# COMPRESSIVE SENSING APPLICATION IN IMAGE DENOISING

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# ABSTRACT

Compressive sensing theory basically presents that the sparse or compressible signals can be reconstructed from a small number of linear measurements, which provides the measurements satisfy an incoherence property. In order to improve the work of single path network reliability failure case this put forward a set of single backup path algorithm based on the path. In this algorithm using two disjoint paths as work path to transmit data and uses the path does not interact with the backup path. This algorithm is based on a single backup path algorithm of shortest path set to ensure data under the case of second work path of effective transmission.

#### Keywords

#### Compressive sensing, Incoherence, Image Denoising

### **INTRODUCTION**

Image denoising is an open problem and has received considerable attention in the literature for several decades. According to people's intuitive feelings, noise can be understood as "factors that prevent the human sense organs to receive and understand the source of information". The noise in the image will degrade image quality, influence the visual effect of image, or even cover up some specific features of the image, this will have a direct effect on the subsequent image processing have great influence. Therefore, denoising as an important technology of image pretreatment image can effectively increase the signal-to-noise ratio; improve the quality of the image, which is more helpful for the subsequent image processing.

Because of the importance of image denoising, image denoising method has been one of the focuses in the field of image processing; the researchers have proposed many kinds of denoising schemes. But with the demands of continuous development and application of continuous extension, denoising algorithm still has a long way to go to seek the effective image. Sparse representation is proposed and its successful applications in many fields theory, has become a new idea and direction of research in the field of image denoising.

Research on image denoising is carried out around this effect, make them be well balanced, to ensure the maximum degree of original image after denoising approach without noise. Image denoising technology has had certain development, and commonly used in image denoising method has many higher requirements for image processing. Therefore, the image denoising technology kinds, but with the new problems emerged, the existing methods can not satisfy still has very important research significance.

From the point of view of technology of digital image processing, image denoising processing belongs to the category of image restoration technology; from the analysis of the

entire image process, image denoising belongs to the pre-processing stage of image processing. It is important to study the image denoising method, mainly in the:

(1) To get rid of the noise with noise image processing, can effectively guarantee the correct identification of image information. When the noise in the image contains more serious, image blur, the image has lost the practical significance of stored information.

(2) Denoising image not only can improve the recognition accuracy of visual information, but also provides a basis for further image processing. If directly on the image feature extraction and fusion processing signals with noise, it is hard to obtain satisfactory processing results.

(3) At present, people have proposed many image denoising methods, but these methods are not perfect, further improve the existing image denoising methods, or research new image denoising method is still important.

Traditional data or image acquisition method based on Nyquist sampling theorem, it can ensure the information by sampling to completely restore the original signal, otherwise the signal spectrum aliasing, unable to accurately recover the original signal. This theory, the signal (image) affects all aspects of the collection, storage, processing, transmission and other major. However, due to the demand for the amount of information is increasing, which makes the sampling theorem restricts the signal (image) the development of all aspects of the collection, storage, processing, transmission, people need to put some more effective sampling methods.

# COMPRESSED IMAGE DENOISING METHOD

For image denoising, we first transform the image corrupted with noise to sparse domain using

$$\boldsymbol{\Phi} = \boldsymbol{\Psi} \times (\mathbf{x} + \mathbf{z}) \tag{1}$$

Where z is the Additive noise. Then we sample from  $\Phi$  by mixing matrix  $M_{m \times n}$  where M is stable and incoherence with the matrix transform:

$$\Psi Y = M \times = M \times \Psi \times (X + Z)$$
<sup>(2)</sup>

And  $M_{m \times n} \times \Psi_{m \times n}$  which would be called the compressed sensing matrix *A*. According to the observation vector  $Y = A \times X$ , we need to reconstruct the original image from this observation. It is known that sparsity is a basic principle in fidelity reconstruction. Also it is known the noise is not sparse in common domain. Hence most of part will be removed by compressed sensing due to recovery a just M dimensional vector of noise which is reconstructed. Also we can reconstruct the exact signal due to sparsity. Stated principle is basic idea for compressed sensing image denoising (CSID) (Fig.1) and has steps.

# **CSID ALGORITHM:**

- Firstly, Do sparse transform for signal X + Z formed by mixing signal X and noise Z, and obtain  $\Phi = \Psi \times (X + Z)$ .
- Secondly, Design a M × N dimensional observation matrix  $\boldsymbol{M}$  which is stable and unrelated with the transform basis  $\Psi$ , then use  $\boldsymbol{M}$  to measure  $\Phi$  and acquire the observation vector  $\mathbf{Y} = \boldsymbol{M} \times \boldsymbol{\Phi} = \boldsymbol{M} \times \Psi \times (\mathbf{X} + \mathbf{Z})$ .
- Finally, Restore signal X by reconstructing Y (There are many reconstruction algorithms, such as orthogonal matching pursuit method, etc.) which complete the denoising of signal X.

### THE SYSTEM MODEL AND THE PROPOSED SCHEME

Compressed sensing theory is a theory of information retrieval that is based on sparse representation theory. Now, the compressed sensing theory achieves good effect in the study of signal denoising reconstruction. Compressed sensing can use a small amount of measurement data to restore the original signal, and almost no signal loss. According to the compression theory, first, transform are used to get the sparse representation which includes noise image, then using the algorithm to reconstruct the original image and achieve the purpose of removing noise.

Compared with the traditional denoising method, the image denoising based on compression perception has more superiority, it collects less amount of data and the recovery effect is more accurate. However, a classic compression perception does not use a priori knowledge of the image information (such as image features, texture, etc.), therefore it has not the adaptability and can't get satisfied denoising effect at some time. The adaptability of compressed sensing is mainly decided by the sparse representation, in order to achieve this kind of adaptability, we must use an adaptive sparse representation method.

As is known to all, the principal component analysis algorithm is a kind of commonly used methods of adaptive data analysis. Therefore, how to apply principal component analysis algorithm to compressed sensing to improve the adaptability of compressed sensing and apply the adaptive compressed sensing to image denoising becomes the focus of research in this chapter. The principal component analysis algorithm is mainly for multivariate analysis of one dimensional signal, but its analysis ability is not strong for multidimensional, multiscale signal.

In addition, the principal component analysis consider all the sampled signal in the same model and it often need forced map different high dimensional space vector to the same low dimensional space. This single linear no classification algorithm will cause an incompleteness of wiping off relevance and limitations on the analysis of the sampling signal of high dimension. In order to solve this problem, Yi Ma and others proposed a principal component analysis algorithm that is more universality in 2005.

This algorithm dynamical projected the high-dimensional sampling signal to different low dimensional space, each sample point in space has higher correlation, and better able to achieve the demand of the dimension reduction, also can satisfy the need for high dimension signal analysis. On the basis of predecessors' research, therefore, the generalized principal component analysis (GPCA) will be introduced to the CS framework to get a denoising method based on adaptive compression perception. Compared with traditional denoising method and classical compression perception method, the adaptive denoising method of compression perception can remove the noise at the same time to effectively retain more image details, has a good denoising performance.

Generalized principal component analysis is a kind of data clustering and dimensionality reduction algorithm, it cluster according to the sample of subspace, each type of data can be obtained indicate in its low-dimensional space. A data set  $X \in S$ , and K is the space S, set to, respectively,  $S^1, S^2, S^3, \dots, S^K$ ,

*X* can be represented as  $X = (X^1, X^2, X^3, \dots, X^K)$  among them  $X^i \in \mathbb{R}^N$ , then for the data set any element  $X^i$ ,

$$b_{i}^{T} X^{i} = 0$$

$$\bigcup_{i=1}^{I} S^{i} = S$$
(3)
(4)

Multiplication operation for type (1) can be arbitrary  $X^{1}$ 

$$\prod_{j=1}^{k} \left( b_j^T X^i \right) = 0 \tag{5}$$

Namely

$$\prod_{j=1}^{k} \left( b_{j1} X_{i1} + b_{j2} X_{i2} + \dots b_{jN} X_{iN} \right) = 0$$
(6)

Because the polynomial has one and only one solution, thus subspace constant k is given as

$$K = \min\left\{i : rank\left(L_{i}\right) = M_{i} = 1\right\}$$

$$\tag{7}$$

When the K value was determined, the problem can be transformed into a polynomial decomposition, the decomposed each child polynomial is a child space model. GPCA to data in high dimension space projection separately to low dimensional space, Figure 1 to Barbara image.



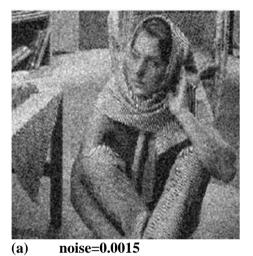
Fig 1: subspace application example

# **RESULTS OF SIMULATION**

Experiments to contain rich texture information of Barbara image as an example, the proposed denoising method based on adaptive compression perception experiment. The control group including median filtering method, DCT denoising method, wavelet denoising method and classical method of compression perception in the experiment. The sampling matrix use parameters of 10 random sparse matrix, refactoring decoding using SSMP algorithm. Type of additive white Gaussian noise, noise intensity are 0.01 and 0.005 is divided into two, the experiment results are shown in Figure 2, Figure 3, respectively.

We can see from the Figure 3, compared with low noise image, median filtering method, DCT noise removal method, wavelet denoising method of noise removal effect and its texture damage effect basic on the same level. However, based on the compression of GPCA perception model can under the condition of the premise of protecting the texture to remove noise very well. In the same way, the classic compression perception method due to its adaptability limits the denoising performance. For low noise image, therefore, this paper puts forward the method of adaptive compressed sensing based on GPCA has obvious advantages.

No matter for high noise or low noise image, based on the generalized principal component analysis method of adaptive compression perception is better than the traditional denoising method, and it has a very big improvement on the basis of classical CS model. Especially for low noise with complex texture images, the traditional methods have do not possessed noise removal ability, however the adaptive compression perception model still has good effect of noise removing.







(b) median filter method



(c) wavelet method (d) proposed method Fig 2: Four Compared with High Noise Schemes



(a) noise=0.005



(b) median filter method





(c) wavelet method (d) proposed method

## Fig 3: Four Schemes Compared with Low Noise

#### **CONCLUSION:**

This paper proposes a new image denoising method based on adaptive compression perception. On the basis of classical compression perception, we introduce adaptive high-dimensional data analysis method GPCA and increase the adaptability of the compression perception model. At the same time, we make the proposed denoising method an experiment contrast with the traditional denoising method (such as median filtering method, DCT denoising method, wavelet denoising method, *etc.*,) as well as the classic of compressed sensing method. We can see that based on adaptive compression perception of generalized principal component analysis method has good performance in removing image noise, the method can remove noise while protecting the texture information of the original image.

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