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Localization and Recovery of Peripheral Neural Sources with Beamforming Algorithms

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Abstract

The peripheral nervous system carries sensory and motor information that could be useful as command signals for function restoration in areas such as neural prosthetics and Functional Electrical Stimulation (FES). Nerve cuff electrodes provide a robust and safe technique for recording nerve signals. However, a method to separate and recover signals from individual fascicles is necessary. Prior knowledge of the electrode geometry was used to develop an algorithm which assumes neither signal independence nor detailed knowledge of the nerve's geometry/conductivity, and is applicable to any wide-band near-field situation. When used to recover fascicular activities from simulated nerve cuff recordings in a realistic human femoral nerve model, this beamforming algorithm separates signals as close as 1.5mm with cross-correlation coefficient, $R > 0.9$ (10% noise). Ten simultaneous signals could be recovered from individual fascicles with only a 20% decrease in R compared to a single signal. At high noise levels (40%), sources were localized to $180 \pm 170 \mu\text{m}$ in the 12x3mm cuff. Localizing sources and using the resulting positions in the recovery algorithm yielded $R = 0.66 \pm 0.10$ in 10% noise for 5 simultaneous muscle-activation signals from synergistic fascicles. These recovered signals should allow natural, robust, closed-loop control of multiple degree-of-freedom prosthetic devices and FES systems.

Index Terms

Beamforming; blind source separation; cuff electrode; flat interface nerve electrode; inverse problem; localization; selective neural recording; spatial filters

I. Introduction

Localization and recovery of electromagnetic sources in volume conductors are often solved using Inverse Problem techniques. These techniques require high levels of model accuracy and signal-to-noise ratios (SNR). In particular, the reliable recovery of fascicular sources from whole nerve recordings has presented an unsolved problem. Peripheral nerves of the body carry both command and sensory signals in more accessible forms than found in the central nervous system, and could provide signals necessary to control high degree-of-freedom prosthetics, and closed-loop Functional Electrical Stimulation (FES) systems. Nerve recording methods are relatively non-invasive and safe [1]. While numerous studies have documented the selective stimulation properties of conventionally round (i.e., transverse geometry) and even self-sizing electrodes [2], there is little experimental data concerning the ability of such electrodes to record and distinguish between different active fascicles [3]. Blind Source Separation techniques are able to decompose fascicular signals from Flat Interface Nerve Electrodes (FINEs), but require that each signal is independent

from the others [4, 5]. Muscle synergies are the clearest example of why this may not be a valid assumption.

Several other methods have been described in the literature for localizing or separating nerve trunk signals such as Neuro-fuzzy algorithms that use prior knowledge implicit in fuzzy systems with Artificial Neural Networks [6]. Good single subject performance was achieved, but with only small angular oscillations of the ankle joint. Inverse Problem methods have also been investigated including an application of Radial Basis Functions (Kansa's method) by [7], and the sLORETA algorithm by [8]. However, Ling, et al. [7] required close initial guesses for convergence and no testing was done with realistic or varying geometry. Zariffa and Popovic have recently provided data on the accuracy of localization (but not recovery) of their approach in a single-fascicle simulated rat model [9] as well as their ability to perform forward model reduction [8]. Neither group discusses algorithm speed so it is unclear whether these methods would be appropriate for real-time control applications.

We propose a different approach that takes into account available *a priori* knowledge not previously utilized and does not rely on the specific anatomy of the nerve, avoiding poor generalization. The proposed technique is based on antenna array beamforming, or spatial filters [10], and can be applied to any near-field wide-band case, particularly where the signal propagates too fast for timing information to be helpful. Linear, time-invariant real-valued weights are applied to the voltage recorded at each contact on the FINE nerve cuff electrode to shape the receptive field within the nerve. Due to the low frequency components of the signals, and the very short distances between the contacts, it is not practical to include phase or time delays in these weights, as is common in traditional beamforming. The algorithm is based on *a priori* knowledge of the cuff geometry (*a priori* Finite Element Model), and was tested on a realistic nerve model with anisotropic conductances (realistic Finite Element Model). Moreover, no assumptions on signal independence were required as is the case for blind separation method. This work was previously presented in abstract form [11]

II. Method

A. Beamforming Algorithm

The algorithm is divided into 2 training stages: First, a transformation matrix is built from the *a priori* Finite Element Model (apFEM). The Transformation matrix requires no additional information about the nerve, and is time-invariant. It is built using only prior information about the electrode geometry and an estimate of the epineurial conductivity. This matrix operates on the recorded voltages to produce an image of estimated activity levels within a cross-section of the nerve. The second training step takes place following cuff implantation, or using the realistic FEM (rFEM) for the simulation. Source localization is performed using a map of the estimated activity produced by the transformation matrix. The source localization training must be done after the cuff is implanted and signals are recorded. Once these training stages are complete, the algorithm consists of multiplying the recorded voltage at each contact by the transformation matrix (created from the lead-field matrix of the *a priori* model) and averaging the values of the pixels selected for the fascicle of interest (identified during source localization) in the resulting image.

1) The *a priori* Finite Element Model (apFEM)—The *a priori* FEM consists only of the insulating cuff electrode, large saline volume conductor, and simple rectangular epineurium filling the cuff. It was created in MAXWELL 3D (Ansoft Corp.), and is shown in Figure 1a, b with lengths and conductances given in Table 1. This model is used to calculate the sensitivity (or lead-field) matrix, which provides the calculated voltages on all recording

channels due to sources placed throughout the epineurium (the “forward problem” we are attempting to invert) and is calculated using reciprocity similar to Weinstein et al. [12] by placing a source on each recording contact in turn and recording the resulting voltage throughout the epineurium. It is calculated using only prior information about the electrode geometry and an estimate of the epineurial conductivity, since this information is all that is present in the apFEM. Each of the 22 contacts was set to 1mV in turn, with the outer faces of the volume conductor grounded, and the voltage was calculated in the x-y plane in the middle of the cuff. The vectors corresponding to the voltage generated by each contact were concatenated into the sensitivity (or lead-field) matrix, S . It is known from Electromagnetic Reciprocity theorem that the measurement will not change if the field point and source point are interchanged [13]. Thus, this sensitivity matrix also gives the recorded voltage at each contact due to a source at each pixel (i.e. the lead-field matrix [12]). Since the system is linear and superposition applies, linear combinations of these sensitivities can be generated to optimize the sensitivity for each pixel and generate the transformation matrix.

2) The Transformation Matrix—To calculate the transformation matrix, the weights (t_i) on the sensitivity vectors (S) for each contact are optimized for a source signal located in a single ideal pixel (δ_i). The following equation (1) is solved for each pixel i where,

$$S t_i = \delta_i \quad (1)$$

Assuming n recording contacts and m pixels in the desired reconstruction, the variables are $S^{\{m \times n\}}$, the sensitivity matrix, and $t_i^{\{n \times 1\}}$ the linear coefficients of the transformation matrix. Note that this equation is entirely independent of time and considers only the static behavior of the model. For increased efficiency, the reduced QR factorization of $S^{\{m \times n\}}$ is first calculated so that for δ_i equal to the delta function at index i , the solution reduces to Equation 2, below, where q_i^* is the i^{th} row of Q (since Q is orthogonal, the inverse is equal to the transpose). Normalization is performed for each set of weights, as in Equation 3.

$$t_i = R \backslash q_i^* \quad (2)$$

$$t_i = \frac{t_i}{\|S t_i\|} \quad (3)$$

The column vectors t_i can then be concatenated to form the transformation matrix $T^{\{m \times n\}}$, which operates on a single time point t of observed data ($o^{\{n \times 1\}}$) to produce the estimated activity at each pixel ($\hat{a}^{\{m \times 1\}}$) at time t (4). This activity vector can then be displayed as an image of the estimated activity in the plane of interest. Repeated application of the Transformation matrix at different time points gives the time dependence to this procedure.

$$\hat{a} = T o \quad (4)$$

B. Source Localization

When the transformation matrix is multiplied by the vector of voltages on each contact (Equation 4), an image is created providing an estimate of the activation of each pixel within the cross-section of nerve. A simple local-maxima-based algorithm was used to locate sources in the estimate using automatic thresholding to remove areas of low activity (Otsu's method [14]). Morphological opening (erosion followed by dilation) which removes islands and peninsulas below a given size from a binary image was applied to prevent the algorithm

from finding small sources near the periphery associated with noise. Once the fascicle locations are determined, the beamformers for those locations are applied to the full time-signal in order to reconstruct the fascicular activity. Post-processing techniques, such as RMS windowed averaging or BSS, can improve SNR and reduce cross-talk.

C. Realistic Finite Element Model (rFEM) for Testing the Algorithm

FEM simulations for validation of the recovery algorithm were performed with a realistic nerve model consisting of the same cuff as previously described but with the addition of realistic nerve geometry obtained from histological analysis of a human femoral nerve [15] (Figure 1c,d) with conductivities given in Table 1. Ten fascicles, out of the 22 in the model were chosen to contain active sources representing a broad distribution of location, diameter, and separation distance. Ten axons were placed in the center of each fascicle, and these axons were each assigned a random diameter between 5.5 and 12.5 μm . Nodes of Ranvier were placed corresponding to each diameter, starting from a random center position on each fiber. Each node of Ranvier was simulated separately to create a lead-field matrix.

D. Axonal Activity Simulations

The 1978 Moore model of the myelinated axon was used to generate diameter-specific space (node) – time action potential transmembrane currents [16], (Figure 2a). This waveform is similar in shape to the leaky patch clamp recordings of Meeks, et al. [17]. Due to the linearity of the medium, these transmembrane currents are proportional to the nodes' extracellular voltages. The lead-field matrix from the rFEM is multiplied by the voltage at each node to calculate the voltage recorded due to that node. These voltages are then summed to generate a Simulated Single Unit Action Potential (SSUAP), shown in Figure 2b. A fixed number of SSUAPs were randomly distributed within given windows of activity for each active fascicle and summed to generate a simulated recording (SR) of a neural signal [18], shown in Figure 2c (top) along with a typical experimental recording (bottom). The sampling rate for all simulations was 20kHz. Gaussian white noise was added to a given percentage of the variance of the signal.

III. Results

A. Localization of Sources

A propagating source simulating realistic neural signals made by summing a fixed density of randomly delayed action potentials over a 100ms window of activity (Figure 3a) was placed in a single fascicle. The signal power (RMS) at each contact was calculated in 10ms bins, the beamforming localization procedure was applied to each one (Figure 3b) and the mean of the resulting list of sources calculated. This estimated location (green cross, Figure 3c) was then compared to the known location (red square, Figure 3c) and overlaid onto the fascicle map of the nerve for reference. The estimated sources are found to be within the correct fascicle. This process was repeated 10 times, at 3 different noise levels, for each of the 10 fascicles tested. The results for one trial of all 10 fascicles at the highest noise case (40%) are shown in Figure 3d, where the estimated source is shown as a green circle and the true location a red square. Even at this noise level, the figure clearly shows that all 10 sources are located to within their respective fascicles.

Without noise, the mean distance between recovered and actual source position over all trials and all sources was $0.14 \pm 0.03\text{mm}$ ($N=100$). As the noise level is raised, the mean and especially the standard deviation increase to $0.18 \pm 0.17\text{mm}$ ($N=100$). The results for all noise levels are presented in Table 2. These results suggest that the location of single sources can be identified to $180 \pm 170\mu\text{m}$ even in the presence of significant noise in the signal.

To determine the ability of the algorithm to localize two simultaneously active fascicles, a fixed density of action potentials from axons in 2 fascicles were randomly distributed over a 100ms window with 80ms on-time for each fascicle and offset by 20ms to account for the fact that source amplitudes are likely to vary with respect to each other (not shown). Signal power (RMS) was calculated for each 10ms bin, and the beamforming algorithm applied. An unsupervised k-means classifier (for $k=2$) was used to group the putative sources. This procedure was repeated 5 times for each possible pair of fascicles, in 0, 10, and 40% noise. The localization error was 0.34 ± 0.09 mm ($N=225$) at 0% noise with little variation due to source separation. At 40% noise, the overall error was 0.6 ± 0.7 mm ($N=225$) although close source pairs showed much higher error than the others. When separation was greater than 3.5mm, the 40% noise results were similar to those at 0% noise. In high levels of noise, close sources may be confused as a single source, causing the algorithm to mistakenly identify distant noise as the second source. More complex algorithms able to estimate the number of local-maxima to search for may perform better in these cases. However, as this localization step only needs to be performed once during training, the restriction to 1 or 2 simultaneous fascicles or functional groups is reasonable. During this short training, specific movements or stimulation can be used to ensure only 1 or 2 fascicles are active at a given time. It is also often possible to judge from the resulting image both how many fascicles are active and their approximate locations.

B. Recovering Fascicular Activation in Time

1) Recovery of two active sources—To determine the ability of the algorithm to recover the signals in time once the localization of the source is known, simulated single fascicle recordings (SR) were summed, two at a time with 0, 10, or 40% added Gaussian noise. The beamforming algorithm was applied at each time point and the pixels corresponding to each fascicle were used to generate the Reconstructed Fascicle 1 (RF1) and Reconstructed Fascicle 2 (RF2) signals. In order to determine the accuracy of the recovery algorithm alone, the known fascicular locations were used. The same procedure was repeated 10 times for each possible pair of fascicles with Fascicular Activity (FA) signals regenerated randomly each time, and multiplied by the FEM lead-field matrix to create new SRs. A 10ms RMS windowed average was applied to all signals, both to improve noise tolerance and correct for differences in the shape of single unit activity at the individual nodes of Ranvier (in the FA signals) and the recording contacts (in the SR and RF signals), as shown in Figure 2a and b.

An example of the RMS averaged actual (FA) and recovered signals (RF) is shown in Figure 4a. These signals show very low cross-talk and each pair is highly correlated ($R > 0.9$). Each possible pairing of the 10 fascicles was tested 10 times for each of the 3 noise levels, for a total $N=1350$. The cross-correlation coefficients are plotted in Figure 4b versus the distance between the fascicle centers. The figure shows R exponentially increasing towards 1 with increasing separation distance, as expected since less mixing occurs between sources that are farther apart. Recovery with $R > 0.9$ was achieved for sources separated by a minimum distance of approximately 1.5 mm, or about twice the diameter of a typical fascicle and half the height of the cuff. Note that for some pairs of close fascicles, the cross-correlation is still very high compared to others with similar separations, suggesting that the geometry of the surrounding fascicles plays a significant role in the quality of recovery.

2) Effect of Multiple Active Fascicles—In a physiological situation, there would likely be more than two fascicles from which to record (depending on the nerve and location). Therefore, we tested the ability of the algorithm to recover signals from n simultaneously active fascicles, for n from 1 to 10, again assuming the true source locations were known. In each trial, exactly n fascicles were active at all times, and all possible combinations of n

active fascicles were used in each trial. An example showing the input Fascicular Activity (FA) signals for $n=2$ is given in Figure 5a, where each plot shows the RMS activity of a single fascicle for the duration of the test. Note that exactly 2 fascicles are active at each time point, and over the course of the trial, all fascicle pairs are tested. Ten trials were performed for each value of n (1 to 10) at each of the three noise levels, for a total $N=300$. The reconstruction accuracy as a function of both the number of active fascicles and the noise level is shown in Figure 5b. For up to 5 simultaneously active fascicles, the reconstruction accuracy is unchanged with a mean value of $R=0.74\pm0.18$ ($N=50$). The accuracy decreases steadily as the number of active fascicles grows larger than 5, reaching 80% of the single fascicle value for 10 simultaneously active fascicles. Recording noise has a strong effect on the reconstruction, lowering the mean value of the $n=1\dots5$ trials to $R=0.61\pm0.18$ ($N=50$), and dropping to 65% of the noisy single fascicle value for 10 simultaneously active fascicles.

3) Functional Recovery—In order to test the ability of the algorithm to recover meaningful muscle activation data in a realistic case, the fascicles were grouped by the muscles they innervate, and the localization algorithm was used to determine recording pixels, instead of the known locations. Due to the distributed nature of the sources, the final averaging step was omitted from the localization algorithm, leaving the full list of putative sources. Each group was then activated simultaneously (each action potential was assigned to a unique axon in a single fascicle within the group while the group was active). The pattern of stimulation was similar to the one shown in Fig. 5a except that combinations of muscle groups were tested instead of individual fascicles. However, contrary to the previously presented experiments, localization was performed on each signal, and the resulting source locations used for the recovery throughout the test. Thus, these results combine the localization and recovery sections of the algorithm to show how the system could be used in a real application. The groups used and their relationship to muscles innervated by the femoral nerve cross-section above are shown in Table 3.

As shown in Figure 6, correlation coefficients for the functional recovery tests are higher than for the multiple active fascicle tests above, as may be expected due to the proximity of the grouped sources. Figure 6a shows that increasing the number of fascicles results in a decrease in correlation coefficient from 0.80 ± 0.18 ($N=10$) with a single group active to 0.70 ± 0.11 ($N=10$) with all 5 groups active in the noise-free case. Figure 6b shows the coefficients separated by group number; the quality of recovery is not consistent across groups. Group 1 (Rectus Femoris) has by far the lowest R values, having a mean 0.42 ± 0.10 ($N=50$) compared to 0.87 ± 0.09 ($N=200$) for the other 4 groups. This difference could be explained by the location of group 1, a small single fascicle, close to the edge of the nerve almost directly centered between the contacts and directly beside the large superficial fascicle 9. The signal from fascicle 9 was picked up as cross-talk in the recordings of group 1. The group 1 signal was also observed in fascicle 9 recordings, although to a lesser degree. All other groups except 5 (Sartorius) contained multiple fascicles. These results indicate that it may be possible to recover meaningful muscle activation signals *in vivo*, without knowing the locations of the relevant fascicles *a priori*. Figure 6c shows the estimated locations of each group for a single trial of the test. Due to the distributed nature of the groups the mean position was not used, simply the aggregate of all identified pixels. The estimated locations are shown as dark dots overlaid on the lighter fascicle map. All fascicles in the nerve are outlined and those that were active are shaded with a separate color for each group. This distributed nature of the sources also makes it difficult to infer any quantitative results, but qualitatively the estimates are distributed over the general area of the source fascicles. In group 2 the estimated locations mainly cluster around the more superficial of the two fascicles, and in both groups 1 and 5 there is a considerable offset towards the center of the

nerve, possibly due to the higher-conductivity saline around the far right contact compared to the apFEM.

IV. Discussion

While the beamforming idea presented here is similar to non-adaptive algorithms applied previously in other fields [10, 19], these results show that it could also be helpful for recovering neural signals. Since the training of the algorithm is independent of the nerve anatomy, this method should be robust for realistic changes in conductivity and anatomy when moving from *in silico* to *in vivo* models. The simulation results presented span a broad range of situations, from simple single source localization, to a realistic functional-group localization-then-recovery, with 5 active groups each with up to 3 independent fascicles.

With 40% Gaussian noise, the beamforming algorithm is able to locate sources with a sub-fascicular accuracy of $0.18 \pm 0.17\text{mm}$ ($N=100$). This accuracy is reduced when multiple fascicles are active, but even when a window of single fascicle activity cannot be found, pair-wise tests showed localization was accurate to $0.33 \pm 0.08\text{mm}$ ($N=225$) in 10% noise. The algorithm could be further improved by modifying the unsupervised classifier so that the number of sources does not have to be estimated *a priori*. Perhaps more important than localization, the algorithm shows excellent ($R > 0.9$) signal reconstruction for fascicles whose centers are only 1.5mm apart. As expected due to the effect of mixing in the volume conductor, the fidelity of recovery increases asymptotically as source separation increases. This is promising for functional recovery, since fascicles innervating the same muscle are often located close to each other [15]. In tests with the fascicles grouped by muscle enervation, recovered muscle activities with all 5 test groups active showed correlation coefficients of 0.70 ± 0.11 ($N=10$) in the noiseless case and 0.66 ± 0.10 ($N=10$) in 10% noise. Moreover, the pixels of interest in this recovery were determined by localization on the simulated recordings themselves, showing that the combination of the two components of the algorithm provide a coherent solution to the recovery problem. In tests designed to recover simultaneous activity in 10 active fascicles, with no assumptions made regarding the independence of their activity, correlation values dropped only 20% from the single fascicle case.

The correlation coefficient presented above is a metric of reconstruction *accuracy*; however it is difficult to extend this value to assess the *utility* of a reconstruction. The correlation coefficient does provide a convenient way of comparing accuracy with other groups, and when squared, provides a measure of the proportion of variance in the signal explained by the reconstruction. Clearly, reconstructions with higher R-values will be more useful than those with low values; however the necessary and sufficient values will depend strongly on the application and difficulty of the control problem to which they are applied. Comparing to other results in the literature, the values of $R > 0.95$ at 10% noise and 1.5mm separation from this algorithm are higher than results published in other studies including [5] where correlation coefficients of 0.8 with Blind Source Separation were achieved at the same noise level, and the small ankle oscillation results of [6] who obtained $R = 0.93 \pm 0.09$ from *in vivo* recordings using two ENG cuffs. Each of these algorithms applies a different constraint to analyze the recorded data. BSS assumes independence, and because it does not require amplitude information it is able to extract signals from arbitrarily placed sources with no training. The neuro-fuzzy algorithm of [6] requires fully online training, and was used only for small perturbations of the ankle joint with constant velocity. The beamforming algorithm presented here uses a very different constraint: the known geometry of the electrode. This allows most of the training to be done ahead of time with no assumptions made on the signals of interest, neither that they are small perturbations, that related variables are held constant, nor that they are statistically independent. The method does require that sources be

spatially separated in order to achieve good reconstruction. This lower spatial resolution (compared to some techniques) is similar to the philosophy behind sLORETA, one of the more popular and successful inverse problem algorithms for EEG and cardiac surface potential mapping. However, sLORETA involves a regularized matrix inversion at each data point and is generally slower (for the same level of detail) than the initial training matrix inversion, followed by single matrix multiplications at each data point required here [20]. As a benchmark, the Beamforming algorithm required 0.19ms of calculation time per time point in MATLAB on a dual-core 2.4GHz Pentium with 4GB of RAM. Still, a comparison of sLORETA with the beamforming algorithm would be interesting, and will be investigated as part of future work. We have shown that the required separation is on the order of fascicular diameter and so should allow for fascicle-level signal reconstruction.

The most interesting property of this algorithm is its robustness. The algorithm was trained without any information on the nerve anatomy. It was tested with a complex, anatomically realistic model comprised of conductivities far different from the empty rectangular epineurium it was trained on, including anisotropic endoneurium and highly resistive perineurium. Thus the addition of fascicles and epineurium appears as a perturbation from the empty *a priori* model. Despite this large perturbation, and high noise levels, the beamforming algorithm still shows good reconstruction and localization. The beamforming algorithm requires only a single matrix multiplication, and therefore may be applied in real-time. Several post-processing techniques have been developed in the literature which could be used to improve the resolution of the algorithm, and subsequently improve recordings. Iterative Inverse problem techniques may be particularly well suited since they derive the most benefit from the close initial guess the beamformer generates. The FOCal Underdetermined System Solver (FOCUSS), in particular, seems promising due to the focal nature of the fascicular sources [21]. Blind Source Separation may also be applied to the individual pixel sources – the results could then be correlated with position in the image to solve the permutation ambiguity and localize the activity in one step [5]. Adaptive beamforming has also been investigated for far-field, narrow-band situations [22]. With some modifications, for example replacing the steering matrix with a lead-field matrix and using the transformation matrix as an initial weight set, they may be able to improve noise tolerance and multi-source reconstruction.

V. Conclusions

In 10% noise, the beamforming algorithm separates signals as close as 1.5mm with $R > 0.9$, with a drop in accuracy of only 20% when simultaneously recovering 10 active signals. No assumptions on the independence of these signals were necessary. This distance is on the order of fascicular diameter and should be sufficient for functional separation of motor signals. The localization algorithm showed sub-fascicular accuracy, even in 40% noise for segments of single fascicle activity as short as 100ms. Post-processing techniques to improve the resolution, noise tolerance and multiple-source recovery will be investigated, primarily FOCUSS [21], BSS [5], and adaptive beamforming [22].

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Figure 1.

Finite element models generated to test and train the beamforming algorithm. Parts a) and b) show isometric and cross-sectional views (respectively) of the *a priori* model (apFEM) containing an insulating cuff with 22 contacts (in addition to upper and lower tripoles) and a simple rectangular epineurium filling the cuff. This model was used to generate the spatial filters, or beamformers, for the transformation matrix. Parts c) and d) show isometric and cross-sectional views (respectively) of the realistic model (rFEM), which contains the same cuff but with anisotropic endoneuria, and perineuria around each of the 22 fascicles. Fascicles used in testing are numbered, and color-coded to correspond to functional group. The geometry for this model is obtained from realistic cross-sections of the human femoral nerve presented in [15].

Figure 2.

Creating Simulated Recordings. a) Simulated transmembrane current in space and time (compare to loose patch recordings in [17]). b) Simulated single unit action potential recording from tripolar cuff recording. c) Comparison of simulated (top) and experimental (bottom) recordings. The simulated recording is obtained from sources in fascicle 3, recorded from the closest contact, with 40% noise. The experimental recording is taken from [23].

Figure 3.

Localization Using Realistic Signals. a) Sample signal of single fascicle activity recorded on a single contact. The signal power (RMS) is shown dashed, while the raw signal is solid. b) Localization results for each of the 5 marked timepoints in (a). The estimated location is marked with a cross, and the actual location with a square. c) To locate the source, the mean location of all reconstructions is used. This final localization result is shown superimposed on the fascicle map, with the estimate marked by a cross and the true location by a square. d) Localization results for all fascicles (single trial at 40% noise). The fascicle map is shown in grey, with true source locations as red squares, and a green circle centered on the estimated location. 10 trials, each 100ms, were performed for each of the 10 fascicles modeled. The accuracy for the 40% noise trials, as pictured here, was $0.18 \pm 0.17\text{mm}$ ($N=100$). For full results see Table 2.

Figure 4.

Separating Signals from Pairs of Simultaneous Active Fascicles. a) Example recovered signal when fascicles 1 and 5 are active, including the actual activity level for each fascicle. Fascicles 1 and 5 are 5.5mm apart and this trial resulted in $R = 0.97$. b) Correlation coefficients and standard deviations for each fascicular separation distance at three noise levels. 10 trials were performed for each noise level and each trial included every possible pair of fascicles. Recovery with negligible cross-talk is seen at $R = 0.9$, which for 10% noise occurs at approximately 1.5mm – half the height of the cuff, and about twice the average fascicular diameter.

Figure 5.

Separating Signals from Multiple Simultaneous Active Fascicles. a) Input fascicular activity signals for the $n=2$ test, when all possible combinations of 2 fascicles are active. The ten figures each show the input signal for a single fascicle. b) Correlation coefficient as the number of active sources increases. The overall effect is a 20% drop in R when 10 sources are active, compared to 1. Up to 5 simultaneously active fascicles, the mean accuracy was $R=0.74\pm0.18$ ($N=50$) at 0% noise and $R=0.61\pm0.18$ ($N=50$) at 40% noise.

Figure 6.

Functional Recovery Without True Source Locations. a) Correlation coefficient for 1 to 5 groups of active fascicles. Fascicles were grouped by terminal muscle enervation. Each bar represents 10 trials. b) Correlation coefficient for each group during testing, each bar represents 50 trials (10 repetitions for n active groups, for n from 1–5). Every possible combination of active groups was tested. Note that group 1 consists of a single small fascicle at the extreme center and side of the nerve, and so exhibited poorer recovery. Fascicles were grouped by terminal muscle enervation and unlike previous experiments the true source locations were not used. Instead, the localization algorithm was used during the $n=1$ trial to identify source locations. Thus this experiment simulates what may be possible to achieve during *in vivo* experiments. c) Estimated group locations from Localization algorithm. Note that the final center-of-mass step was removed because of the distributed nature of the sources. The estimated locations are the dark dots, shown overlayed onto the nerve cross section. All fascicles are outlined and those active during the tests are shaded. Each group is shaded with a different color.

Table 1

Parameters used in FEM Simulations.

Material	Conductivity (S/m) [24]	Parameter	Length (mm)
Epineurium	0.083	Cuff Height	3
Saline	2.000	Cuff Length	15
Endoneurium (trans.)	0.083	Cuff Width	12
Endoneurium (long.)	0.571	Saline Volume	150x200x150
Perineurium	0.002		
Saline	2.000		

Table 2

Summary of localization results for both single active fascicles, and pairs of active fascicles.

Number of Active Fascicles	0% Noise	10% Noise	40% Noise
1 (N=100)	0.14±0.03mm	0.13±0.04mm	0.18±0.17mm
2 (N=225)	0.34±0.09mm	0.33±0.08mm	0.6±0.7mm

Table 3

Fascicular groupings for functional test and their corresponding muscles from realistic FEM, refer to Figure 1 for FEM with numbered fascicle locations [15]

Muscle	Fascicle Number(s)
Rectus Femoris	1
Vastus Lateralis	2, 10
Vastus Medialis	3, 7, 8
Saphenous	4, 5, 6
Sartorius	9