A Novel Approach for Detection of Medial Temporal Discharges Using Blind Source Separation Incorporating Dictionary Look Up

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Abstract

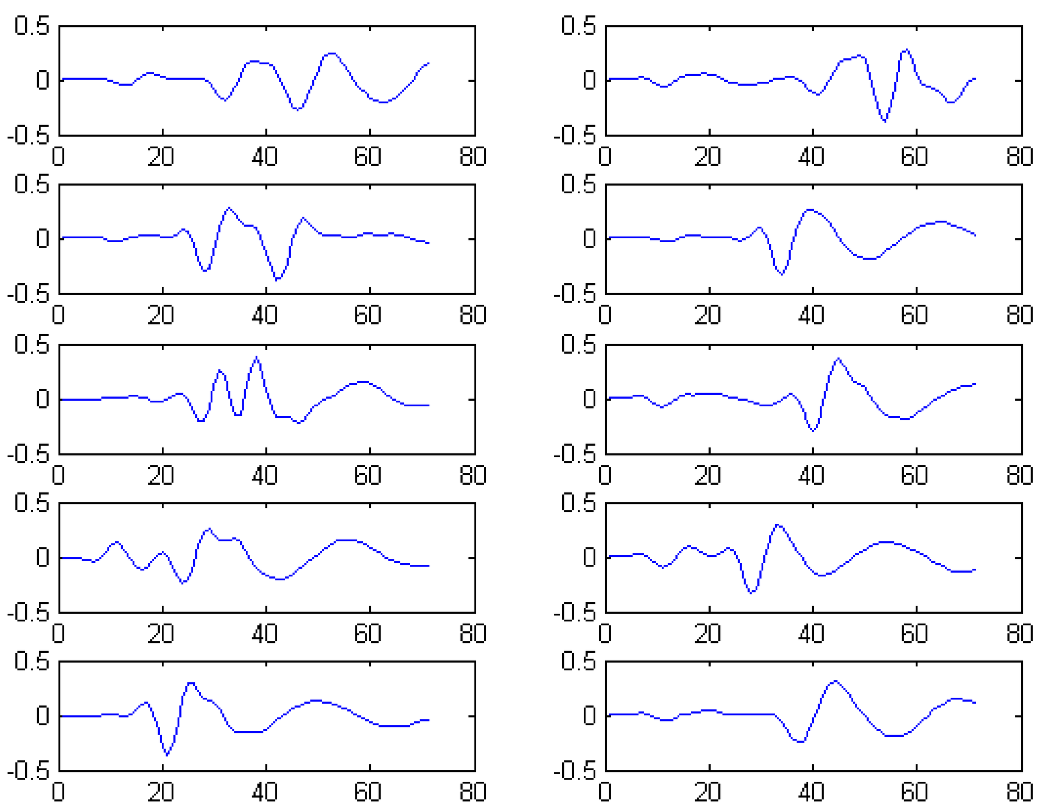
- In blind source separation (BSS), sparsity is proved to be very advantageous. If data is not sparse in its current domain, it can be modelled as sparse linear combinations of elements of a chosen dictionary.
- The choice of dictionary that sparsifies the data is very important. In the proposed method, the dictionary is pre-specified based on chirplet modelling of various kinds of real epileptic spikes.
- In this work, a hybrid dictionary look up – source separation is introduced to extract the closest source to the source of interest from the scalp EEG measurements. The algorithm has been tested on synthetic and real data consisting of epileptic discharges, and the results are compared with those of traditional BSS.

Objectives

- Extract intracranial sources corresponding to epileptic discharges from scalp EEG
- Build up a fixed dictionary from different shapes of epileptic discharges in intracranial EEG, which are scored by clinicians
- Model the epileptic discharges using chirplets, so that they are more representative of the spike morphology without the extra components in the signal
- Build up the dictionary in a way that the components cover many forms of epileptic discharges
- Develop an algorithm by combining dictionary look up and source separation
- Apply the algorithm to some sets of simulated as well as real data in order to test the performance

Creating the Dictionary

- The dictionary is pre-specified based on various morphologies of real epileptic discharges in the intracranial EEG scored by clinical experts.
- These discharges are modelled using a limited number of chirplets, some of them are shown in the following figure.



- As shown, epileptic discharges are usually made up of a sharp peak followed by a slow wave.

Sparse Recovery

- Sparse recovery is the procedure of estimating the coefficients for representing the sparse signal from the measurement signal and the dictionary.
- Generally, sparse recovery is also referred to as atom decomposition. It requires solving one of the following equations, which is usually done by a pursuit algorithm.

$$(P_0) \quad \min_{\mathbf{s}} \|\mathbf{s}\|_0 \quad subject\ to \quad \mathbf{x} = \mathbf{D}\mathbf{s}$$

$$(P_{0,\epsilon}) \quad \min_{\mathbf{s}} \|\mathbf{s}\|_0 \quad subject\ to \quad \|\mathbf{x} - \mathbf{D}\mathbf{s}\| \le \epsilon$$

- Solving L_0-norm minimisation is an NP-hard problem. Therefore, an approximation to that is often employed. Matching pursuit (MP) and orthogonal matching pursuit (OMP) algorithms select the dictionary atoms one by one.
- In these algorithms, inner products between the signal and dictionary atoms are computed mostly by minimising least square error. Initially, the atom which has the largest inner product with the signal is found, and its contribution is subtracted from the signal.
- This procedure is repeated until the signal is decomposed completely. By changing the algorithm stopping rule, both above equations are addressed. If the required solution is sparse enough, these algorithms and similar techniques are able to recover it accurately.

Multichannel Source Separation

- The created dictionary and the sparse recovery theory are used in order to help extracting the original sources from a set of mixtures. If the following BSS model is considered:

$$\mathbf{Y} = \mathbf{A}\mathbf{X} + \mathbf{V}$$

- The sources of interest are intracranial epileptic discharges and the mixtures are scalp EEG recordings of epileptic patients. If all the channels of scalp recordings are saved in a matrix $\mathbf{Y}$ then, stacking all the channels in one row makes a single vector $\mathbf{y}$. The extracted desired source matrix $\mathbf{X}$ is also vectorized and shown as $\mathbf{x}$. Therefore, the BSS model above is changed because the signals here are all in one vector rather than matrix. The new equation is:

$$\underline{\mathbf{y}} = (\mathbf{I} \otimes \mathbf{A})\underline{\mathbf{x}} + \underline{\mathbf{v}}$$

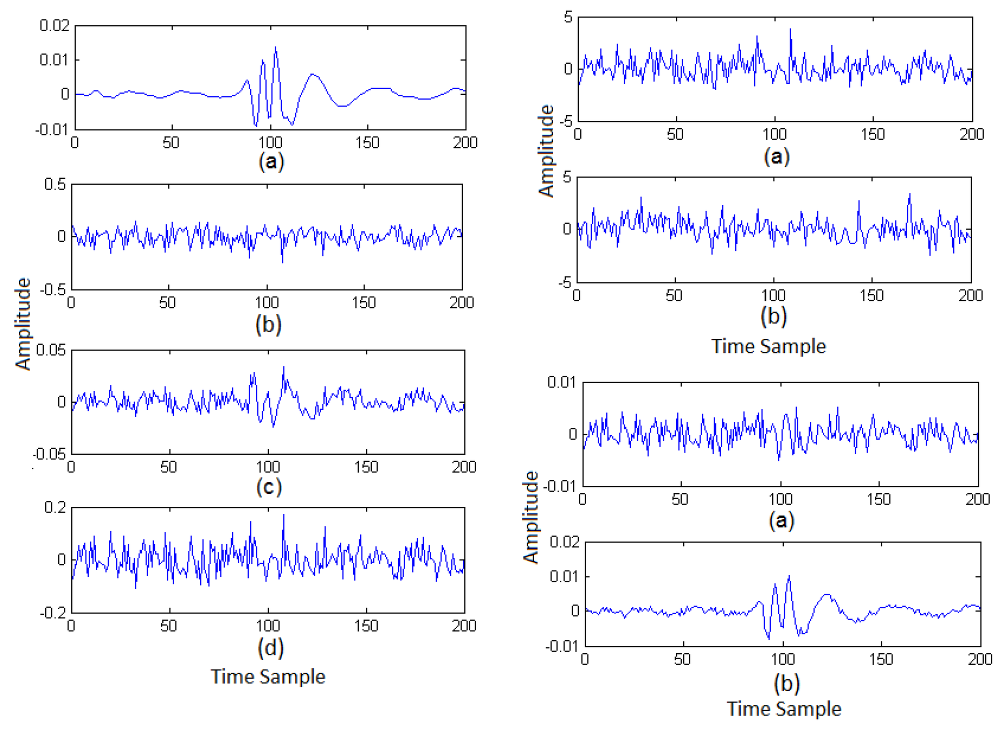
- The overall source separation problem is expressed as:

$$\min_{\{s_i\},\underline{x},A} \lambda\|\underline{\mathbf{y}} - (\mathbf{I}\otimes\mathbf{A})\underline{\mathbf{x}}\|_2^2 + \sum_{i=1}^{p}[\mu_i\|\mathbf{s}_i\|_0 + \|\mathbf{D}\mathbf{s}_i - \Re_i\underline{\mathbf{x}}\|_2^2]$$

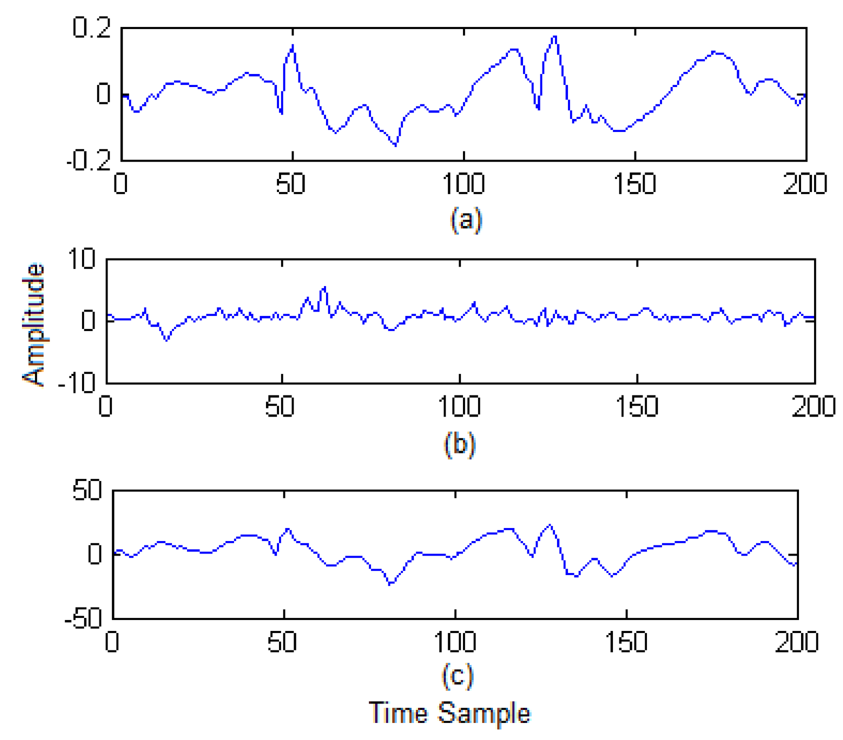
- The process of minimizing this cost function starts with extracting patches of $\mathbf{x}$. Then, the OMP algorithm estimates the sparse coefficients for each patch, having the patch itself and the dictionary $\mathbf{D}$ as inputs. Afterwards, the sparse coefficients matrix and $\mathbf{A}$ are assumed fixed and $\mathbf{x}$ has to be estimated. The matrix of mixtures $\mathbf{Y}$ and the source matrix $\mathbf{X}$ are then used to estimate $\mathbf{A}$.
- The steps of estimating sparse coefficients matrix, $\mathbf{x}$, and $\mathbf{A}$ have to be repeated for a suitable number of iterations in order to minimize the cost function.

Experimental Results

- Simulated Data consists of linear mixture of a piece of intracranial signal, which contains epileptic discharges, with a random signal, and additive Gaussian noise. This makes the overall mixing system underdetermined.



- Real data has been recorded using both scalp and Foramen Ovale (FO) electrodes to measure the scalp mixtures and intracranial sources, respectively. This data has been taken from patients with temporal lobe epilepsy in order to plan for surgical operation. A segment of intracranial signals recorded before the seizure onset and contains epileptic discharges, has been selected. These signals are greatly affected by noise and activity of neighbouring neurons. The scalp and intracranial recordings have been performed simultaneously with the sampling rate of 200 samples per second.



Conclusions

- In this work, taking advantage of the sparsity of original sources in order to better tackle the BSS problem has been investigated.
- It has been shown that even if the sources are not sparse in their current domain, it may be possible to model them as sparse linear combinations of elements in a chosen dictionary.
- The dictionary is pre-specified and contains different models of epileptic discharges. These discharges are produced by chirplet modelling of the actual spikes.
- Iteratively estimating the sparse coefficients, the mixing matrix is used to extract the closest source to the original source from the mixtures. The method has been tested on simulated and real EEG data of epileptic discharges and the results are promising.

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