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Compressed Sensing of EEG for Wireless Telemonitoring with Low Energy Consumption and Inexpensive Hardware

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Short summary: Telemonitoring of electroencephalogram (EEG) through wireless body-area networks (WBAN) is an evolving direction in personalized medicine. However, there are important constraints such as energy consumption, data compression, and device cost. Recently, Block Sparse Bayesian Learning (BSBL) was proposed as a new method to the CS problem. In this study, they apply the technique to the telemonitoring of EEG. Experimental results show that its recovery quality is better than state-of-the-art CS algorithms. These results suggest that BSBL is very promising for telemonitoring of EEG and other non-sparse physiological signals.

I. INTRODUCTION

Telemonitoring of electroencephalogram (EEG) via WBANs is an evolving direction in personalized medicine and home-based e-Health. Equipped with the system, patients need not visit hospitals frequently. Instead, their EEG can be monitored continuously and ubiquitously.

However, there are many constraints

A. The primary one is energy constraint. Due to limitation on battery life, it is necessary to reduce energy consumption as much as possible.
B. Another constraint is that transmitted physiological signals should be largely compressed.
C. The third constraint is hardware costs. Low hardware costs are more likely to make a telemonitoring system economically feasible and accepted by individual customers

It is noted that many conventional data compression method such as wavelet compression cannot satisfy all the above constraints at the same time.

Compared to wavelet compression, Compressed Sensing (CS) can reduce energy consumption while achieving competitive data compression ratio.

However, current CS algorithms only work well for sparse signals or signals with sparse representation coefficients in some transformed domains (e.g., the wavelet domain).

Since EEG is neither sparse in the original time domain nor sparse in transformed domains, current CS algorithms cannot achieve good recovery quality.

This study proposes using Block Sparse Bayesian Learning (BSBL) [1] to compress/recover EEG. The BSBL framework was initially proposed for signals with block structure. This study explores the feasibility of using the BSBL technique for EEG, which is an example of a signal without distinct block structure.

II. COMPRESSED SENSING AND BLOCK SPARSE BAYESIAN LEARNING

CS is a new data compression paradigm, in which a signal of length *N*, denoted by $\mathbf{x} \in \mathbb{R}^{M \times N}$, is compressed by a full row-rank random matrix, denoted by $\mathbf{\Phi} \in \mathbb{R}^{M \times N} \left(M \ll N\right)$,i.e.,

$$\mathbf{y} = \mathbf{\Phi x}, \tag{1}$$

where $\mathbf{y}$ is the compressed data, and $\mathbf{\Phi}$ is called the *sensing matrix*. CS algorithms use the compressed data $\mathbf{y}$ and the sensing matrix $\mathbf{\Phi}$ to recover the original signal $\mathbf{x}$. Their successes rely on the key assumption that most entries of the signal x are zero (i.e., $\mathbf{x}$ is sparse).

When this assumption does not hold, one can seek a dictionary matrix, denoted by $\mathbf{D} \in \mathbb{R}^{M \times M}$, so that $\mathbf{x}$ can be expressed as $\mathbf{x} = \mathbf{Dz}$ and $\mathbf{z}$ is sparse.

$$\mathbf{y} = \mathbf{\Phi D z}. \tag{2}$$

When CS is used in a telemonitoring system, signals are compressed on sensors according to (1). This compression stage consumes on-chip energy of the WBAN. The signals are recovered by a remote computer according to (2). This stage does not consume any energy of the WBAN.

Despite of many advantages, the use of CS in telemonitoring is only limited to a few types of signals, because most physiological signals like EEG are not sparse in the time domain and not sparse enough in transformed domains.

The issue now can be solved by the BSBL framework [1], [2].

It assumes the signal **x** can be partitioned into a concatenation of non-overlapping blocks, and a few of blocks are non-zero. Thus, it requires users to define the block partition of **x**.

However, it turns out that user-defined block partition does not need to be consistent with the true block partition [3]. Further, in this work, they found even if a signal has no distinct block structure, the BSBL framework is still effective.

This makes feasible using BSBL for the CS of EEG, since EEG has arbitrary waveforms and the representation coefficients **z** generally lack block structure.

Currently, there are three algorithms in the BSBL framework. In this experiment, they chose a bound-optimization based algorithm, denoted by BSBL-BO. Details on the algorithm and the BSBL framework can be found in [1].

III. EXPERIMENTS OF COMPRESSED SENSING OF EEG

The following experiments compared BSBL-BO with some representative CS algorithms in terms of recovery quality.

Two performance indexes were used to measure recovery quality. One was the Normalized Mean Square Error (NMSE). The second was the Structural SIMilarity index (SSIM) [4]. SSIM measures the similarity between the recovered signal and the original signal, which is a better performance index than the NMSE for structured signals.

In the first experiment **D** was an inverse Discrete Cosine Transform (DCT) matrix, and thus **z** $\left(\mathbf{z}=\mathbf{D}^{-1}\mathbf{x}\right)$ are DCT coefficients. In the second experiment **D** was an inverse Daubechies-20 Wavelet Transform (WT) matrix.

In both experiments the sensing matrices $\mathbf{\Phi}$ were sparse binary matrices, in which every column contained 15 entries equal to 1 with random locations while other entries were zeros.

A. *Experiment 1: Compressed Sensing with DCT*

This example used a common dataset (‘eeglab data.set’) in the EEGLab. This dataset contains

EEG signals of 32 channels with sequence length of 30720 data points, and each channel signal contains 80 epochs each containing 384 points.

To compress the signals epoch by epoch, they used a 192 ×384 sparse binary matrix as the sensing matrix $\mathbf{\Phi}$, and a 384×384 inverse DCT matrix as the dictionary matrix **D**.

Two representative CS algorithms were compared in this experiment. One was the Model-CoSaMP, which has high performance for signals with known block structure. The second was an L1 algorithm (CVX toolbox) to recover EEG.

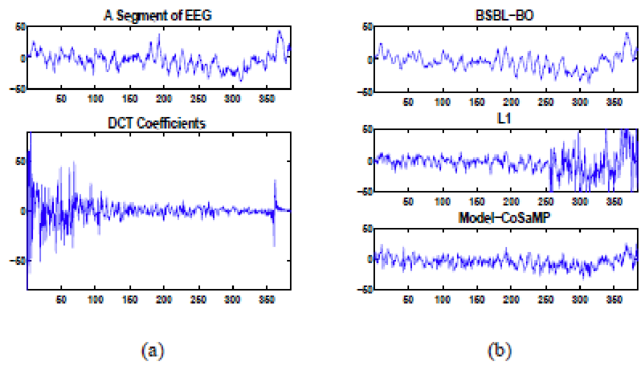


Fig. 1. (a) An EEG epoch, and its DCT coefficients. (b) The recovery results by BSBL-BO, ℓ_1, and Model-CoSaMP when using the model (2).

Figure 1(a) shows an EEG epoch and its DCT coefficients. Clearly, the DCT coefficients were not sparse and had no block structure. Figure 1(b) shows the recovery results of the three algorithms. BSBL-BO recovered the epoch with good quality.

Table I shows the averaged NMSE and SSIM of the three algorithms on the whole dataset.

TABLE I
AVERAGED PERFORMANCE IN EXPERIMENT 1.

	NMSE (mean $\pm$ std)	SSIM (mean $\pm$ std)
DCT-based BSBL-BO	**0.078 $\pm$ 0.046**	**0.85 $\pm$ 0.08**
BSBL-BO without DCT	0.116 $\pm$ 0.066	0.81 $\pm$ 0.09
DCT-based ℓ_1	0.493 $\pm$ 0.121	0.48 $\pm$ 0.11
DCT-based Block-CoSaMP	0.434 $\pm$ 0.070	0.45 $\pm$ 0.10

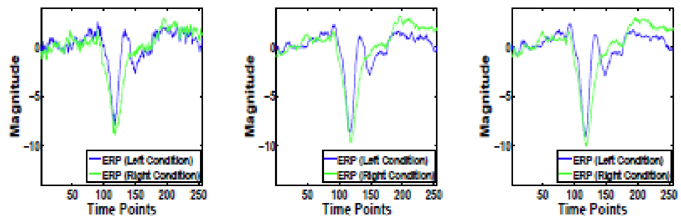
The DCT-based BSBL-BO evidently had the best performance.

B. Experiment 2: Compressed Sensing with WT

The second experiment used movement direction dataset. It consists of multiple channel signals, each channel signal containing 250 epochs for each of two events ('left direction' and 'right direction'). BSBL-BO and the previous L1 algorithm were compared.

The sensing matrix $\mathbf{\Phi}$ had the size of 128 × 256, and the dictionary matrix D had the size of 256 × 256.

For each event, they calculated the ERP by averaging the associated 250 recovered epochs.



(a) ℓ_1 (b) BSBL-BO (c) Original Dataset

Fig. 3. The ERPs corresponding to two event conditions ('left' and 'right') averaged (a) from the recovered epochs by the ℓ_1 algorithm, (b) from the recovered epochs by BSBL-BO, and (c) from the original dataset.

Figure 3 (a) shows the ERP for the 'left direction' and the ERP for the 'right direction' averaged from the dataset recovered by the L1 algorithm. Figure 3 (b) shows the ERPs from the recovered dataset by BSBL-BO. Figure 3 (c) shows the ERPs from the original dataset.

Clearly, the resulting ERPs by the L1 algorithm were noisy.

The ERPs averaged from the recovered by BSBL-BO maintained all the details of the original ERPs with high consistency. The SSIM and the NMSE of the resulting ERPs by the L1 algorithm were 0.92 and 0.044, respectively. In contrast, the SSIM and the NMSE of the resulting ERPs by BSBL-BO were 0.97 and 0.008, respectively.

IV. DISCUSSIONS

Using various dictionary matrices, the representation coefficients of EEG signals are still not sparse. Therefore, current CS algorithms have poor performance, and their recovery quality is not suitable for many clinical applications and cognitive neuroscience studies.

Instead of seeking optimal dictionary matrices, this study proposed a method using general dictionary matrices achieving sufficient recovery quality for typical cognitive neuroscience studies.

The empirical results suggest that when using the BSBL framework for EEG compression/recovery, the seeking of optimal dictionary matrices is not very crucial.

V. CONCLUSIONS

This study proposed to use the framework of block sparse Bayesian learning, which has superior performance to other existing CS algorithms in recovering non-sparse signals. Experimental results showed that it recovered EEG signals with good quality. Thus, it is very promising for wireless telemonitoring based cognitive neuroscience studies.

VI. DISCUSSION & COMMENTS

This method can be applied other research area with non-sparse signal.

Appendix

Experiment codes can be downloaded at:

https://sites.google.com/site/researchbyzhang/bsbl.

Reference

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