

# SEPARATION OF MULTI-CHANNEL SPINAL CORD RECORDINGS USING UNSUPERVISED ADAPTIVE FILTERING

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**Abstract-** In anesthetized animals, evoked motor signals descending through the corticospinal tract were recorded from the spinal cord with selectivity using multi-contact surface electrodes [1]. However, the spatial selectivity needs to be improved for this approach to be used as a multi-channel neural interface. In this study, we applied the blind source separation (BSS) technique to improve the separation between the neural channels. The BSS algorithm improved the selectivity from an initial value of less than 1% to 91% although the signal-to-noise ratio of the signals was as low as 0.46 on average.

**Keywords-** selective neural recording, blind source separation, independent component analysis, signal to noise ratio

## I. INTRODUCTION

Recordings of motor signals from the corticospinal tract with non-penetrating multi-contact electrodes have been investigated [1]. The preliminary data in acute animals showed that the evoked motor signals can be recorded with spatial selectivity from the spinal cord surface. However, the selectivity needs to be further improved for this interface to be used as a multi-channel neural interface.

The problem of extracting multiple source signals from a set of sensor measurements without any prior knowledge on the sources is termed as blind source separation (BSS) [2]. The main objective of this study is to investigate the performance of BSS technique as a method of improving the spatial selectivity of neural channels with multi-contact recordings of spinal cord in the presence of large contaminating sensory neural activity.

## II. METHODOLOGY

### A. Data Collection

The data set used in this study was reported in an abstract from earlier [1]. The motor cortex around the cruciate sulcus was stimulated with tungsten electrodes in cats under Ketamine anesthesia. The evoked potentials descending through the lateral corticospinal tract were recorded from the cervical spinal cord surface using silicone substrate multi-contact electrodes.

Each recording episode had seven contacts and consisted of 256 acquisitions of 10 milliseconds long neural activity following the cortical stimulation. The neural activity was acquired using spike-triggering method in synchronization with the stimulation pulses delivered to the motor cortex at a rate of 2 pulses per second. Two different neural patterns recorded during stimulation of two different cortical points were used to simulate the two neural channels. Only the first two contacts of each recording were used in this test. Fig. 1A shows the neural patterns (only the first contact of each is shown). To eliminate the stimulus artifact the first millisecond of each one of the 256

acquisitions was discarded and the remaining 9 ms long neural signals were padded sequentially to simulate a long episode of spontaneous neural activity. The second neural activity was right shifted by 5 ms to be able to see the neural volleys separately in the plots of the mixed signals.

Fig. 2 shows the flow diagram of the signals. For each neural pattern, the signals recorded with the first two contacts were summed together to simulate the original neural patterns (source signals, see Fig. 1B) before they were recorded by the spinal electrode. Recordings made with the spinal electrode while neural patterns were generated in the spinal cord were simulated by multiplying the source signals with a mixing matrix (A). This mixing matrix represents the relative amplitudes projected onto the contacts due to sources located separately in the cord. The mixing matrix was made near singular to make the initial selectivity very low. Then the simulated neural recordings (Fig. 3) were fed into the BSS algorithm for separation.

### B. BSS Algorithm

We applied the BSS algorithm proposed by Cichocki and Unbehauen [3], which is a further improvement and extension of the method proposed by Jutten and Herault [4]. A single-layer feed-forward neural network with learning capability was used (see Fig. 2). The adaptation rule of the BSS neural network coefficients,  $C(t)$ , based on the gradient method is: 
$$\frac{dC(t)}{dt} = a(t) \times [I - f(S(t)) \times g^T(S(t))] \times C(t) \quad (1)$$

with  $C(0) \neq 0$  and  $\det(C(0)) \neq 0$  (typically  $C(0) = I$ ),

where  $a(t)$  is the learning rate,  $f(\cdot)$  and  $g(\cdot)$  are two non-linear odd functions ( $f(x) = x^2 \times \text{sign}(x)$  and  $g(x) = \tanh(10 \times x)$ ),  $I$  is identity matrix, and  $S(\cdot)$  is the output signal. The learning rate  $a(t) > 0$  was a constant during the first phase (“search” phase of learning), and then it was exponentially decreased to zero in the second phase (“converge” phase of learning).

A two dimensional vector was formed from each pattern by taking the peak-to-peak amplitude of the first volley. After normalization, the Euclidean distance between the vectors was calculated as the selectivity index, which assumed a maximum value of 100% [1].

The signal to noise ratio (SNR) was defined as the ratio of the standard deviation of the averaged signals, which contained only the motor activity, and that of the background noise measured where motor signals were not present. The background noise mainly consisted of the sensory activity recorded from those superficial fibers located between the electrode and the corticospinal tract (see Fig. 1A). Thus, the noise component was always larger than the motor signals.

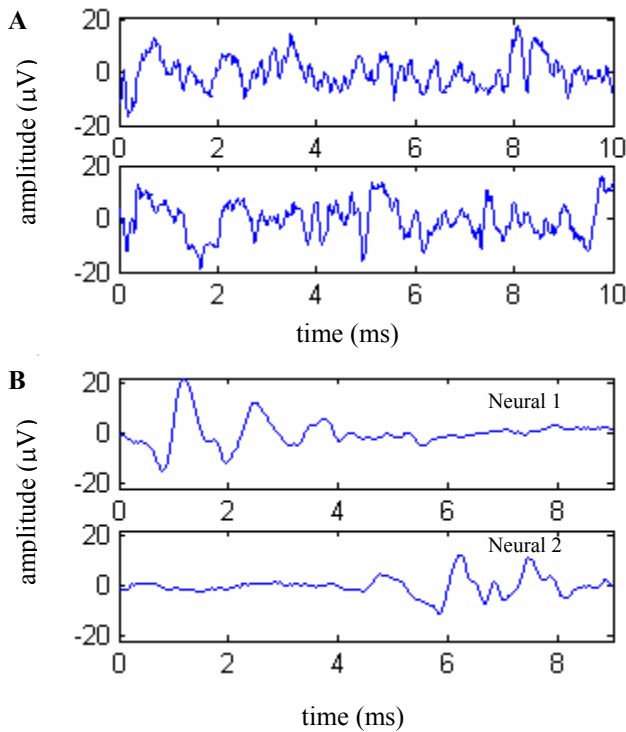


Fig. 1. A: 10 ms raw neural signals (including the stimulus artifact). B: The simulated source signals, Neural 1 and 2 (see Fig. 2.)

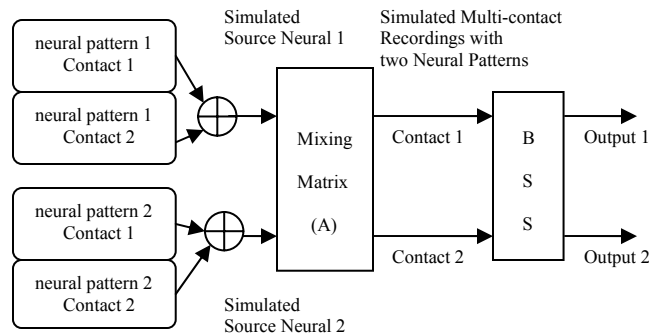


Fig. 2. Signal Flow Diagram.

### III. RESULTS

The SNRs of the four contacts of neural signals were measured as 0.51, 0.69, 0.27, and 0.36 respectively (mean SNR is 0.46 or  $-6.7$  dB). The motor signals are entirely obscured by the sensory neural activity (Fig. 1A). Fig. 3 shows the simulated two-contact recording with two different neural patterns (the correlation coefficient of the two patterns is 0.032), which is applied as an input to the BSS neural network. The mixing matrix  $A$  is  $[1.00 \ 1.00; 1.00 \ 1.01]$ . The arrows in Fig. 3 indicate peak-to-peak measurements used to form the vectors for calculation of selectivity index. In this case, the selectivity is only 0.26% and thus the two inputs look very similar in time (the correlation coefficient is 0.99). The spike-trigger averaged version of the output signals of the BSS neural network is shown in Fig. 4. The source signals are completely separated at the output. The correlation coefficient of the

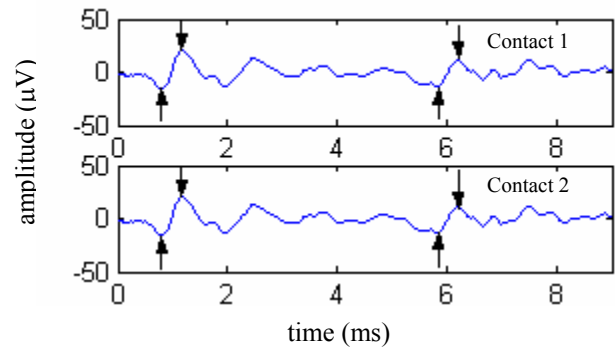


Fig. 3. The input signals to the BSS algorithm that are obtained by mixing the simulated source signals.

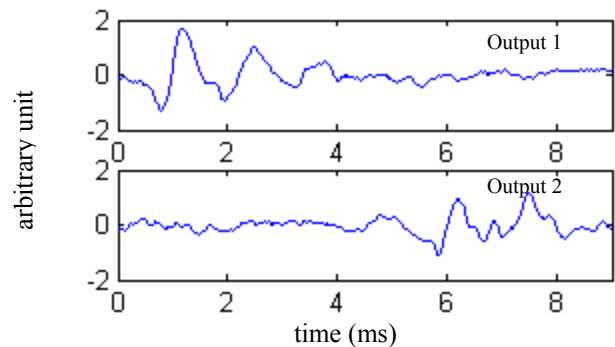


Fig. 4. The averaged output of BSS neural network. The first 156 acquisitions of the output, during which the neural network was still converging, were discarded and only the last 100 acquisitions were averaged. The source signals are recovered exactly by the BSS algorithm.

two outputs is 0.005. The selectivity is improved from 0.26% to 91%.

### IV. CONCLUSION

In this study, we tested the BSS technique for separation of neural patterns (channels) extracted from the epidural recordings of the spinal cord. The results suggest that BSS algorithm can be used for further separation of neural signals recorded with minimum spatial selectivity and low SNR.

### ACKNOWLEDGMENT

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