the iteration of the selected atoms are has nothing to do with the front of the selected atoms linear, this also avoids the repeated select atoms phenomenon [8-9]. On the other hand, due to the Discrete tracking algorithm in each step of the representation of a signal has minimal residual, therefore, discrete differentiation faster convergence speed of the algorithm.

2.2. Matrix Learning Algorithm

Matrix is an iterative learning algorithm, it mainly includes two steps: on the basis of the existing matrix get signal sparse coding and constantly update matrix of each column to better adapt to the signal. Matrix learning algorithm has strong flexibility, it can be used in conjunction with many of the existing algorithms, a better work to accomplish the signal recovery, image denoising.

This determined the training algorithm of matrix learning objective function:

$$\min_{D.X}\{\|Y-DX\|_F^2\}\ s.t.\ \forall i,\|X_i\|_0 \le T_0 \quad (4)$$

The formula (4) $D \in R^{n\times k}$, $Y \in R^n$, $X \in R^k$ Matrix, training and training signals respectively from the sparse coefficient matrix, $Y=\{y_i\}_{i=1}^N$ On behalf of N training signal collection, $X=\{x_i\}_{i=1}^N$ represents a collection of the solution vector *Y*. T_0 is solution vector set zero element is the maximum number of central Africa.

The Formula (4) is an iterative process of solving the, first select an initial matrix D, assumes that the matrix D is fixed, the matrix can be obtained by using Discrete tracking algorithm of the coefficient matrix of the X. Then, in turn, assumes that the fixed coefficient matrix X, further optimize the matrix D. Then continue to assume that the matrix D fixed, coefficient matrix X, cycling, such as epsilon until the error in the range of advance design, the resulting matrix D and matrix X is the optimal solution [10].

This, in turn, through sparse coding phase and matrix update phase word by word, gradually converge into a target function

$$\|E_k\Omega_k - d_k x_T^k \Omega_k\|_F^2 = \|E_R^k - d_k x_R^k\|_F^2 \quad (5)$$

Is defined Ω_k as to the size of the matrix $N\times|w_k|$, It has a value of 1 in place of $(w_k(i),i)$, the rest are 0. Is defined $x_R^k = x_T^k\Omega_k$, which is a result of the filter to remove zero input, the length of the vector x_R^k is $|w_k|$.Similarly, is defined $Y_R^k = Y_T^k\Omega_k$ which the current use atomic sample d_k collection, $E_R^k = E_k\Omega_k$ is error matrix, the length of which is $N\times|w_k|$。Y_R^k and E_R^k are the input data after the removal of zero in the Y and E_k respectively[11-12].

3. The Image Denoising Process Design

Learning algorithm using matrix containing redundancy matrix of image features, and then through the Discrete tracking algorithm of denoising image redundancy decomposition, a selection of a group of atoms from the study of matrix vector, the source image is expressed as a linear combination of these vectors. So as to achieve will be the result of image denoising.

In an image with noise, for example, detailed learning algorithm of discrete differentiation and matrix denoising steps:

3.1. The Initialization: initialize a complete matrix D, l and L, $k=1$, $h=1$.

3.2. Sparse Coding: using discrete tracking algorithm of image decomposition, the noise coefficient matrix X, then use the matrix iterative learning algorithm update matrix of each column d_k as well as the solution of the vector set X in the corresponding line x_T^k

3.3. The Update Matrix: update the matrix D for each column $d_1, d_2......d_k$ in turn. Define a set $w_k = \{i | 1 \le i \le N, x_T^k(i) \ne 0\}$, Said all use the k column d_k of the matrix in the signal collection of index.

3.4. Calculation Error Matrix

$$E_k = Y - \sum_{j \ne k} d_j x_T^j \tag{6}$$

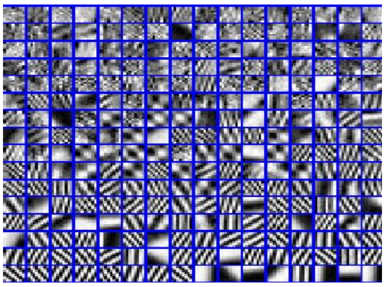
And according to the formula $E_R^k = E_k \Omega_k$ to get a part of the filter E_k to remove after zero input E_R^k

3.5. The error matrix E_R^k singular value decomposition E_R^k can be expressed as the product of two orthogonal matrixes $E_R^k = U \Delta V^T$. Update matrix column k d_k to get $\overline{d_k}$, the first column of the orthogonal matrix U is $\overline{d_k}$, Error matrix E_R^k and V in the first column and the first singular value multiplication update X_R^k to get $\overline{X_R^k}$.

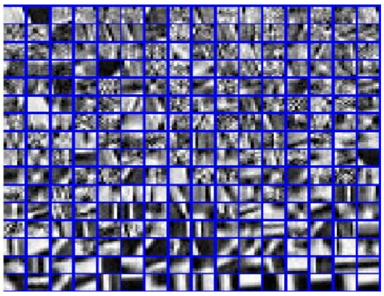
3.6. Matrix by column of the update is complete, with a new matrix $\overline{D}$ of discrete signals do differentiation, whether the iteration counter h reached the preset maximum number of iterations, or detection error value is within the allowed error range, to decide whether iterative operation need to continue. The resulting matrix and the product of the coefficient matrix is the denoising image.

4. Analysis of Simulation Results

Figure 1 is based on Lena image and Boat image respectively, Barbara image and Boat image matrix learning. Experiment with Matlab as the platform, in ordinary PC. Experiment USES the image size is 512×512, a complete matrix size is 64×256, the number of iterations of matrix learning algorithm to 10. Actual problem, can according to the different characteristics of the image, adopt different matrix as the initialization matrix.



Lena adaptive dictionary

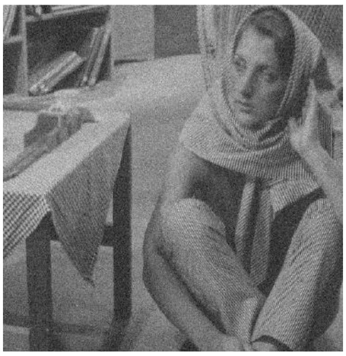


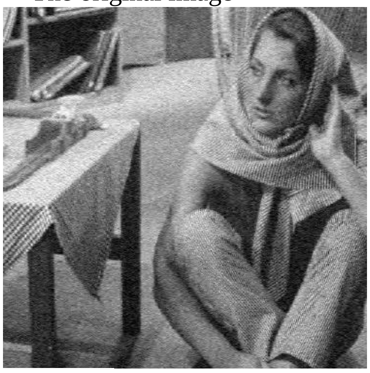
Boat adaptive dictionary

Figure 1. Image Adaptive Dictionary

Below will use the design matrix, to find the signal by using the method of iteration in the matrix of atoms on the best linear combination, to restore the original image.


The original image


Add noise image, signal to noise ratio of 20 dB

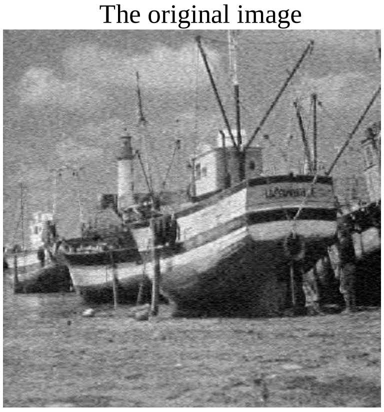

Soft threshold denoising, to noise ratio of 22dB


Signal Matrix learning image denoising, the signal-to-noise ratio of 29dB

Figure 2. Lena Image Denoising


The original image


Add noise image, signal to noise ratio of 20dB


Soft threshold denoising, signal to noise ratio of 23.216dB


Matrix learning image denoising, the signal-to-noise ratio of 29dB

Figure 3. Boat Image Denoising

Above are respectively the initial image, adding noise, wavelet soft threshold denoising images and the matrix learning matrix after denoising image. Image processing first join Gaussian white noise, the standard deviation of 25. Wavelet threshold algorithm and the core idea of different matrix learning algorithm, the wavelet threshold denoising select a threshold, the first will get the wavelet transform coefficients of each compared with the threshold set, in accordance with the rules of a given function or calculation, have to scale back the new wavelet coefficients. Use the coefficient of wavelet inverse transformation after denoising image, this method is simpler to implement and fast computing speed. Matrix algorithm recovered image with high signal noise ratio learning algorithm, visual effect is good, but it also corresponding to the high algorithm complexity, computer processing speed is slow. It can be seen by comparing the same situation in noise intensity, using matrix method to learn to deal with the noise of image matrix obtained from the training, than the method of wavelet threshold denoising effect is good, has the stronger antinoise performance.

5. Conclusion

Combine Discrete tracking algorithm and matrix learning algorithm, is applied to image denoising processing field. This paper discusses the discrete differentiation and matrix learning denoising principle and steps of the algorithm. The algorithm is based on the characteristics of each image itself, the adaptive update matrix, using discrete tracking algorithm decomposed signal sparse representation, and approximation of original image is obtained. Through the simulation experiments show that the method is effective to avoid the traditional denoising algorithm in edge of noise and vibration problems, keep the original characteristic of the image.

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