J. Vis. Commun. Image R. 31 (2015) 26–40

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

Optimized sampling distribution based on nonparametric learning for improved compressive sensing performance ☆

Shimon Schwartz *, Alexander Wong, David A. Clausi

Department of Systems Design Engineering, University of Waterloo, Vision and Image Processing Lab Research Group, Waterloo, ON N2L 3G1, Canada

ARTICLE INFO

Article history:
Received 27 August 2014
Accepted 20 May 2015
Available online 29 May 2015

Keywords:
Compressed sampling
Compressive sensing
Sparse measurements
Data acquisition
Learned sampling distribution
Fluorescence microscopy
Laser range measurement
Markov chain Monte Carlo (MCMC)

ABSTRACT

In this work, an optimized nonparametric learning approach for obtaining the data-guided sampling distribution is proposed, where a probability density function (pdf) is learned in a nonparametric manner based on past measurements from similar types of signals. This learned sampling distribution is then used to better optimize the sampling process based on the underlying signal characteristics. A realization of this stochastic learning approach for compressive sensing of imaging data is introduced via a stochastic Monte Carlo optimization strategy to learn a nonparametric sampling distribution based on visual saliency. Experiments were performed using different types of signals such as fluorescence microscopy images and laser range measurements. Results show that the proposed optimized sampling method which is based on nonparametric stochastic learning outperforms significantly the previously proposed approach. The proposed method is achieves higher reconstruction signal to noise ratios at the same compression rates across all tested types of signals.

1. Introduction

The compressive sensing (CS) research community is very active and its core research can be grouped into three major research areas: sparsity reconstruction basis [1–4], image reconstruction [1,3,5,4,6,7] and generalization of the sampling procedure. While less studied in recent years compared to reconstruction basis and image reconstruction methods, the design of the sampling procedure can have a significant impact on CS performance for practical imaging applications such as robotic vision and medical imaging [8,9], where the objects of interest have structured characteristics, thus making the sampling procedure a worthwhile area to study. Traditional CS-based systems employ a sampling scheme that sample the entire scene in the same manner regardless of the underlying data. However, such an approach is limiting for many practical applications, which involve distinct regions of interest in some basis, since it does not consider data importance. In many cases such region of interest are of greater interest for analysis purposes, one is motivated to obtain higher quality reconstructions for those regions than the background regions. In recent years, there has been interest in optimizing the CS sensing probability density for improving reconstruction performance in imaging applications. These methods range from fixed variable density sampling [10–12], to data guided sampling [13–21]. In particular, recent data-guided methods attempted to improve CS performance by using predefined parametric approaches to data-guided CS sampling without learning.

In applications such as laser range imaging and laser scan imaging systems, the data acquisition process can be a very time consuming process since the image is typically acquired pixel-by-pixel for the entire scene given the point-based acquisition characteristics of such systems. Data acquisition time becomes even more significant for situations where high spatial resolution is required. As such, optimizing the acquisition mechanism is of high importance for measurement applications such as laser range imaging and laser scan imaging. One important characteristic of such systems is that they allow for random sampling at any point in the scene. Motivated by this, we proposed an approach for optimizing the acquisition scheme for such systems to greatly improve efficiency while providing strong image quality and detail preservation. In this work, we aim to address the limitations of the previously data-guided sampling approaches by introducing a stochastic nonparametric learning approach to learn and optimize sampling distribution for improving further CS performance. The learning is based on statistical properties of past measurements from similar types of signals. The learned sampling distribution is then used to better optimize the sampling process based on

☆ This paper has been recommended for acceptance by Yehoshua Zeevi.

* Corresponding author.
E-mail addresses: tsschwar@uwaterloo.ca (S. Schwartz), a28wong@uwaterloo.ca (A. Wong), dclausi@uwaterloo.ca (D.A. Clausi).

http://dx.doi.org/10.1016/j.jvcir.2015.05.010

the underlying signal characteristics for signals of a similar type. By learning a more optimized data-guided sampling probability distribution, the proposed method overcomes the key limitation associated with existing data-guided methods that makes use of a predefined parametric sampling probability distribution.

The rest of the paper is organized as follows. Related work associated with CS sampling are described in Section 2. The proposed method of learning sampling distributions in a nonparametric manner to guide sampling is provided in Section 3. Model validation is discussed in Section 4, and a summary and future research is provided in Section 5.

2. Related work

Current literature in optimizing CS sampling can be generally grouped into two main categories: (i) unguided variable sampling and (ii) data-guided sampling. One of the first attempts at optimizing CS sampling involved the use of a predefined variable sampling distribution where the sampling frequency varies based on the sampling location. For example, representations of MRI images have nonrandom structures since most of the image energy is concentrated close to the representation domain origin [10]. Therefore, it was proposed [10–12] to consider a variable density random under-sampling which will sample more near the origin and less in the periphery of the representation domain. The proposed sampling function was to adjust the probability density according to the power of distance from the origin [10] in the Fourier domain. Based on the same concept, it was proposed in [11] to consider variable density sampling in the spatial domain. Image reconstruction was evaluated [11] with different sampling patterns (radial, logarithmic and random). Similarly [10], the sampling function was to adjust according to the concept of dense sampling near the origin and sparse periphery. The coherence between the sparsity and variable density sensing bases was evaluated [12] confirming that the reconstruction performance was maintained. Even though these methods shows an improvement to CS performance, it is static and not optimized.

In some hardware implementation scenarios, random access to each pixel in the 2D grid can be challenging. Structured compressed sensing was proposed [22,23] where separable (rows and columns) matrices are appropriate. The structured sensing matrix is constructed from random patterns of rows and columns. The non-uniform sensing approaches are static, considering general representation domain properties and hardware constraints in order to improve reconstruction performance.

Another approach to optimizing CS sampling is data adaptive sampling, where the sampling procedure is guided by the underlying data characteristics. There was an attempt to reduce the number of measurements by dividing the scene to blocks [13] and sample each block by uniform distribution random sampling with different number of samples based on average block saliency level. An improved block CS method was proposed [14,15] where an initial sampling process is performed, uniformly for the entire image. compressibility of each block is estimated based on the initial sampling phase. In the second sampling phase the number of samples for each block is adjusted based on the compressibility estimation of the block. This method [14,15] uses samples from both phases therefore is more efficient compared to previous block CS [13]. Block CS approaches are missing saliency information due to low resolution related to averaging block saliency and sampling within the block at the same rate. In addition, these methods are sampling based on an arbitrary block size which reduces sampling effectiveness by missing region of interest within the block.

Sequential adaptive CS techniques have been proposed in a recent work for optimizing the support of the sensing matrix [16]. It has been proposed [16] to construct the measurement matrix adaptively through an iterative process in order to select appropriate rows of the sensing matrix for emphasizing the non-zero vector coefficients. This sequential process iteratively searches for non-zero coefficients by multiple sensing matrices starting with a full ranked matrix which measures and considers the entire coefficient vector (including all zero coefficients) and iteratively converges to a low support matrix. This sequential approach is very time consuming as the CS reconstruction process is repeated every iteration. In addition, this approach does not account for underlying data directly, it searches for low support of measurement matrix in order to eliminate zero coefficients. Moreover, this method uses acquired data from the entire image in the iteration process. In another study of this adaptive method, an assumption of an "infinite number of observations is available" [17] is taken for constructing a sampling matrix with minimum support for noisy signals while ignoring an important goal of image reconstruction based on small subset of sampled locations. The adaptive CS method was compared mathematically to uniform distributed sampling [24] showing that there is not a significant advantage to adaptive CS universally, where the entire image information is considered equally important. Even though the analysis seems to be accurate, this hypothetical case does not represent real-world practical situations where regions of interest exist in the signal as opposed to having all regions in the image being equally important.

Based on the notion that regions of interest exist in the signal that contain more information than other regions, a saliency-guided approach was proposed [20,21] for improving signal-to-noise ratio (SNR) in compressive fluorescence microscopy. Using the previously developed model in data-guided sampling for CS [18], the sampling process adapts to the underlying characteristics of the image based on a saliency-based sampling pdf where regions of interest have a higher probability of being sampled as opposed to sampling the entire image based on a uniform distribution. The results in these studies show that such an approach can yield noticeably improved reconstructions compared to existing sampling approaches at the same sampling rates. An improved multi-scale saliency-guided CS approach [19] was developed based on this concept as well, offering an efficient approach for compressive robotic laser range sensing. This model adapts the sampling process gradually and smoothly between regions with varying levels of saliency. This method uses a parametric logarithmic function that maps levels of saliency in the underlying data to sampling probabilities to better guide the sampling process. It was shown that this approach achieves greater performance in comparison to the recently published saliency-guided sparse measurement model [18] where images are contaminated with high noise levels. The main limitation of this method is that a static parametric function is used to guide sampling based on the underlying signal characteristics, which may not be well suited across all types of signals.

More recently, a new data-guided sampling strategy was proposed in the form of learning based sampling, where the goal is to learn a sampling distribution based on past measurements of similar types of signals. In the work presented in [25], the sampling distribution function in the sampled frequency domain is learned directly based purely on the distribution of energy at specific data locations in the frequency domain. This learned sampling distribution was then used to sample signals with similar signal characteristics in the CS process. It was demonstrated in [25] for the purpose of compressive OCT that such an approach has potential to greatly increase signal reconstruction compared to other sampling approaches. However, this approach is very specific and limited to cases where direct learning from sampled data based only on data location is possible.