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An adaptive sampling method of compressed sensing based on texture feature

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ABSTRACT

An adaptive sampling method of block-divided compressed sensing for images based on textural feature is proposed. First, the SF (Spacial Frequency) is utilized to extract the textural features of image blocks. Then based on the textual features, each block is categorized into the smooth blocks or the textual blocks, and the basic sampling rate can be obtained simultaneously. To the textural blocks, we still use the basic sampling rate is modified adaptively by combing with the statistical characteristics of the coefficients in wavelet domain. To validate the effectiveness of proposed sampling method, the smooth projected Landweber (SPL) is employed to reconstruct the images, and the results are compared with other block-based compressed sensing (BCS) algorithms which proposed in recent years from the aspects of the objective index and the subjective visual impression. The experiment results show that when the compressing ratio is modest, the proposed method can improve the reconstruction quality of image evidently.

1. Introduction

The Nyquist sampling theorempoint out that to recover the discrete signal exactly, the sampling rate should be at least twice the highest frequency of the signal. Nevertheless, in many important and emerging applications, the resulting Nyquist rate is so high that we end up with fat too many samples [1], which lead to the requirement for hardware cannot be reached.

In recent years, Donoho, Candes, Tao, Romberg proposed a theory called Compressed Sensing [2,3]. Compare with the usual measure which compress the data after high rate sampling, the CS theory collect the sample data and compress those data simultaneously and that reduce the collecting period and the level of requirement on hardware. It breakthrough the bottleneck of the Shannon sampling theorem, and become a hot research direction rapidly. For 2D images, it is common to use a Gaussian i.i.d. matrix as the measurement matrix, that makes the dimensional of the matrix pretty high and leads to great difficult in storage and computation. Therefore, compressed sensing is not suitable for the real-time image processing. Gan proposed BCS (block compressed sensing), greatly reduce the storage and the computational complexity, effectively improve the practicability of compressed sensing in image processing [4]. Fowler et al. proposed block compressed sensing with smooth projecting Landweber (BCS-SPL) [5] based on [4], using contourlets [6] and complex-valued dual-tree wavelets (DDWT) [7] as sparse matrix. After that they proposed a multiscale algorithm of BCS-SPL (MS-BCS-SPL), measuring signals in wavelet domain adopts the basic structure of BCS-SPL [8], outperform the algorithm mentioned before. Although those methods extend the effects of reconstruct results in the costs of storage and calculation declined. The fixed sampling rate means that it is non-adaptive with image features. That leads to the methods mentioned above cannot work well in all situations, the visual effects of reconstructed images are instable also. Moreover, finding the optimal sampling scheme that maximizes the incoherence for a given number of samples is a combinatorial problem that is intractable. Wang proposed an algorithm base on BCS-SPL utilizing gray entropy to describe the textural of images, then adjusting the sampling rate based the gray entropy [9]. It improves the reconstruction quality in some degree.

The scheme we proposed classify the image blocks in the light of textural, then combines the statistical characteristic of the coefficient in wavelet domain to allot the measurements. First, the Spatial Frequency (SF) [10] is utilized to classify the image blocks, allotting measurements to every sub-blocks; Then combine the SF and the statistical characteristic of the high frequency coefficients in wavelet domain to adjust the measurement further; The last

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step is to recover the sub-blocks employing SPL. Seen from the experimental simulations, under the same hardware conditions and measurements, it is obvious that the proposed scheme improve the reconstruction quality and the visual effects of textural images evidently.

2. Block compressed sensing

Given a N dimensions signal $\mathbf{x}$, sampled data $\mathbf{y} = \mathbf{\Phi x}$ with length M ($M \ll N$) through the measurement. $\mathbf{\Phi}$ is a $M \times N$ measurement matrix. If $\mathbf{x}$ is not sparse in the time domain, but sparse in the transform-domain, then $\mathbf{x}$ can be represented as $\mathbf{x} = \mathbf{\Omega\alpha}$, where $\mathbf{\Omega}$ is the sparse basis and $\boldsymbol{\alpha}$ is a sparse vector consist of coefficients of $\mathbf{x}$ in $\mathbf{\Omega}$. If there are k non-zero value in $\boldsymbol{\alpha}$, $\mathbf{x}$ is k-sparse with respect to $\mathbf{\Omega}$. The linear measurement can be represented as:

$$\mathbf{y} = \mathbf{\Phi\Omega}\alpha = \mathbf{Ax} \tag{1}$$

where $\mathbf{A}$ is the compound matrix, called sensing matrix.

For 2D images, with the pixels increasing, the dimension of the measurement matrix would become very large. That brings great challenge for measurement, storage and computation. Gan proposed an algorithm in which the images are divided into $B \times B$ blocks, then the blocks are sampled, respectively by $\mathbf{y}_i = \mathbf{\Phi x}_i$, where the size of $\mathbf{\Phi}$ is $M_B \times B^2$. $M_B = S/B^2$, denoting the ratio of sample rate S to block signal length. This method greatly reduces the storage, simplifies the reconstruction complexity, and makes it possible to handle images of any size [4]. However, BCS and BCS-SPL destroy the correlation of image signals, and the reconstruction quality of each algorithms is dissatisfactory. MS-BCS-SPL samples and reconstructs signal in wavelet domain, and improves the reconstruction quality evidently [8].

All the algorithms aforemetioned don't adjust the sampling rate utilizing the textural information. Wang proposed arsBCS in 2013. First, they sample blocks at a low rate, then obtaining the solution from the minimum mean square error (MMSE) estimation to predict gray entropy of each block, adjusting sampling rate based on the gray entropy at last [9].

For reconstruction, Kutyniok [11] generalizes the algorithms into three classes: convex optimization, greedy algorithms and combinatorial algorithms. Furthermore Qaisar et al. [12] generalize them into six: Convex Relaxation, Greedy Iterative Algorithms, Iterative Thresholding Algorithms, Combinatorial Algorithms, Non Convex Minimization Algorithms and Bergman Iterative Algorithms. In 2006, Haupt [13] proposed a specific instance of a Projected Landweber (PL) algorithm, starting from initial approximation x(0), then calculating approximation by using the following equations:

$$\boldsymbol{\varphi}^{(t)} = \mathbf{x}^{(t)} + \frac{1}{\gamma}\boldsymbol{\psi}\mathbf{\Phi}^T\left(\mathbf{y} - \mathbf{\Phi\Psi}^{-1}\mathbf{x}^{(t)}\right) \tag{2}$$

$$\mathbf{x}^{(t+1)} = \begin{cases} \boldsymbol{\varphi}^{(t)} & \text{if} \left|\boldsymbol{\varphi}^{(t)}\right| \geq \tau(i) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

here γ is the largest eigenvalue of $\mathbf{\Phi}^T\mathbf{\Phi}$, used as the scaling factor. In order to reduce the blocking artifacts, SPL employs Wiener filtering [4] after every iterative. Fowler cast the reconstruction in the domain of directional transforms, DDWT and CT are utilized as $\mathbf{\Psi}$ [5], applying Bivariate Shrinkage thresholding [14].

3. Basic sampling rate

Most of the natural images can be divided into smooth, textural/edge regions. The textural/edge region should be sampled at higher rate than smooth region to keep the details of images. In this section we generalize the sub-blocks into two categories: smooth blocks and texture/edge ones, obtaining basic sampling rates for each blocks, respectively.

3.1. The blocks classification

Statistics, structure and spectrum analysis are the common methods for image texture analysis, and statistics analysis is the dominant one. In these methods, it is common to use the smoothness descriptor, coherence descriptor or the 2D gray entropy to analyze the textural features. Those descriptors describe the average information. But all of them relay on the statistics analysis. Studies have indicated that the spatial frequency [10] can not only measures the overall activity level in an image, but also reflects the change of gray scale more intuitively. The SF would be quite large if the gray scale changes steeply, or would be very small on the contrary. In this paper, the textural features of each sub-block are estimated by using SF, and then classified into smooth blocks or the textual ones. Here, the size of the whole image is $I_r \times I_c$, and the size of blocks is $B \times B$. So the spatial frequencies can be obtained through (4)–(6), respectively:

$$A_i = \sqrt{R_i^2 + C_i^2} \tag{4}$$

$$R_i = \sqrt{\frac{1}{B \times B}\sum_{x=1}^{B}\sum_{y=2}^{B}(f(x, y) - f(x, y-1))^2} \tag{5}$$

$$C_i = \sqrt{\frac{1}{B \times B}\sum_{x=2}^{B}\sum_{y=1}^{B}(f(x, y) - f(x-1, y))^2} \tag{6}$$

where A_i denotes the SF of the ith block ($1 \leq i \leq I_rI_c/B^2$), R_i is the row frequencies and C_i is the column frequencies. In order to recovery signals rapidly, and to acquire better reconstruction performance, we set $B = 32$ by experience.

If $A_i > \tau$ (τ is the threshold), the corresponding block belongs to textural blocks, otherwise it belongs to smooth ones.

$$\tau = \frac{B^2}{I_rI_c} \cdot \sum_{i=1}^{I_rI_c/B^2} A_i \tag{7}$$

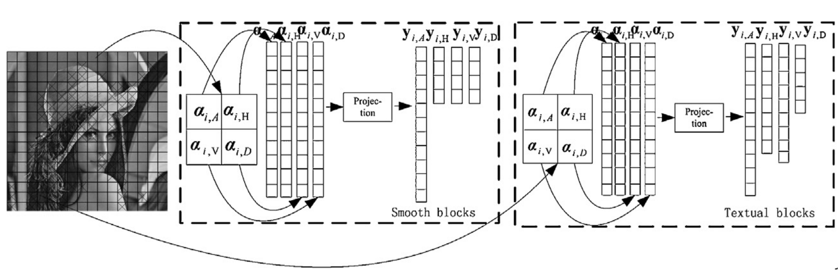

Fig. 1. The sampling steps when $L = 1$.