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Control signals generated through Blind Signal Separation of neural recordings

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Abstract

Functional electrical stimulation can be used to partially restore lost motor activities in neurologically impaired patients. The control signals for these neural prostheses can be generated from selective recordings of neural signals through nerve cuff electrodes.

However, selective recordings are still a weighted aggregate of the electrical activity of the fascicles within the nerve. The actual fascicular signals remain unknown. We propose to test, through a simulation study, the hypothesis of using blind source separation (BSS) of neural recordings made using the FINE to recover independent fascicular signals which will be used to generate the control signals. In BSS, original source signals are recovered from a recording of their linear mixtures. We introduce here a post-BSS processing method that will deterministically relate a separated fascicular signal to a contact point virtually locating a fascicle within a nerve.

1. INTRODUCTION

Loss of lower body function is generally caused by a proximal lesion or interruption of the nerve connected to the affected peripheral muscles leading to paralysis. One of the most prevalent methods of restoring lost peripheral function is through functional electrical stimulation (FES) by neural prostheses of muscles that have lost neural inputs. Neural recordings through nerve cuff electrodes are used to generate control signals for the FES systems. To this end, nerve cuffs have been used to record neural activity. In addition, selective recording of peripheral multi-fasciculated nerves have been used to record several control signals from a single implant. These recordings however, are an aggregate of the electrical signals stemming from different fascicles within the nerve. The actual fascicular signals remain unknown even with spatially selective recordings. We propose here the use of an alternative signal processing method, blind signal separation (BSS), for the recovery of fascicular signals from multi-contact recordings of peripheral neural activity.

2. METHODS

II.1-Simulation of Fasciular Signals and neural recordings

A fascicular signal is simulated from superposition of a randomly delayed compound action potential AP(t). AP(t), generated in Neuron [7], is a triphasic compound action potential with a duration of 1 ms and represents the signal from a small subpopulation of fibers as voltage with respect to time. Signal *s*, which is the fascicular signal, is generated from N AP(t) signals, according to the equation shown below, which is given in [13] and shown sufficient to simulate fascicular electrical activity. In this study N = 61,790.

$$s(t, t_{01}, \ldots, t_{0N}) = \sum_{i=1}^{N} AP(t - t_{0i})$$

Background noise invariably present in neural recordings is simulated by a linear addition of a uniformly distributed random signal to *s*. The SNR of the fascicular signal in this study was approximately 20 dB.

Comment [MM1]: Should you reference Jezernik somewhere in here?

The potential distribution at the surface of the nerve which comprises electrically active fascicles is simulated through a finite element software package (ANSOFT). In AUTOCAD, the Flat Interface Nerve Electrode (FINE) was added to the model as a silicone cover over an area of the nerve. The conductivities were 0.0826 S/m radial and .5714 S/m longitudinal for endoneurium, 0.0826 S/m for epineurium, 0.0021 S/m for perineurium, 2 S/m for saline, and 10^{-7} S/m for silicone (used to make the cuff electrodes). The nodes of Ranvier were introduced in the fascicles as equidistant small cylinders of 6 μm diameter and 4 μm length. The instantaneous potential distribution all over the cuff electrode could be obtained whenever electrical activity, signal *s(t)*, travelled through a fibber in one of the fascicles.

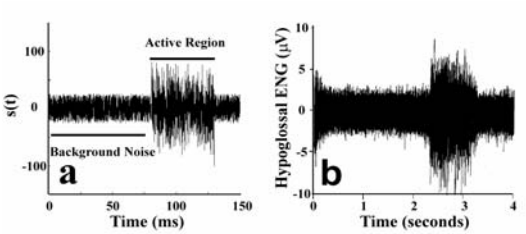

Fig 1. (a) Simulated fascicular signal. The region during which the fascicle is active has Gaussian distribution. (b) Experimental recorded nerve signal

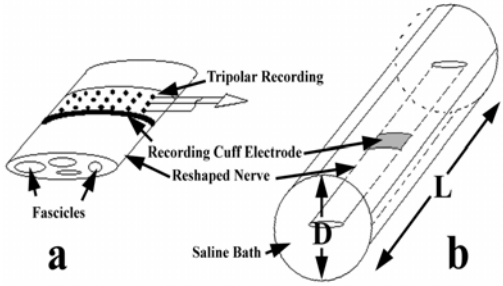

Fig. 2. Geometry of simulated nerve submerged in saline. (a) The nerve comprised of four fascicles with the FINE electrode wrapped around it. (b) The nerve submerged in Saline bath (D = 6mm and L = 60mm).

It should be noted here that the signal in the fascicles is a traveling signal and the potential distribution generated at the electrode surface is accordingly time dependent. The potential distribution at the electrode was also calculated in cases where several fascicles were simultaneously active.

II.2- Blind Source Separation and post-BSS processing

M channel recordings of *P* linearly mixed independent signal sources can be separated to recover the original *P* signal sources as long as $M \geq P$. In our case, the array of recorded signals *x(t)*, obtained from neural recordings made using the FINE, can be written in terms of the original source signals *s(t)*, the mixing matrix *A*, and recorded noise *n(t)* as

$$x(t) = As(t) + n(t)$$

The approximated independent sources *a(t)* would then be

$$a(t) = Wx(t)$$

where *W* is a demixing matrix,

$$W = A^{-1}$$

W is obtained by minimizing an objective function which measures the degree of independence between the elements of *a* obtained using *W*. Objective functions are real-valued functions of the distribution of *x(t)*. They should be at a minimum once the original source signals have been recovered.

The objective function used here is of the information theoretic class and consists of an approximation to negentropy, its maxima are at the zero crossing of a known equation. The solutions to the zeros crossing are estimated using Newton's method, where the Jacobian is approximated by a diagonal matrix making its inversion much less computationally intensive[9].

Post BSS processing; matching a contact point to a fascicle

Inherently, BSS methods have a permutation ambiguity. The separated fascicular signals cannot be consistently matched to a fascicle. This is problematic because the estimated signals must be associated with their corresponding fascicles if they are to be useful as control signals. This problem can be overcome by using a first estimate of the mixing matrix obtained through BSS as a template to rearrange the columns of subsequent estimations. The columns of the estimated mixing matrix relay a fascicular signal to a contact point.

3. RESULTS

The simulated fascicular signals are shown in fig 3.A. The recorded signals at the contact points are shown in figure 3.B.

The simulated signals were then separated using FastICA and are shown in figure 3.C. The vector *a(t)* of separated signals comprises the estimation of the original fascicular signals which can be recognized by comparing waveforms of the original and separated signals. In fifty trials the mean values and the standard deviations of the correlation coefficients between the original signals and their estimates were 0.86 and 0.15 respectively. However, the relationship between the reconstructed signals and the fascicles from which they originate is ambiguous.

Figure 4 is a colour coded plot of the normalized columns of the estimated mixing matrices. In figure 5, the original source signals and the estimated source signals after post-BSS processing are shown.

Comment [MM2]: Do these come from windowed/rectified signals? OR are these the correlation coefficients between A and A2?

4. DISCUSSION AND CONCLUSIONS

We have showed in this study that fascicular signals can be deterministically estimated from peripheral nerve recordings using the FINE.

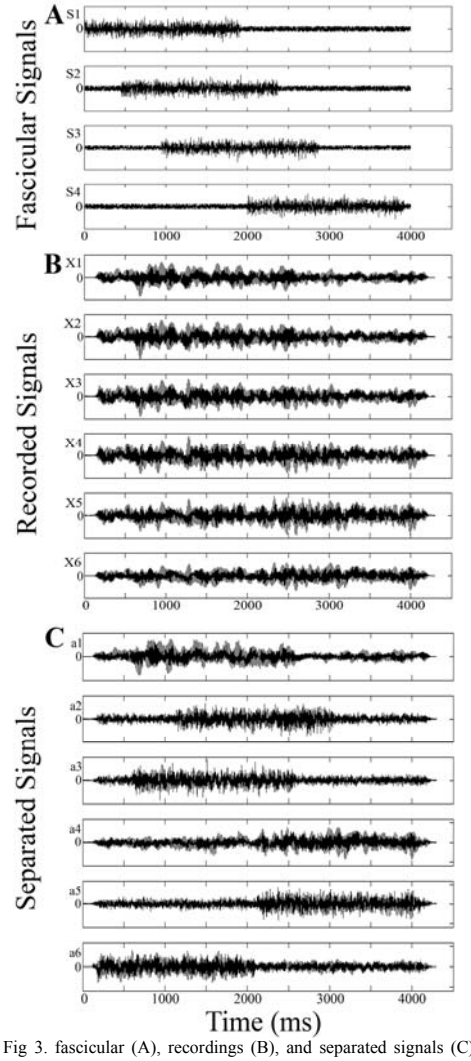

Fig 3. fascicular (A), recordings (B), and separated signals (C). The active regions of the fascicles can clearly be seen in the fascicular and separated signals.

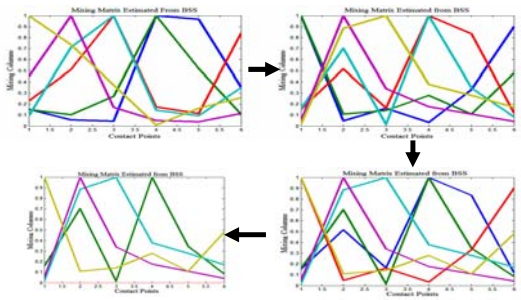

Fig 4 Color coded plot of the columns of the estimated mixing matrix. While following the arrows, we go from a first estimate of the mixing matrix to a second estimate. The columns of the estimated matrices are then rearranged with the first matrix as a template and finally two of the least independent columns are dropped to complete the post-BSS processing.

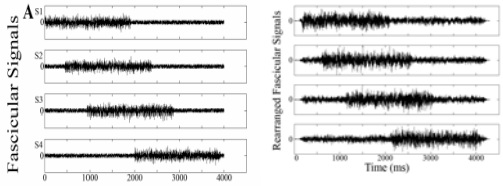

Fig 5. Original fascicular signals (left figure) and estimated fascicular signals after post-BSS processing to fix BSS' inherent permutation ambiguity

The fascicular signals were separated by Independent Component Analysis, implemented by the FastICA algorithm of Hyvarinen. The permutation ambiguity of BSS was solved by using a first estimate of the mixing matrix as a template to rearrange the columns of all subsequent estimations.

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Acknowledgements

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