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Blind source separation of neural recordings and control signals

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Abstract— **Neural signals recorded in parts of the body where voluntary movement has been retained can be used to control prosthetic devices that assist patients to regain lost function. The number of signals recorded to control these devices can be increased by using a single multi-contact electrode placed over a muti-fasciculated peripheral nerve. Recordings made using these electrodes can then be separated using Blind Signal Separation (BSS) methods to recover individual fascicular neural activity.**

In this study, we investigate the feasibility of separating peripheral neural recordings, obtained using a multi-contact electrode, to recover individual fascicular signals. We implement BSS through independent component analysis (ICA) and investigate the effects of the number of contacts used and electrode layout on separation.

Peripheral neural signals were simulated using a finite element model of the hypoglossal nerve of adult beagle dogs with a multi-contact cuff electrode placed around it. FastICA was then used to separate simulated neural signals. The separated and post-ICA processed neural signals were then compared to the original signals in the fascicles that caused them through correlation coefficient (CC) calculations. For n = 50 trials, the CC values obtained were all higher than 0.9 indicating that BSS can be used to recover linearly mixed independent fascicular neural signals recorded using a multi-contact cuff electrode.

I. INTRODUCTION

Patients with neurological disorders can be assisted to regain lost motor function through functional electrical stimulation (FES), which has so far been used to treat respiratory disorders [5, 13, 22], and to restore bladder continence [1, 7, 22]. The stimulating signals can be controlled by recordings of afferent sensory neural signals, which complete a closed-loop prosthetic device.

In closed-loop prosthetic devices, neural signals are recorded using cuff electrodes which have been shown to be stable for long-term recordings [6, 9, 18, 19, 21], and to increase the SNR of the neural recordings [16].

Fibers in peripheral nerves functionally organize into fascicles, and may contain both afferent and efferent signals. Therefore, peripheral nerves may contain several independent signals, which can be selectively recorded to obtain control signals. To this end several methods, including microneurography [15, 20] and nerve cuff electrodes [6, 14], have emerged to selectively record from peripheral nerves. Selective recording of fascicular signals in a peripheral nerve is achieved by optimally placing each contact of a cuff electrode to the nearest fascicle. Selectivity may be further increased by using the flattening interface nerve electrode (FINE), which Yoo and Durand [22] have shown can achieve a selectivity index of up to 0.76. The design of the FINE further increases the proximity of a contact to a fascicle in a nerve by reshaping the latter and rearranging the fascicles within it.

In microneurography, selective recording is achieved by inserting the micro tips of an electrode array, such as the Utah Slanted Electrode, directly into different fascicles [2, 3, 21]. In addition, selective recording can also be achieved using nerve cuff electrodes placed around the nerve. In Rozman et al. [15], selective recording from fascicles is achieved by optimally placing the contacts of a cuff electrode over the nerve so that each contact is affected by the nearest fascicle. For a similar effect, Yoo and Durand [22] used the Flattening Interface Nerve Electrode (FINE) and achieved a selectivity index of up to 0.76. The advantage of the FINE design over other cuff electrodes is that the nerve is relatively flattened by the electrode, causing the fascicles to rearrange and increase their proximity to specific contacts. Cuff electrodes have also been used to achieve fascicular selectivity based on, among other techniques, the velocity of the neural signals in each fascicle [18].

In this study, we investigate the feasibility of using ICA as a BSS method to recover fascicular signals from simulated peripheral neural recordings. Known statistical properties of neural signals are used to generate the fascicular source signals [12]. A finite element model of the hypoglossal nerve of a beagle dog was used to simulate FINE neural recordings.

II. METHODS

We start the study by implementing a model of a peripheral nerve to simulate realistic neural signals and by reviewing the process of recovering fascicular signals.

A. Simulating the neural recordings

A.1. Generating the fascicular signals

Recorded neural electrical activity has been shown to result from the superposition of randomly delayed *N* single fiber action potentials recorded extracellularly [12]. The single fiber action potential (SFAP) was obtained from a computer model (NEURON®, [8]) of a myelinated axon using mammalian membrane dynamics [17] and has a duration of 1ms (figure 1). The fascicular signal *s(t)* is calculated in a

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finite, fixed length time window t ϵ [0,T], where T >> 1ms. A stochastic process of *N* realizations is used to generate random shifts t_{0i} ϵ [1ms, T-1ms]. The signal *s(t)* is generated by superposition of *N* SFAP signals each delayed by t_{0i}.

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

The Kolmogorv-Smirnov test was used to verify that signal *s(t)* is Gaussian as predicted by the central limit theorem. Background noise present in neural recordings was simulated by adding a uniformly distributed random signal to *s(t)*. The SNR of the generated fascicular signal was in most cases between 15 and 25 dB (figure 1.b). The active region in figure 1b during the recording represents a period where the fascicular activity consisted of a functional stimulus.

A.2. Simulating nerve cuff recordings

The neural signal on the surface of the nerve was simulated using a finite element model (FEM) of the hypoglossal nerve. A two dimensional image of the nerve cross-section was generated in AUTOCAD and extruded into a three dimensional FEM (Maxwell 3D, Ansoft Corp). The model is described in [22]. In the model, thirty one nodes of Ranvier were inserted in the axons as equidistant small cylinders of voltage sources. The voltage source at a node of Ranvier in a fascicle consisted of one realization of the fascicular signals S_1- S_4 shown in figure 1b.

B. Blind Source Separation by independent component analysis

Given *M* channel recordings of *N* linearly mixed source signals, it is possible to recover the *N* original source signals from the *M* channel recordings if 1) the *N* source signals are mutually independent, 2) the independent source signals are linearly mixed, and 3) $M \geq N$ [4, 10]. The array of recorded signals *x(t)* can be expressed as a function of the original source signals *s(t)*, the mixing matrix *A*, and recorded noise *n(t)*:

$$x(t) = As(t) + n(t) \quad [2]$$

The estimated source signals *c(t)* can then be obtained from

$$c(t) = Wx(t) \quad [3]$$

W, the estimated demixing matrix, is obtained by optimizing an objective function which implicitly measures the degree of mutual independence in the estimated source signals. The optimization is achieved when the iteratively estimated source signals are maximally mutually independent [10, 4, 11]. An example of such an objective function would be one that measures the non-gaussianity of the distribution of the estimated signals. Studies have shown that an objective function that measures the negative entropy (negentropy) of a variable is equivalent to one that measures non-gaussianity [4]. Practically, an objective function that approximates negentropy, *J(x)* (equation [4]) is optimized in a multi-dimensional landscape.

$$J(x) \approx k_1(\varepsilon\{G_1(x)\})^2 + k_2(\varepsilon\{G_2(x)\} - \varepsilon(G_2(\upsilon))\})^2 \quad [4]$$

with $G_1(x) = (1/a_1) \log \cosh(a_1 x)$, $G_2(x) = -\exp(-x^2/2)$, ν is a Gaussian variable, $1 \leq a_1 \leq 2$, and K_1 and K_2 are constants.

The set of simulated recordings, described in III.A.2, were separated using ICA to estimate the fascicular source signals that generated them. The similarities between the original fascicular sources and their estimates were quantified by calculating the correlation coefficients between the two signals. Since correlation coefficients (CC) calculated between the raw signals would not have provided accurate information about their similarity, instead, the coefficients were calculated between the envelopes of the signals.

The reliability of ICA to consistently separate simulated recordings and estimate the underlying fascicular source signals was tested by simulating the neural recordings for fifty sets of four fascicular source signals, each with a random delay before onset of spontaneous activity, and separating them using ICA. The CC's between the envelopes of the source signals and their estimates were then calculated.

B. The effects of electrode layout and contact number

The effects of using three different electrode layouts on the success of separation were also investigated. Three different layouts of six recording contacts around the cuff electrode were chosen (table 3). The simulated recordings for each layout were then separated and the CC between the original and estimated fascicular sources was calculated. The effects of electrode layout were investigated in 10 trials and the results given in table 3. The effects of the number of contacts used on separation were investigated by using a different number of contacts (4 through 9) to obtain each set of recordings. The CC between the original and estimated fascicular signals were then calculated for 10 trials and shown in table 2.

III. RESULTS

A. Generation, mixing, and recovery of fascicular signals

A sample set of four fascicular signals, each independently generated as indicated in the methods section, is shown in figure 2a. In each fascicular signal, the delay of onset of the active region is progressively increased. A sample set of neural signals calculated using finite element simulations (FEM) and obtained from the top six contacts of the FINE electrode is shown in figure 2b. While the FINE in the FEM had 12 contacts total, only recordings from the top six contacts were used in this study. The simulated neural recordings are a mixed representation of the original source signals (S_1-S_4). A set of fascicular source signals recovered by separating the set of six neural signals (figure 2b) using FastICA is shown in figure 2c. Four out of the six estimated fascicular signals shown in

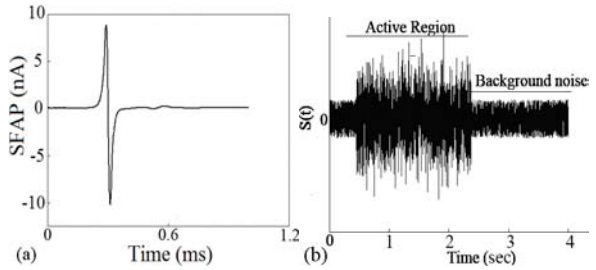

Figure 1. SFAP and the fascicular signals. **a)** Current waveform of a single fiber action potential SFAP obtained from a computer model. **b)** Fascicular signal *s(t)* simulated by summing randomly delayed *N* SFAP's, where *N* = 67,000

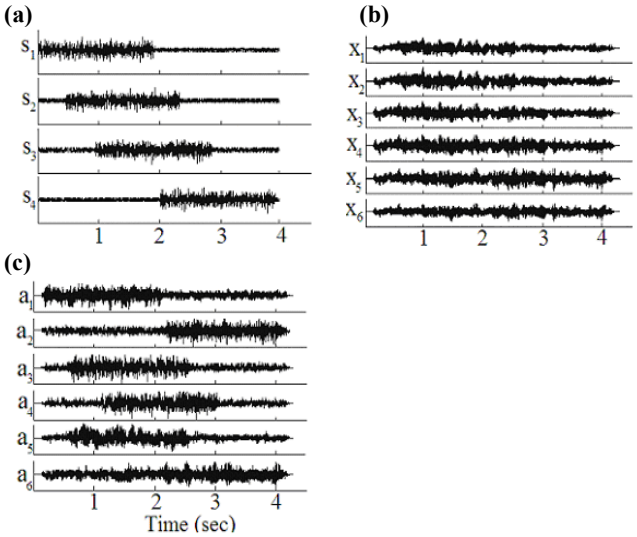

Figure 2. A set of fascicular source signals (a), the simulated neural signals they cause recorded at the surface of the nerve (b), and the estimates of the fascicular signals (c)

figure 2c correspond to the original fascicular source signals shown in figure 2a. The remaining two estimated signals in figure 2c appear to consist of combinations of several fascicular signals and have no counterpart in figure 2a. The four estimated fascicular signals with the highest CC with the original signals were accepted as the estimates.

Fifty sets of fascicular sources were generated as described above, linearly mixed, and separated using ICA. The CC between the separated signals and the source signals were then calculated. For each trial, fascicular and separated signals with the highest CC were identified as a pair of source and estimate. The mean and standard deviation, out of fifty trials, of the CC's calculated between each pair are given in table 1. In all fifty trials, the CC's were higher than 0.9. These results show that a set of four fascicular source signals, whose functional activity may arbitrarily overlap and are linearly mixed, can be successfully and simultaneously recovered from a set of six signals of their mixtures.

B. The effect of electrode layout and number of contacts

The effect of the number of contacts chosen for each set of recordings on separation with ICA was studied by varying the number of contacts from four to nine and calculating the CC's between each fascicular source signal and its estimate, estimated from sets of recordings with a given number of contacts. Ten trials (10) were conducted for each number of contacts used during recordings. These results are presented in table 2. The mean CC values calculated for four contacts were higher than 0.95 for three of the estimates, but fell below 0.4 for one of the fascicular sources and its estimate (table 2). However, the mean CC's for the remaining sets of recordings, five to nine contacts, were higher than 0.95 for all four fascicular sources of each set (table 2). These results show that a set of recordings with five contact signals is sufficient to recover a set of four fascicular source signals using ICA.

The effects of the location of the contacts around the electrode were studied through three sets of simulated recordings, with each set consisting of a different combination of six contacts of the FINE (table 3). The simulated recordings for the three different combinations were then separated using ICA. The CC's calculated between the fascicular sources and their estimates were higher than 0.95 for all three sets of simulated recordings. These data suggest that a good estimate of the fascicular signals could be obtained independently of the combination of contacts chosen for the sets of recordings as long as five or more contacts are chosen. This set of signals was chosen to determine the ability of the algorithm to recover signals that overlap (S_1 through S_4) and those that do not (S_1 and S_4).

IV. DISCUSSION

Closed loop controlled neural prostheses can be used for successful restoration of lost motor function. Blind Source Separation (BSS) of a set of neural signals recorded using a multi-contact cuff electrode can be used to obtain multiple control signals. The feasibility of BSS of neural signals was investigated by using a finite element model of the hypoglossal nerve of adult beagles to simulate the potential distribution at the surface of a nerve caused by traveling fascicular signals and recorded using the FINE.

	S_1 & estimate 1	S_2 & estimate 2	S_3 & estimate 3	S_4 & estimate 4
Mean CC	0.97	0.98	0.96	0.96
STD	$0.15*10^{-3}$	$0.81*10^{-3}$	$0.31*10^{-3}$	$0.88*10^{-3}$

Table 1. Mean and standard deviation of the CC values calculated between the source signals and their estimates for 50 trials

	CC between each original and estimated fascicular signals			
Layout	S_1	S_2	S_3	S_4
1	0.97	0.96	0.97	0.34

2	0.97	0.98	0.97	0.94
3	0.97	0.98	0.96	0.95
4	0.97	0.97	0.98	0.95
5	0.97	0.97	0.98	0.95
6	0.97	0.97	0.98	0.95

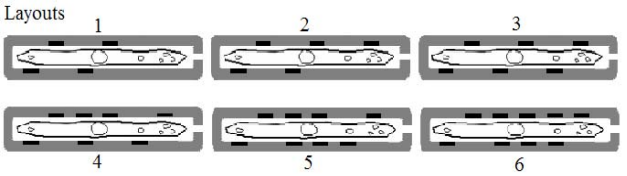

Table 2. The CC values between original and estimated fascicular signals for recordings obtained using different numbers of contacts

	CC between original and estimated fascicular signals			
Layout	S_1	S_2	S_3	S_4
1	0.97	0.98	0.97	0.94
2	0.98	0.97	0.97	0.93
3	0.97	0.98	0.98	0.94

Table 3. CC values calculated between estimated and original fascicular signals when recordings are obtained using three different combinations of contacts

The feasibility of using ICA to estimate fascicular source signals from simulated recordings was verified by the high mean CC's (> 0.9) between the envelopes of the original and estimated fascicular signals for fifty trials.

We also found that, contrary to what is stipulated in the conditions of ICA, it was necessary to have a minimum of five recording contacts to recover four fascicular source signals from the recordings. This may be due to the very small separation space between contacts, which reduces the difference between simulated neural signals recorded at each contact

The matrix representation of the intraneural medium is also dependent on the location of the recording contacts on the nerve. However, the simulation results have shown that all four fascicular source signals can be recovered independently of the location of the contacts. This may be due to the fact that amplitude variability of the source signals has little or no effect on the objective function as long as it is within a certain range. Therefore, it is possible to recover fascicular signals from a range of fascicles each consisting of fibers with different fiber-diameters and by using a FINE whose contacts are arbitrarily spread around the nerve.

V. CONCLUSION

Simulated neural recordings obtained with a multi-contact FINE were separated to recover the fascicular source signals using an ICA algorithm. Four independent fascicular sources were recovered from six simulated channel recordings with CC > 0.95. The recovery was independent of the location of the recording contacts on the nerve, the overlap between the signals. Animal experiments must be conducted to verify whether afferent peripheral neural information can be efficiently extracted from FINE recordings for the implementation of closed-loop controlled prosthetic devices

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