Digital Signal Processing 29 (2014) 54–66

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

# Self-adaptive sampling rate assignment and image reconstruction via combination of structured sparsity and non-local total variation priors

Jiawei Chen [a,*], Xiaohua Zhang [a], Hongyun Meng [b]

[a] Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education, Xidian University, Xi'an 710071, China
[b] Department of Mathematics, Xidian University, Xi'an 710071, China

ARTICLE INFO

*Article history:*
Available online 25 February 2014

*Keywords:*
Compressive sampling
Assignment of sampling rate
Compressibility
Structured sparsity
Non-local total variation

ABSTRACT

Compressive sensing (CS) is an emerging approach for acquisition of sparse or compressible signals. For natural images, block compressive sensing (BCS) has been designed to reduce the size of sensing matrix and the complexity of sampling and reconstruction. On the other hand, image blocks with varying structures are too different to share the same sampling rate and sensing matrix. Motivated by this, a novel framework of adaptive acquisition and reconstruction is proposed to assign sampling rate adaptively. The framework contains three aspects. First, a small part of sampling rate is employed to pre-sense each block and a novel approach is proposed to estimate its compressibility only from pre-sensed measurements. Next, two assignment schemes are proposed to assign the other part of the sampling rate adaptively to each block based on its estimated compressibility. A higher sampling rate is assigned to incompressible blocks but a lower one to compressible ones. The sensing matrix is constructed based on the assigned sampling rates. The pre-sensed measurements and the adaptive ones are concatenated to form the final measurements. Finally, it is proposed that the reconstruction is modeled as a multi-objects optimization problem which involves the structured sparsity and the non-local total variation prior together. It is simplified into a 3-stage alternating optimization problem and is solved by an augmented Lagrangian method. Experiments on four categories of real natural images and medicine images demonstrate that the proposed framework captures local and nonlocal structures and outperforms the state-of-the-art methods.



## 1. Introduction

Conventional approaches to sampling a signal follow the Shannon's theorem: the sampling rate must be at least twice the maximum frequency of a signal (i.e. Nyquist rate). As is commonly known, since typical images have much redundant information, only a few of well-chosen observations suffice to reconstruct original image without much perceptual loss. Recently, a new theory of compressive sensing (CS) [1,2], built on those prominent works of Candès, Tao and Donoho [1,2] is a revolution to the traditional way for acquisition of signals and has been taken significant interested. A fundamental idea behind CS is sampling and compressing is synchronous instead of two independent processes. It means that data are directly sensed in a compressed form (i.e., at a lower sampling rate), instead of being sampled and compressed alternatively. A sparse or compressible signal $\mathbf{x}$ can be reconstructed with high probability from its linear projections $\mathbf{y}$, named CS measurements

$$\mathbf{y} = [y_1, \dots, y_m]^T = [\boldsymbol{\varphi}_1\mathbf{x}, \dots, \boldsymbol{\varphi}_m\mathbf{x}]^T = \boldsymbol{\Phi}\mathbf{x} \tag{1}$$

where $\boldsymbol{\Phi} = [\boldsymbol{\varphi}_1^T, \dots, \boldsymbol{\varphi}_m^T]^T$ is an $m \times n$ sensing matrix and the sensing vector $\boldsymbol{\varphi}_i \in \mathrm{R}^n$ is a row vector of the matrix $\boldsymbol{\Phi}$ which satisfies the restricted isometry property (RIP) [2]. The sampling rate is defined as $SR = m/n$. Compared with the conventional sampling, CS is a new method of acquiring, compressing and reconstructing signals in the field of signal processing. The former samples uniformly ambient data within local region as local features of image, while the latter can be considered as a process of information sensing, which operates on the structure information of image via the randomized projections in the form of linear combinations of the image.

In a typical CS system in image processing, each measurement is the projection of an image onto an individual random vector. Computing these projections would result in a very huge and cumbersome system when the size of signal is large. Therefore classical CS is not directly suitable for those large scale applications such as high density signals and high resolution images. These application-specific limitations naturally point out that the practical sampling systems depend only on a portion of the entries of an acquired signal. In current literature [3–5], the idea of block compressive

* Corresponding author at: No. 2 Taibai road, Xi'an Shaanxi province, China.
*E-mail address:* jawaechan@gmail.com (J. Chen).

http://dx.doi.org/10.1016/j.dsp.2014.02.011
1051-2004/

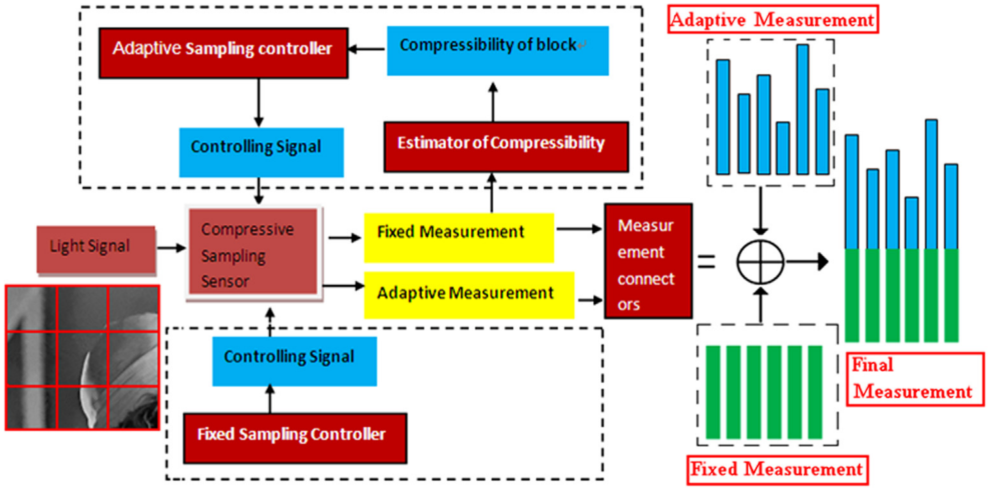


**Fig. 1.** Overall architecture of the adaptive CS.

sensing (BCS) is proposed to reduce the size of the sensing matrix where the whole high resolution image is divided into many blocks and image sensing and reconstruction are conducted in a block-by-block manner. Therefore the computational complexity of sampling and reconstruction are greatly reduced.

However, the assignment of sampling rate is fixed so that the sampling rate of each block is identical without consideration of the structures of the blocks. To overcome this drawback of the identical sampling rate, several adaptive assignment schemes are proposed. Stankovic [6] assigned the sampling rate of the current frame by predicting its sparsity based on the previous frames. However, this approach is difficult to be employed in single-image acquisition. Ying Yu et al. [7] proposed a saliency-based compressive sampling scheme for images, where more sensing resources are allocated to the more salient image regions. To extract saliency information embodied in a scene, a complementary optical sensor is employed to acquire a low-resolution optical image of the scene. However, this low-resolution image is discarded after saliency computation which is an obvious waste of resource. Another method of adaptive assignment of sampling rate is proposed in [8]. More sampling resources are assigned to low frequency coefficients and the process of sensing image is implemented in the wavelet transform domain. However, for general optical images, it is more difficult that sensing is implemented in transform domain than in spatial domain.

One of the key issues in adaptive assignment framework is the estimation of compressibility of blocks. In current literature, to estimate compressibility of image blocks, an optical image always is required [7–9], and estimation is processed in image domain or transform domain. But before sensing there is no prior information about the compressibility of each block and it is difficult to estimate original image only with sensed measurement. Until now it is still an open problem how to estimate the compressibility from the CS measurements of image blocks. It is well known that the compressibility is related to the redundancy of images. Inspired by this, in this paper, a scheme is firstly proposed to estimate the compressibility only based on the local redundancy (here, local redundancy means the smoothness of the image block which is measured by statistics of the pre-sensed measurements). In this method, a relationship between an image block and its measurement is described by an equation. And then a two-stage compressive sensing framework is proposed and the overall architecture of the proposed self-adaptive CS scheme is shown in Fig. 1. The total sampling rate is divided into two parts: a pre-sampling rate (or fixed sampling rate) and an adaptive sampling rate. At the pre-sensing stage, a small part of the sampling rate is assigned to each block identically to obtain the pre-sensed measurements. They are not only used to estimate compressibility of each block, but also they can ensure the fundamental reconstructed quality of image blocks. At the adaptive sensing stage, the remaining sampling resource is assigned to each block according to the estimated compressibility. The final measurement is the combination of the pre-sensed measurement and the adaptively assigned measurement.

The CS theory also indicates that if a signal is sparse or compressible, it can be exactly reconstructed from a small set of linear, non-adaptive measurements by solving an optimization problem. Generally, the reconstruction of $\mathbf{x}$ from $\mathbf{y}$ is an ill-posed problem. Without any prior information, there exist many different candidate signals $\mathbf{x}$ corresponding to the same measurement $\mathbf{y}$. But there exists rich redundancy in natural images. This is a fundamental that an original high-dimensional image can be compressed without perceptual loss and the image can be reconstructed from a few CS measurements. In short, performance of CS reconstruction is mainly determined by two sub-problems, the one is how to exploit the priors in an image to reduce the feasible space, and the other one is how to carry out searching in this reduced space to find the reconstructed image. Recently, many efficient computational methods have been developed to solve the reconstruction problem. They include iterative shrinkage methods [10], Bregman iterative algorithms [11], fixed point continuation algorithms [12], iterative reweighted algorithms [13] and some hybrid algorithms [14]. More recently, sparse and total variation (TV) constraint are combined and an alternative minimization scheme is employed to accelerate the convergence [15]. However, most of them search the optimal solution under sparse and local smooth assumption. However for CS reconstruction problem, especially at relatively low sampling rate, only a local sparsity prior is insufficient to perform well. A multi-scale multi-hypothesis prediction (MS-MH-BCS) method [16] is proposed. In this method, a block is reconstructed by multiple hypothesis predictions which are made by spatially surrounding blocks and these predictions are generated at multiple scales. Then, these predictions are weighted to generate the final image. Structural sparsity is also a useful prior to model image compressibility and is employed in image restoration more recently. A reconstruction method based on structural group sparse representation (SGSR) [17] is proposed. Spatially surrounding blocks are employed to learn a dictionary which is employed to reconstruct the current block.

In this paper, inspired by non-local means (NLM) [18,19] model, a new reconstruction algorithm is proposed by combining local and non-local priors, where the former is modeled by the