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A block-wise random sampling approach: Compressed sensing problem

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Abstract
The focus of this paper is to consider the compressed sensing problem. It is stated that the compressed sensing theory, under certain conditions, helps relax the Nyquist sampling theory and takes smaller samples. One of the important tasks in this theory is to carefully design measurement matrix (sampling operator). Most existing methods in the literature attempt to optimize a randomly initialized matrix with the aim of decreasing the amount of required measurements. However, these approaches mainly lead to sophisticated structure of measurement matrix which makes it very difficult to implement. In this paper we propose an intermediate structure for the measurement matrix based on random sampling. The main advantage of block-based proposed technique is simplicity and yet achieving acceptable performance obtained through using conventional techniques. The experimental results clearly confirm that in spite of simplicity of the proposed approach it can be competitive to the existing methods in terms of reconstruction quality. It also outperforms existing methods in terms of computation time.

Keywords: *Compressed Sensing, Sparse Recovery, Signal Processing, Random Sampling, Matching Pursuit, Measurement Matrix.*

1. Introduction

Recently, the new theory of compressed sensing (CS) [1, 2] has emerged and brings on new findings regarding signal sampling. This theory states that for certain type of signals one can recover the original samples from fewer measurements than those required by Nyquist-Shannon theory [3, 4]. Compressed sensing is valid for signals with underlying sparse structure. A sparse signal has merely few non-zeros. The CS experts originally showed that random measurement matrices are suitable for compressed sensing problem. However, later it shows that a carefully designed measurement matrix improves the performance. Generally, the maturity of a sampling strategy for CS can be judged in the following aspects:

- *Optimality of the sampling process:* the required number of measurements for exact recovery is desired to be as small as possible. Although random sampling can lead to an exact recovery, the required number of measurements is not optimal yet;
- *Low complexity and simplicity for hardware implementation:* the complexity and required memory space in sampling techniques should be minimized to become suitable for large-scale problems ;
- *Universality:* the random measurement matrices are universal and can be obtained non-adaptively. This means that their performance does not vary with changing the sparsifying matrices. Any designed (or optimized) measurement matrix should also have this property.

Two categories of algorithms have been proposed for improving the signal sampling in CS framework; First, the family of algorithms which attempts to propose a particular structure (e.g. by exploiting prior knowledge about the signal of interest) for sampling the signals. Second, those approaches which attempt to improve the structure of an initially random measurement matrix using optimization techniques [5-10]. In this paper, the first family of approaches is addressed.

In [11], which is an application to magnetic resonance imaging (MRI), the authors define an incoherence criterion based on point spread function (PSF) and propose a Monte Carlo scheme for random incoherent sampling of this type of data. They believe that a pure random sampling of k-space in all dimensions is not generally practical due to hardware implementation issues.
In short, k-space is a special representation of data points in Fourier transform of the MR images. Hence, they design an incoherent sampling technique (still by following the existing incoherence properties of random undersampling) to allow rapid data collection. Based on their observations, a better performance is achieved by less undersampling near the k-space origin and more in the periphery of k-space. Other related techniques for MRI acquisitions can be found in [12, 13].
Wang et al. [14] proposed a variable density sampling strategy by exploiting the prior information about the statistical distributions of natural images in the wavelet domain. Their proposed method is computationally efficient and can be applied to several transforming domains. In another work [15], Wang et al. show that if the spectral characteristics of the underlying signal are not expected to be uniform, then, the less number of measurements is required compared with when using conventional compressed sensing. They first propose to generate colored random projections using a bandpass filter when the spectral profile of the signal to be sampled is known, and then propose an adaptive scheme to generate colored random projections when such a priori is not available.
In this paper, a novel random sampling scheme for compressed sensing framework is proposed. The aim is to propose a technique which can offer at least the same reconstruction performance as that exists for the conventional compressed sensing, but allows a simpler implementation and less required storage for the measurement matrix.
The rest of this paper is as follows. Next section describes the basics of compressed sensing theory. Section 3 gives an example of the advantages of random undersampling and applying CS recovery methods over linear recovery. The proposed method is then described in section 4. The simulation results and concluding remarks are drawn in sections 5 and 6, respectively.

2. Compressed sensing

The basic compressed sensing scenario can be expressed as follows. Assume a one-dimensional signal $x \in \mathbb{R}^n$ which can be represented sparsely in a known transform domain (e.g. Fourier, or wavelet). Although x can be sparse in the current domain (e.g. time, or pixel), we always assume that x is sparse in a known transform domain, unless otherwise stated. The sparsifying transform can be expressed in matrix form denoted by $\Psi \in \mathbb{R}^{n\times m}$, with Ψ containing m columns vectors $\{\psi_i\}_{i=1}^{m}$ of length $n \leq m$. The case of $n < m$ is treated as overcomplete sparse representation. Considering the above notations, the signal x can be expressed as:

$$x = \sum_{i=1}^{m} s_i \psi_i = \Psi s \quad (1)$$

where, $s \in \mathbb{R}^m$ is a column vector of sparse coefficients, having merely $k \ll m$ non-zero samples. Clearly, x is the representation of the signal in non-sparse domain (e.g. time, space) and s is the representation in sparse domain (e.g. wavelet, frequency). The signal x is called k-sparse since it can be generated as a linear combination of only k vectors from Ψ. Here, the signal s is called exact-sparse since it has k non-zeros and the rest of the elements are exactly equal to zero. However, there might be some cases where the coefficient vector s includes only few large components and many small coefficients. In this case, x is treated as a compressible signal and sparse approximation methods are applied.
Now the acquisition process is defined as follows, where the measurements $y \in \mathbb{R}^p$ with $p < n$ are computed as a set of linear measurements from x. This process is mathematically expressed as:

$$y = \Phi x = \Phi\Psi s = \Theta s \quad (2)$$

where, $\Phi \in \mathbb{R}^{p\times n}$ is called the measurement matrix (or sensing matrix) and y is treated as measurements.

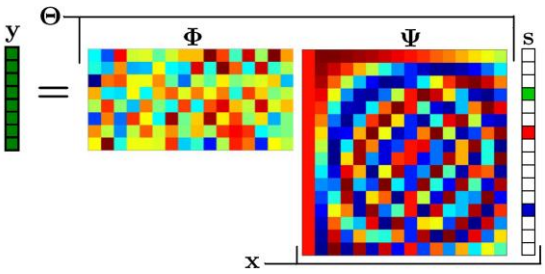


Figure 1. Graphical schematic of the basic compressed sensing model.

Figure 1 depicts a graphical representation of the basic CS model, which clearly implies that y of length $p < n$ is a compressed version of x. It is important to note that CS model is non-adaptive.

It means that the measurement matrix does not basically depend on the signal x. This has the advantage of universality of this sampling method. However, the minimum possible number of measurements p and the structure of Φ are two critical factors which should be determined based upon some specific criteria [1, 2].

Assume sampling of a signal using the above scheme and then transmitting the measurements y via an available media. The second crucial task (at the receiver) is to recover (decode) the original samples x with the knowledge about the measurements y and the measurement matrix Φ. The recovery problem is ill-conditioned since the number of available measurements p is less than the number of unknown samples n. However, several methods have been proposed to tackle this problem.

3. Random undersampling

In order to demonstrate the effectiveness of random undersampling (sub-Nyquist–Shannon) for compressed sensing problem here, we present a simple example. Consider the following periodic signal comprised of three harmonics:

$$x(t) = \cos(2\pi t) + \cos(10\pi t) + \cos(40\pi t), \quad (3)$$

The aim is to downsample the above signal using a random scheme, and then reconstructing it using CS techniques. The maximum frequency in the above signal, related to $\cos(40\pi t)$, is $f_{max} = 20$ Hz. Based on the Nyquist–Shannon rule the sampling frequency must obey $f_s \geq 2f_{max} = 40$ Hz. However, we do not follow the Nyquist–Shannon rule and undersample the above signal by taking only $p = 50$ (equivalent to $f_s = 10$ Hz) random samples in the time interval of $t \in [0\ 5]$ seconds. Note that p is called the number of measurements (equivalent to length of vector y). The random sampling is carried out simply by taking samples from x(t) at random locations which follow a Gaussian distribution. Note that this way of random sampling differs from the conventional CS where a set of linear measurements should be taken rather than the actual samples. However, for illustrative purposes and to show the strength of CS, we use such a simple scheme.

Consider DCT transform of x(t) where only three major components exist (Figure 2 (a)). Three different methods are applied to the undersampled vector of length p to approximate the components of the original signal. The first method is (nonlinear) OMP, the second is linear interpolation and the third method is a simple zero padding. The linear interpolation is applied as the concatenation of linear interpolants between each pair of data points of y(t). Zero padding is simply carried out by inserting zero at random locations within the components of y(t) until its length gets equal to x(t). The corresponding resulted signals in DCT domain are shown in figure 2 (b), (c) and (d), respectively. It is clearly illustrated that OMP can successfully recover the major components from the random undersampled signal, while linear interpolation and zero padding fail to do so. This shows the influence of random undersampling and using CS techniques to recover the original signal. Next, we propose a new sampling technique with less required storage for the measurement matrix.

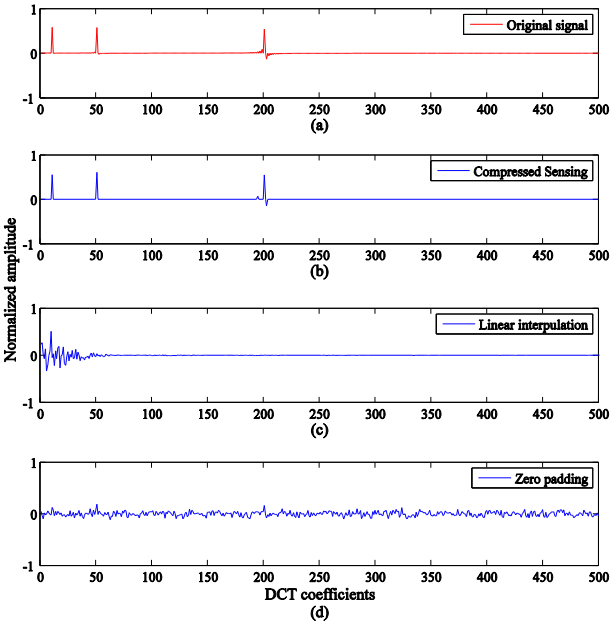


Figure 2. From top to bottom: Original signal, the result of compressed sensing reconstruction, the result of linear interpolation, and simple zero padding. All the signals are shown in the DCT domain and the amplitudes are normalized.

4. The proposed method

In conventional compressed sensing, the measurement matrix Φ of size $p \times n$ is normally selected randomly. However, dealing with this matrix in large scale problems is challenge and requires large size memory. In order to alleviate this problem, we propose a different random sampling scheme which requires less memory for storing the measurement matrix.

In spite of conventional random samplers in CS framework which takes p linear measurements from the input signal $\boldsymbol{x}$, we propose to break $\boldsymbol{x}$ into M segments of length L, and then take $p_i <$

L, (for $i = 1,2, \dots M$) random projections from each segment, independently. This can be equivalently defined as:

$$\boldsymbol{y}_i = \Phi_i \boldsymbol{x}_i \quad \text{for } i = 1, \dots M, \tag{4}$$

where Φ_i's are measurement matrices of size $p_i \times L$. Now, if we concatenate all $\boldsymbol{y}_i$'s, which are of length p_i, and create vector $\boldsymbol{y}$ of length $M(p_1 + p_2 + \cdots + p_M)$, the following equation can be obtained:

$$\boldsymbol{y} = \Phi \boldsymbol{x}: \begin{bmatrix} \boldsymbol{y}_1 \\ \boldsymbol{y}_2 \\ \vdots \\ \boldsymbol{y}_M \end{bmatrix} = \begin{bmatrix} \Phi_1 \boldsymbol{x}_1 \\ \Phi_2 \boldsymbol{x}_2 \\ \vdots \\ \Phi_M \boldsymbol{x}_M \end{bmatrix} \tag{5}$$

$$= \begin{bmatrix} \Phi_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \Phi_2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \Phi_M \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_1 \\ \boldsymbol{x}_2 \\ \vdots \\ \boldsymbol{x}_M \end{bmatrix}.$$

Equation (5) is the mathematical representation of a sampling strategy proposed above. In fact, taking random projections from segments of input signal can be mathematically illustrated as multiplying a block-diagonal matrix Φ by full-length input signal x.

The main advantage of this scheme is that the measurement matrix Φ, comparing with the measurement matrix in conventional CS, is block-diagonal and thus requires less memory for storage and lower transmission band. In addition, this block-wise strategy gives more flexibility so that one can use different measurements $p_1 \neq \cdots \neq p_M$, per segment--a kind of variable density sampling.

The above block-wise procedure can be seen as sliding a rectangular window across the signal and taking few random projections at each slide. However, in many applications we prefer to use overlapping windows to avoid any possible loss of information at the segment boundaries. Therefore, we introduce τ as the number of overlapped components and use such overlapping scheme in practice. Figure 3 demonstrates a random measurement matrix with overlapping blocks. It is obvious that such measurement matrix has many zero elements and can be stored with less effort. Due to such a special shape of the obtained measurement matrix, we choose the term "block-wise" for the proposed approach.

After applying the proposed sampling method, the projection vectors $\{\boldsymbol{y}_i\}_{i=1}^{M}$ and the measurement matrices $\{\Phi_i\}_{i=1}^{M}$ should be transmitted to the receiver. At the receiver side, the actual measurement matrix, i.e. Φ, should be formed using small sub-matrices $\{\Phi_i\}_{i=1}^{M}$.

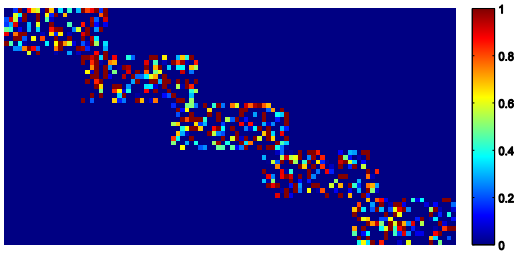


Figure 3. Illustration of a block diagonal Φ resulted from applying the proposed segmented sampling. Notice the overlapping between the blocks for avoiding information loss.

The knowledge about overlapping parameter τ is also required at this step. Then, the original sparse signal can be reconstructed by applying one of the common sparse recovery techniques [16-18]. Indeed, the recovery process should be carried out jointly over the entire random projections. Figure 4 represents an illustrative block diagram of a send-receive paradigm using the proposed method.

One important point which should be noted here is how one can choose M and L. One feasible approach is based on characteristics of the input signal/image. For instance, depending on the amplitude/energy of the signal at specific intervals, appropriate M, L, and corresponding p are chosen. Based on this adaptive strategy, more emphasis is applied to parts of the signal which contain important information and vice versa. Such decision can also be made based on any other *a priori* about the signal.

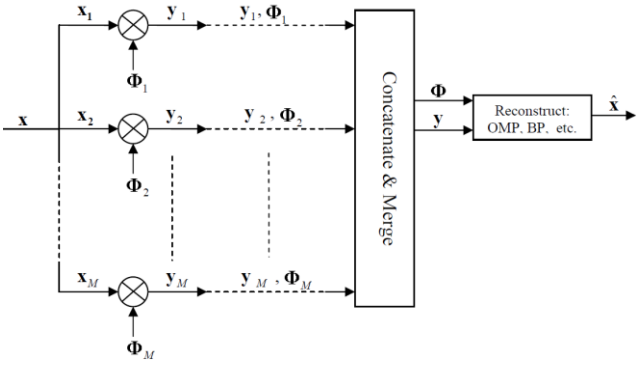


Figure 4. Block diagram of the proposed sampling method in a send-receive paradigm.

5. Experimental results

The first experiment was carried out by making a synthetic sparse signal x of length n = 100 and s = 15 non-zeros with random locations. In this experiment, we treated x as a sparse signal in the current domain and not with respect to a sparsifying matrix, i.e. $\Psi = \mathrm{I}$. The proposed algorithm was then applied to x, with the

following parameters; the number of segments: $M = 5$, overlapping each segment: $\tau = 6$, and measurements number per segment: $p_i = 10$, for $i = 1,2,\dots M$. We then reconstructed this signal by solving ℓ_1-norm minimization problem, i.e. BP. The corresponding algorithm was taken from ℓ_1-magic [19], which is a well-designed and simple MATLAB toolbox available online for solving the convex optimization problems mainly based on standard interior-point methods. Figure 5 displays the recovery results along with SNR as the quality measure.

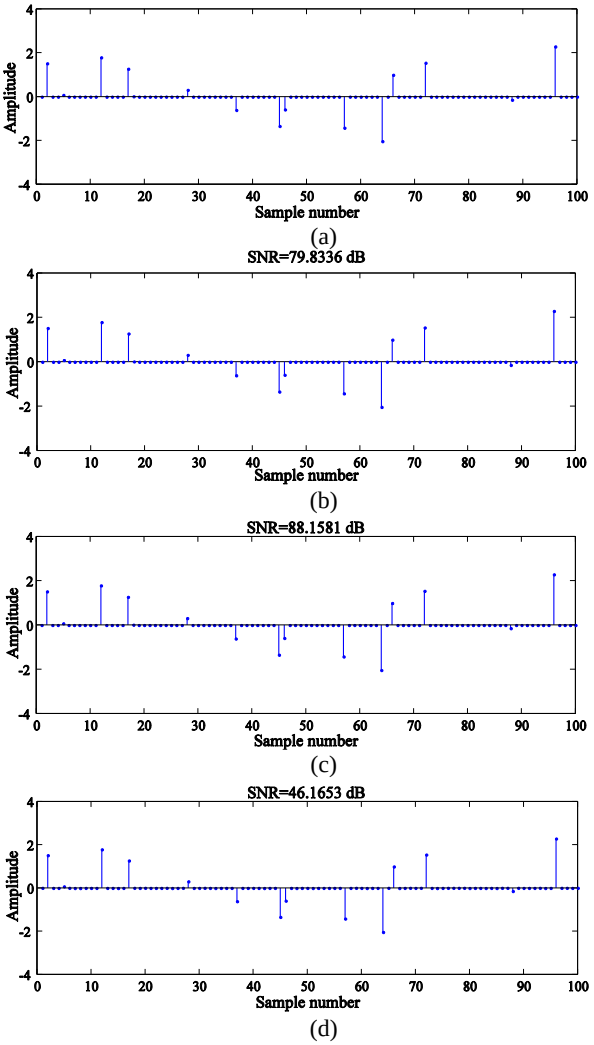


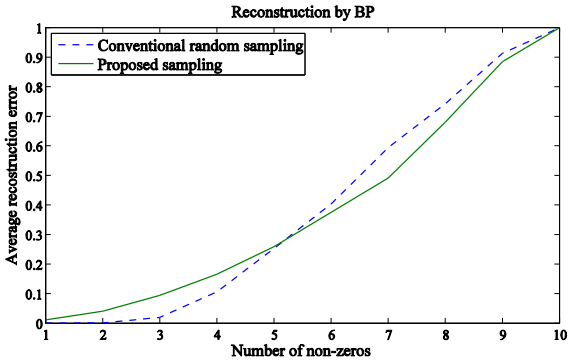
Figure 5. The reconstruction results with corresponding SNRs when the proposed sampling method is used; (a) original signal, and those recovered using (b) BP, (c) OMP, and (d) SL0.

Signal to noise ratio (SNR) is the measure of the ratio between signal power and the power of reconstruction error. It is mathematically defined as $\mathrm{SNR}_{\mathrm{dB}} = 20\log_{10}\frac{\|x\|_2}{\|\hat{x}-x\|_2}$, where x and $\hat{x}$ are the original and estimated signals, respectively. We have also applied two other methods named OMP, taken from "SparseLab" toolbox [20], and SL0 (smoothed ℓ_0) [21], taken from [17], for reconstruction. SL0 is a fast optimization method which attempts to solve ℓ_1-norm minimization problem by approximating the ℓ_0-norm reconstruction using a smoothing function $F_\sigma(.)$, where σ determines the quality of approximation [21]. As it is seen from figure 5, the common recovery algorithms could successfully recover the underlying sparse signal when the proposed sampling strategy is applied.

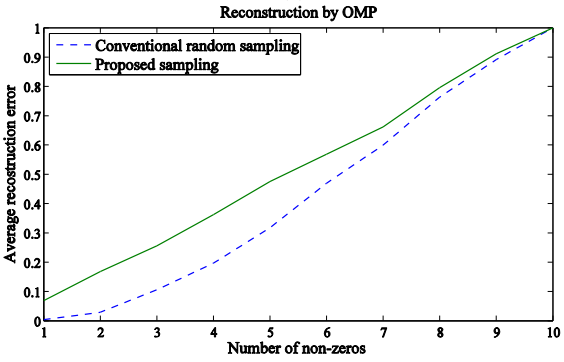
Due to block-diagonal structure of the obtained measurement matrix in the proposed method, we expected the reconstruction algorithm to perform faster. In order to verify this expectation, we set up an experiment in which the response times of three reconstruction methods (i.e. BP, OMP and SL0) were recorded. This experiment was repeated for different signal dimensions, 5 segments, and total of 50 measurements. Table 1 demonstrates the corresponding results. Table 1 shows that the common recovery algorithms perform faster when the proposed measurement matrix is used compared with the conventional random measurement matrices. This is more noticeable at higher dimensions, especially for BP which is a more complicated algorithm among others. However, the computation times of different methods do not change significantly when the proposed scheme is used in low dimensions (e.g. the signal length of 100 in table 1). In the second experiment, a fixed number of measurements $p = 30$ was selected for signals of length $n = 120$.

Then, we varied the non-zeros of 10000 sparse signal ensembles from 1 to 10 and applied the proposed method. In this experiment the proposed method was used with $M = 5$, $p_i = 6$ for $i = 1,2,\dots M$ and the segments had 50% overlap. Finally, we applied several recovery methods to reconstruct the sparse signals and evaluated the recovery performance. The results of this experiment are depicted in figure 6. As expected, the recovery error increases with increasing the number of non-zeros. In addition, figure 6 demonstrates that the degradation in the reconstruction performance is negligible, when the proposed sampling scheme has been used. Also, less recovery error of the proposed method, observed in figure 6 (a) and (c) for large number of non-zeros, cannot be fairly explained since the performance of recovery techniques are not reliable at these dimensions.

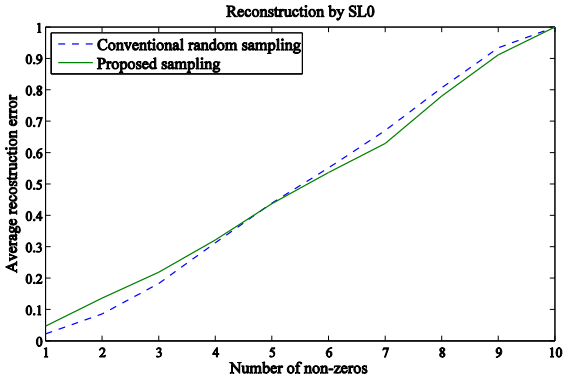
In the third experiment, we evaluated the performance of the proposed algorithm against variations in the number of measurements.



(a)



(b)



(c)

Figure 6. The reconstruction error against number of non-zeros when (a) BP, (b) OMP and (c) SL0 used as the recovery method.

In order to do this, we computed the average recovery error for 1000 signal ensembles of length 120 and 15 non-zeros. This experiment was carried out while we varied the total number of measurements from 10 to 80. The results are given in figure 7 when different numbers of segments were chosen in the sampling stage. The parameter η in the graphs, represents the percentage of free space (zeros) in the measurement matrix.

As the graphs in figure 7 show, increasing the number of measurements leads to smaller recovery error in all curves. However, the resulting curves behave slightly different for different segment numbers (i.e. M). Obviously, more segments mean more percentage of zero components (η) in the corresponding measurement matrix (based on the model in (5) and in Figure 3). This means the overall block-diagonal measurement matrix requires less memory which is desired.

However, figure 7 shows that choosing very large number of segments causes degradation in performance, which is a disadvantage. This behavior can be because of the fact that choosing large number of segments (for a signal of fixed length) leads to very small segment-size, and consequently, the segments cannot convey much information about the signal. In fact, there is a trade-off between the number of segments and the recovery performance and the number of segments and their sizes (compared with the total length of signal) should be obtained empirically.

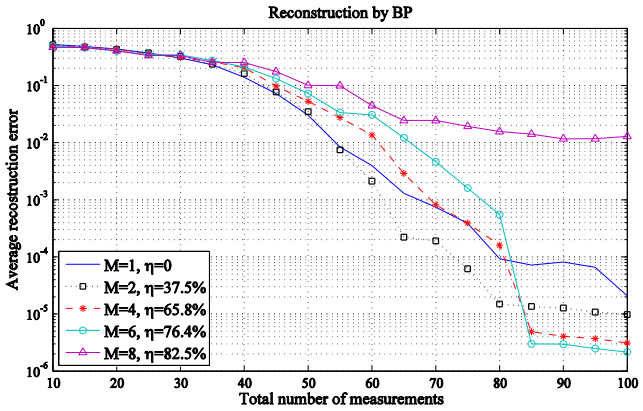
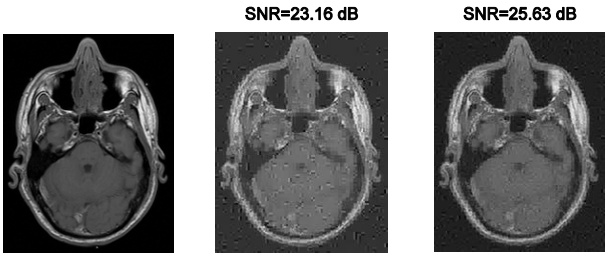


Figure 7. Average recovery error versus number of measurements. *M* denotes the number of segments and *η* indicates the percentage of zero components in Φ .

Like the last experiment, we used the proposed method for compression and reconstruction of an MR image of size 230×180. Conventionally, we first applied Haar wavelet transform to the image in figure 8 (a). Then, detailed coefficients (horizontal, vertical and diagonal) were rearranged into a single sparse vector x of length 7830. This vector was then multiplied by the measurement matrix Φ, leading to the measurements $y = \Phi x$. Two types of measurement matrices were chosen for this experiment; traditional random Gaussian Φ of size 2100×7830, and proposed block-diagonal Φ where $M = 30$, $p_i = 70$ and $\tau = 100$.

The results of reconstruction using BP are given in figure 8. These results were obtained after reconstruction of sparse vector and taking inverse wavelet transform.

Figure 8 shows that the achieved SNR using the proposed method is higher than that obtained using traditional CS.



(a) (b) (c)

Figure 8. MRI reconstruction results: (a) input image. The reconstructed image using (b) traditional CS, and (c) the proposed method.

6. Conclusions

A new and simple method to design the measurement matrix in compressed sensing has been presented in this paper. The proposed method obtains random linear measurements by dividing the input signal into several overlapping segments.

The resulting measurement matrix has a block-diagonal structure which is more efficient in terms of required memory storage and transmission costs. In addition, the overlapped segments avoid possible loss of information at the segment boundaries. Our simulation results revealed that by using the proposed method, one can achieve similar recovery performance as that obtained when conventional random sampling is used. Furthermore, the recovery time is reduced when the proposed scheme is used due to simpler structure of the proposed measurement matrix. However, more investigation is required to improve the recovery performance as well as optimizing the sampling process.

Another important aspect of the proposed approach is its applicability for real-world scenarios. There exist numerous applications which can benefit from this approach. For example, in compressed sensing based MRI, generating a fully random measurement matrix is a challenging issue.

Therefore, the proposed mitigated technique could be practical. Also, in terahertz imaging systems [22] achieving a simple acquisition operator is of interest. All these applications and other related problems can be further investigated and studied.

Table 1. Computation time (in second) per iteration for different methods for M=5 segments.

		Signal length				
		100	1000	4000	7000	10000
Random Sampling	BP	0.0077	3.0271	10.0603	20.7773	41.1924
	OMP	0.0031	0.0043	0.0060	0.0102	0.0113
	SL0	0.0021	0.0189	0.0353	0.0521	0.747
Proposed Sampling	BP	0.0076	1.2730	4.8648	12.9129	21.3821
	OMP	0.0032	0.0039	0.0057	0.0082	0.0107
	SL0	0.0022	0.0154	0.0252	0.0418	0.0575

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نشریه هوش مصنوعی و داده کاوی

دانشگاه شاهرود

روشی مبتنی بر نمونه برداری تصادفی محلی در حسگری فشرده

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چکیده:

در این مقاله مساله حسگری فشرده مورد بررسی قرار می‌گیرد. در حسگری فشرده تحت شرایط خاص میتوان نمونه برداری از یک سیگنال یا تصویر را با فرکانسی کمتر از فرکانس نایکوییست انجام داد. برای نیل به این منظور طراحی عملگر نمونه بردار از اهمیت بالایی برخوردار است. اکثر روش‌های موجود در این زمینه به دنبال بهینه کردن یک ماتریس نمونه بردار تصادفی جهت بهبود کیفیت بازسازی سیگنال موردنظر می‌باشند. با این حال، این روش‌ها عمدتاً منجر به تولید ماتریس‌هایی با ساختار پیچیده می‌شوند که پیاده‌سازی سخت افزاری آنها بسیار دشوار خواهد بود. در این مقاله ساختاری ساده بر مبنای نمونه برداری تصادفی مبتنی بر بلاک (زیر ماتریس) ارائه می‌گردد. بطوریکه به جای استفاده از یک ماتریس نمونه بردار بزرگ از تعدادی نمونه بردار کوچک که می‌توانند همپوشانی نیز داشته باشند استفاده می‌گردد. بزرگترین مزیت نمونه برداری با روش مبتنی بر بلاک، سادگی پیاده‌سازی و در عین حال نتیجه بازسازی قابل قبول در مقایسه با روش‌های موجود می‌باشد. نتایج شبیه سازی ارائه شده در این مقاله تاییدکننده این مساله است. مهم‌تر اینکه سرعت اجرای الگوریتم پیشنهادی در مقایسه با روش‌های موجود بالاتر می‌باشد.

کلمات کلیدی: حسگری فشرده، بازسازی تنک، پردازش سیگنال و تصویر، نمونه برداری تصادفی، ماتریس نمونه بردار.