Study on Compressed Sensing of Action Potential

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Abstract

Compressive sensing (CS) is a signal processing technique that enables sub-Nyquist sampling and near lossless reconstruction of a sparse signal. The technique is particularly appealing for neural signal processing since it avoids the issues relevant to high sampling rate and large data storage. In this project, different CS reconstruction algorithms were tested on raw action potential signals recorded in our lab. Two numerical criteria were set to evaluate the performance of different CS algorithms: Compression Ratio (CR) and Signal-to-Noise Ratio (SNR). In order to do this, individual CS algorithm testing platforms for the EEG data were constructed within MATLAB scheme. The main considerations for the project were the following. 1) Feasibility of the dictionary 2) Tolerance to non-sparsity 3) Applicability of thresholding or interpolation.

Index Terms

Compressive Sensing (CS), Nyquist-Shannon Sampling, Electrocephalography (EEG), Sparsity

I. INTRODUCTION

Electrophysiological signals present brain activities in the form of electrical signals. Action potential is the activity of single neuron, which consists of rapid polarization and depolarization process. Action potential is key in understanding neuron activities and brain-machine interface applications. Action potential is typically recorded at ten of kilohertz [1]. Unfortunately, recording action potentials from multiple neurons pose significant power penalty [2]. In order to conquer the power limitation, we study the use of compressive sensing (CS) for acquiring action potential signals.

Unlike traditional sampling-to-compression method, CS takes advantage of the sparsity of the signal [3]. Ideally, the sampled data can be near losslessly reconstructed [4]. Yet, reconstruction results critically depends on the sparsity of the signal of interest [5]. If a signal fails to be sparse in any representable domain, a promising reconstruction cannot be obtained.

Using the CVX tool and the BSBL-BO CS algorithm on MATLAB, seven distinct domains were tested for CS reconstruction results. The implementation was successful, however, the achievable compression ratio is limited. Although the reconstruction result may be further improved with better sparse dictionary, we conclude CS is not ideal for compressing action potential signals. Hardware sensing implementation is left for the future work with the random matrix prepared in this experiment.

II. ACTION POTENTIAL DATA

The dataset used for this work was collected in our lab [6-7]. The original sampling rate is 15kSps. An analog gain of 60dB is applied when acquiring the data. A sample length of N = 256 was used, as shown in Fig. 1. The sampled signal vector is composed of single spiking greater than 250µV and noise limited by thermal and instrumentation used. Without loss of generality, N, M, and different segment of sample can be selected for the experiment with desired compression ration (CR) [8].

III. EXPERIMENTAL RESULTS

A. CVX Sparse-Dictionary CS Result

On MATLAB, CVX convex optimization solver tool was installed to solve the reconstruction. The sampling matrix was constructed with normally distributed pseudorandom numbers. To retain consistency
Fig. 1. An example action potential data vector with a length of 256 samples.

of the testing, The sampling matrix was fixed. Time domain reconstruction result is shown in Figure 2-(a). The result shows weak reconstruction due to nonsparsity of the signal in time domain, as expected. Figure 2-(b) illustrates reconstruction result with discrete cosine transform (DCT) matrix. The matrix was constructed by transforming an identity matrix \( N \times N \).

Fig. 2. The results from compressive sensing reconstruction on 6 different sparse-basis.

The sparse-matrix used in the reconstruction in Figure 2-(c) was composed of discrete prolate spheroidal sequence (DPSS) with time-half bandwidth set to 8.5. DPSS forms highly efficient basis for sampled bandlimited functions, compared to conventional fourier series [9]. Figure 2-(d) illustrates the reconstruction result with sparse-matrix formed by fast fourier transform (FFT).

Only real parts of the result was extracted for the reconstruction vector \( x_{\text{recons}} \) with magnitude of the imaginary components. Gabor basis for 2-(e) was formed with sine and cosine basis with Gaussian kernels. The dictionary functions suggested by Abdulghani et al., where the parameters \( n \) is the sample size, \( n_0 \) is the sample number of the centre of the envelop, \( \omega > 0 \) is the sinusoid’s frequency, \( \sigma \), 0 is the spread of the envelope, and \( \theta \) is the phase angle [10]. Noiselet dictionary, composed of functions complementary to wavelet, was constructed with the generation code available, constructed by Laurent Duval. And lastly, real sinusoid transform (RST) was performed on identity matrix using SparseLab2.1-Core tool.
Operation time wise, RST showed the best performance with 2.48s followed by DPSS with 2.73s. Both SNR and time wise, DPSS illustrated the overall superior performance.

B. BSBL-BO Sparse Dictionary CS Result

It has been verified in the pervious section that basis pursuit with CVX tool failed to give aimed result, SNR > 10dB at CR = 0.5. This is due to inherent non-sparsity of the tested EEG signal. A CS reconstruction algorithm that is less sensitive to the non-sparsity was necessary. The algorithm Block Sparsity Bayesian Learning-Bound Optimization, or BSBL-BO by Zhilin Zhang is tolerant to the non-sparsity of the signal while successfully reconstructing the signal using block sparsity.

With block-partition sparsity and intra-block correlation, the algorithm itself is less sensitive to the choice of sparse-dictionary. That is, although the performance still depends on the sparse-dictionary, the reconstruction result is overall better than CVX results. The same procedure was followed for testing BSBL-BO with time domain replaced by Wavelet of Daubechies-20, using WaveLab850.

Refer to figure 3, All the reconstruction results except for noislet, gabor, and wavelet basis show SNR level > 10dB for the aimed reconstruction result. The algorithm execution time is optimized and overall faster than CVX solver. Fourier basis illustrated the best performance in PSNR with 30.15dB and SNR with 13.91dB. DCT demonstrated the shortest operation time with 0.075s, which shows marginal difference of 0.003s compared to FFT. In short, sparse-dictionary composed of fourier series showed superior performance for BSBL-BO algorithm.

The window size of 30 or the total size of 60 was set with respect to the spike on the center. The SNR was derived from that window only, that is, the spike SNR was calculated. The purpose was to verify performance of the reconstruction of spikes that likely contain information related to neuron firing activity. The basis comparison results are presented in Table 1.

Further testing was performed by varying CR with Fourier sparse matrix and fixed sensing matrix A. The code constructed by Igor Carronw as used to construct sparse sampling matrix that composed of only binary number entries. Graphical results are presented in Figure 4.

Interpolation was tested with a window size of 30 with respect to the spike centre, the reconstruction was tested. The sampling matrix was fixed with random binary number matrix and Fourier basis was used for sparse-matrix on BSBL-BO. The data length of N = 60 was extracted. However, the lack of data
TABLE I
BSBL-BO DICTIONARY PERFORMANCE TABLE

| Basis          | PSNR(dB) | SNR(dB) | CR  | Time (s) |
|----------------|----------|---------|-----|----------|
| Discrete Cosine| 30.0193  | 13.7786 | 0.5 | 0.075    |
| Fourier        | 30.1583  | 13.9176 | 0.5 | 0.182    |
| Gabor          | 25.32    | 9.0793  | 0.5 | 0.078    |
| DPSS           | 28.1563  | 11.9156 | 0.5 | 0.078    |
| Noiselet       | 21.0742  | 4.8335  | 0.5 | 0.201    |
| Real Sinusoidal| 28.9772  | 12.7365 | 0.5 | 0.086    |
| Wavelet        | 21.9056  | 5.6649  | 0.5 | 0.303    |

points illustrated rugged signal representation, so the data was interpolated to generate values inbetween each integer data points. The results were PSNR of 14.64 and SNR of 3.53 with a CR of 0.5. However, the result was worse than the \( N > \) window: size reconstruction in the previous sections. Thus, interpolation method failed to give aimed result.

Fig. 4. BSBL-BO CS reconstruction results using FFT dictionary were recorded. Variations to the number of observations \( M \) and accordingly CR were made.

IV. DISCUSSION

In this project, two different algorithms were used to test CS reconstruction performance. For CVX tool based CS reconstruction, discrete prolate spheroidal sequence basis showed a satisfactory result. For Block
Sparsity Bayesian Learning-Bound Optimization (BSBL-BO) CS reconstruction, Fourier basis achieved a satisfactory result. Algorithm-wise, BSBL-BO demonstrated a superior overall performance, considering SNR-to-CR performances and algorithm execution time.

Figure 6 shows the SNR-to-CR performance comparison result. In this project, BSBL-BO was the strongest algorithm candidate for our future work, considering the inherent non-sparsity of the signal of interest. However, a higher compression ratio was not achievable in this work. CS may or may not be suitable for compressing action potential signals, depending on the target applications and the hardware resources.

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