31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Models of the Peripheral Nerves for Detection and Control of Neural Activity

DM Durand, H.J. Park and B. Wodlinger

ABSTRACT

Functional electrical stimulation (FES) can restore volitional motion of patients with neurological injuries or diseases using electrical stimulation of nerves innervating the muscles to be controlled independently. The Flat interface nerve electrode (FINE) enables the selective control of different muscles at the same time. In addition, multiple contact electrode designs allow selective recording of the various signals within the cuff. However, motion control of neuromuscular skeletal systems using multi-contact electrodes is a challenging problem due to the complexities of the systems and the large number of channels required to activate the various muscles involved in the motion. The localization and the recovery of many signals pose a significant challenge to the low signals to noise ratio and the large number of fascicles. Using computer models of the peripheral nerve, we have tested the ability of various algorithms to control the neuromuscular skeletal dynamics. Computer models have also been used to develop new methods to recover fascicular signals within the nerve. Both the control and the detection algorithms are currently being tested experimentally and preliminary results are included. The goal of this study is to develop the ability to detect nerve signals and use these signals to control joint motion in patients with stroke, amputation or paralysis.

Keywords — Nerve Recording, Stimulation, Control, Inverse Problem.

I. INTRODUCTION

Patients with stroke can have severe neurological deficits caused by complex combinations of intact and disable functions. For patients with unilateral stroke, signals on the uninjured side could be used to restore function on the injured side. Similarly, patients with spinal injury still have many sensory signals that do not reach the brain but could still be used to control a neural prosthesis. Moreover, the nerve and muscles can still be activated. Patients with amputated limbs also have neural signals that could be used to control an artificial limb. In order to take advantage of these signals, it is important to develop systems that can interface with peripheral nerves to detect physiological signals and used by the patients to allow a natural control of the restored function.

However, developing motion control algorithm for FES is a challenging problem due to inherent complexities of musculoskeletal systems including highly nonlinear, strongly coupled, time-varying, time-delayed, and redundant properties [1]. Musculoskeletal systems are redundant since the number of muscles acting on a joint motion is larger than the degrees of freedom of the joint. Although this redundancy enables the dexterity in human motor control, it causes difficulty in finding an inverse model of many-to-one system for control purpose [2].

The Flat Interface Electrode [3] has been developed to place electrical contacts close to the fascicles and allows both selective recording of neural signals and stimulation of specific fascicles. The signals can be amplified and processed to control limb motion as shown in Figure 1.

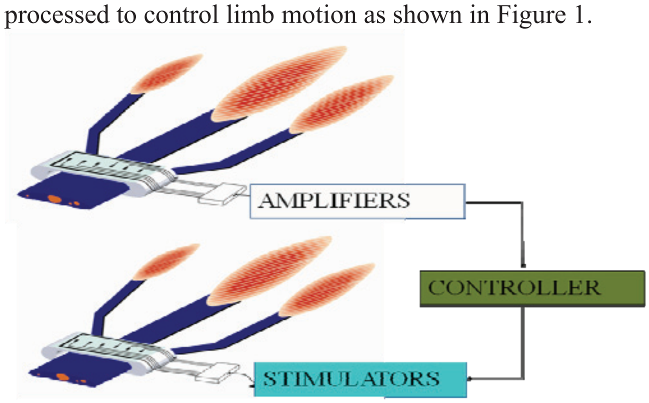

Figure 1: Detection and control of neural activity in peripheral nerves.

METHODOLOGY:

NERVE MODEL: Finite element model (FEM) of the human sciatic nerve including several fascicles, many electrode contacts are used to simulate the nerve-cuff interface voltage distribution along the axons inside the fascicles. Computer simulations of the axonal dynamics are used to determine whether each axon will fire or not depending on the extracellular voltage distribution. Similarly, action potential propagation is simulated and generates to calculate the voltage at each contact.

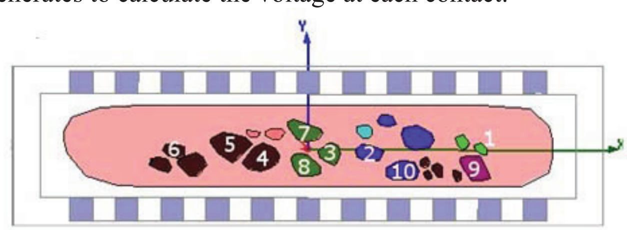

Figure 2: Realistic nerve cross section.

DETECTION OF SIGNALS: The localization and detection of electromagnetic sources are often solved using Inverse Problem technique [4] However, these techniques require model accuracy and signal-to-noise ratios (SNR) difficult to achieve in biological situations. In particular, the reliable recovery of fascicular sources from whole nerve recordings has presented an unsolved problem. These methods required close initial guesses for convergence and are rather slow. We have used a beamforming algorithm based on antenna array design [5]. The algorithm is based on a priori knowledge of the cuff geometry (a priori Finite Element Model). It was tested on a realistic nerve model with anisotropic conductances (realistic Finite Element Model) and with a large population of concurrently active axons in 10 fascicles. Moreover, no assumptions on signal independence were required.

BEAMFORMING ALGORITHM:

A finite element model of an insulating cuff electrode, homogeneous nerve, and large saline volume conductor was created in MAXWELL 3D (Ansoft Corp.). Simulations are used to create a lead-field, or sensitivity matrix, giving the sensitivity of each contact to a source each pixel in a cross-section of the nerve. Since the system is linear and superposition applies, linear combinations of these sensitivities can be used to create new "virtual contacts" which approximate a desired sensitivity vector simply by solving a well-conditioned, over-determined system. The coefficients of these new measurements form the transformation matrix which transforms the observation to an activity estimate for each pixel [6].

MUSKULO-SKELETAL MODEL

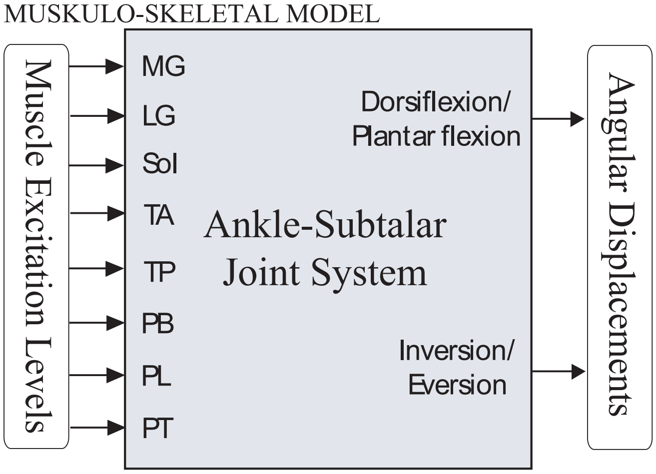

Figure 3: Musculoskeletal model

SIMM and SD/FAST are used for modeling and simulation of a 2-DOF joint system. There are eight muscles in this model: Medial gastrocnemius (MG), Lateral gastrocnemius (LG), Soleus(Sol), Tibialis anterior (TA), Tibialis posterior (TP), Peroneus brevis (PB), Peroneus longus (PL), Peroneus tertius (PT). The muscle activation dynamics are modeled with fourth order differential equation.

CONTROL METHODOLOGY

A human computational ankle-subtalar joint model with eight Hill-type muscles modified from a lower extremity SIMM model was used for the simulation [3]. The proposed controller is composed of three parts: inverse steady state controller (ISSC), feedback controller and feedforward controller (Figure 4). By placing the inverse steady state controller in front of the neuromuscular system, the redundancy problem can be solved. ISSC is obtained by trial and error using linear interpolation or extrapolation of three pre-obtained

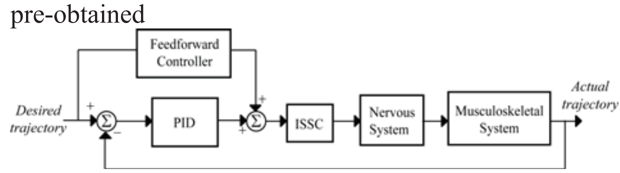

Figure 4: Block diagram of the proposed controller structure. ISSC is the inverse steady state controller.

III RESULTS

Modelling Results: Fascicle localization

A propagating source simulating realistic neural signals made by summing a fixed density of randomly delayed action potentials (figure 5 top) over a 100ms window of activity [6].

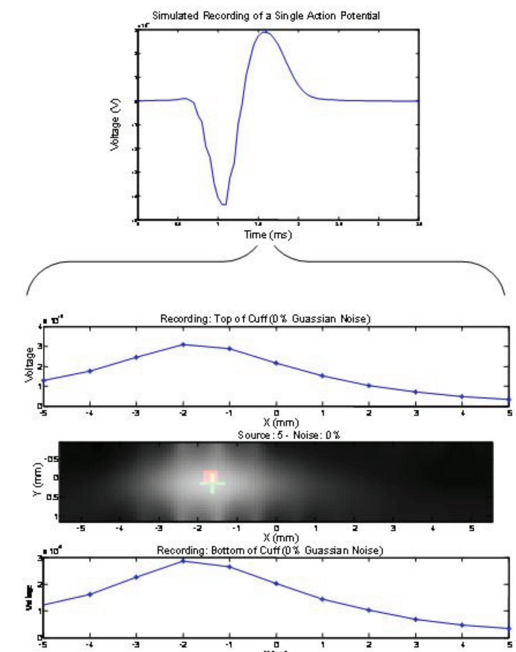

Figure 5: Localization of fascicles within the nerve.

The signal power (RMS) at each contact was calculated in 10ms bins, and the beamforming localization procedure was applied to each one (Figure 5) and the mean of the resulting list of sources found. This estimated location (green cross, Figure 5) was then compared to the known location (red square) and overlaid onto the fascicle map of the nerve for reference. The estimated sources are found to be well within the correct fascicle. 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). Once the localization is known, simultaneous signals could be recovered from individual fascicles with only a 20% decrease in cross correlation compared to a single signal. At high noise levels (40%), sources were localized to within 180µm in the 12x3mm cuff. Localizing sources and using the resulting positions in the recovery algorithm yielded R=0.66±0.10 in 10% noise for 5 simultaneous muscle-activation signals from synergistic fascicles.

Preliminary Experimental Tests of Localization

Recordings were obtained from the proximal main sciatic trunk of rabbits while stimulating the distal peroneal and tibial branches. Compound action potentials (CAPs) were recorded from spatially distinct areas in the main trunk. The beamforming algorithm was applied to recordings of all 16 contacts at the peak of the CAP. The resulting images from each source were compared against each other and against other images from stimulation artifact and background noise.

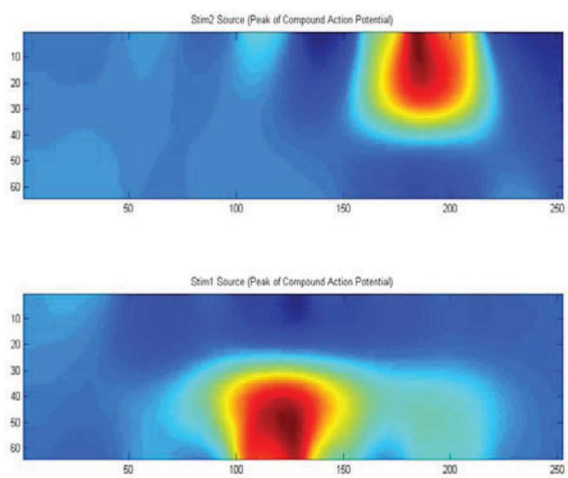

Figure 6: Fascicle locaization from tibial excitation (top) and peroneal excitation (bottom).

In 10 randomly selected CAP peaks from a 30 second segment of stimulation activity in one branch, the local maxima suggested the source was located at 4.40±0.02mm from the medial edge of the cuff, and 0.36±0.01mm from the dorsal row of contacts. Thus, the images each show a focal, roughly circular source at a distinct spatial position in the nerve cross-section (figure 6). Histological analysis will be used to validate that these locations correspond to the position of the fascicles belonging to the branch stimulated.

Motion control of ankle-subtalar joint systems using flat interface nerve electrode on the sciatic nerve

A FINE with 20 contacts was placed on the sciatic nerve

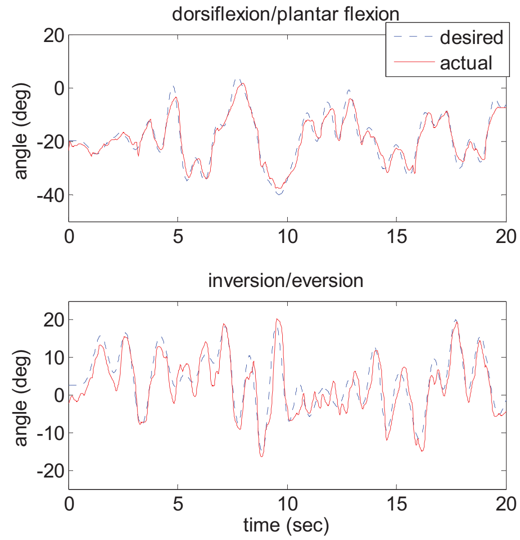

Figure 7: Computer simulations compared the desired and actual trajectory in a 2-degree dynamic model of the ankle.

model with fascicular distribution assigned based on anatomical data. In additional to sinusoidal, pseudo-random noise signal was used to test the controller. The results in figure 7 show that both the control system can track the system output trajectories that match the reference trajectories within 3% RMS errors for both dorsiflexion/plantar flexion and inversion/eversion [7].

Preliminary Experimental Tests of Controller

A 14 contact FINE was placed on the sciatic nerve of rabbits proximal to branching point of tibial and common fibular nerves. The knee joint was fixed and the ankle joint angle measured with an encoder. A charge balanced biphasic cathodic first stimulation was applied to the contacts. Each phase had a pulse width of 50 us and the time delay between consecutive channels was 200 us. The stimulation frequency was set to 33Hz, and the pulse amplitude for each contact was modulated. A-M Systems 2200 analog stimulus isolator was used to convert voltage waveform from PC to corresponding current, and two analog multiplexers, MAX308 from MAXIM are used to distribute the current to each of 14 contacts of FINE. The results of the proposed controller for the sinusoidal reference trajectories are shown in figure 8. The RMS errors for 0.5 Hz and 1.0 Hz are 1.2 and 1.4 degrees respectively.

CONCLUSIONS

At physiological noise levels, the beamforming section of the algorithm separates signals as close as 1.5mm with R>0.9. This distance is comparable to the average fascicular diameter in this nerve of approximately 1mm. Thus, these simulations suggest that the beamforming algorithm alone is able to reconstruct fascicular-level activity. Preliminary experiments applied to the compound action potentials have shown that is possible to recover signals within the nerve selectively. These signals could be used for control joint movement. Computer simulations show that a control algorithm that separates the dynamic from the steady state is clearly capable of choosing correctly the contacts and apply the correct amplitude to a multiple contact nerve electrode for motion control. Preliminary experiments confirm that the this control procedure can indeed produce real time ankle motion.

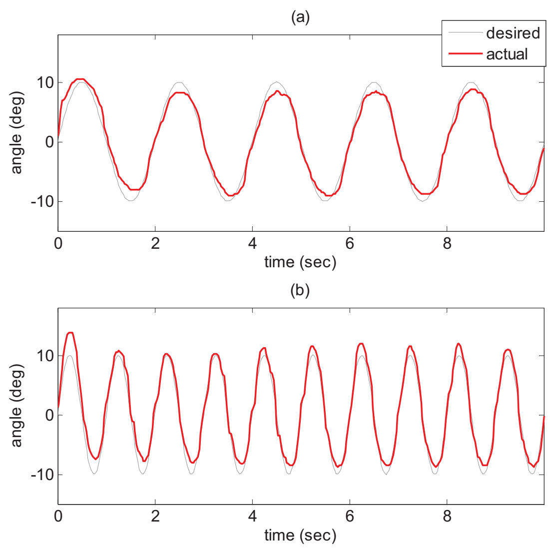

Figure 8: Experimental control of the ankle joint movement. Desired and actual trajectory are shown.

ACKNOWLEDGMENTS

Financial support for this work was provided by the National Institutes of Health (NINDS) # NIH R01 NS032845-10

REFERENCES

[1] Crago PE, P.P., Thrope GB, Modulation of muscle force by recruitment during intramuscular stimulation. IEEE Transactions on Biomedical Engineering, 1980. 27(12): p. 679-684.

[2] Karniel, A. and G.F. Inbar, Human Motor Control: Learning to Control a Time-Varying Nonlinear, Many-to-One System. IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews, 2000. 30(1): p. 1-11.

[3] Tyler DJ and Durand DM. Functionally Selective Peripheral Nerve electrode: Stimulation with a flat interface nerve electrode IEEE Transactions on Neural Systems and Rehabilitation;10(4):294-303, 2002

[4] Ling L. et al. Inverse source identification for Poisson equation. Inverse problems in science and engineering, 2005. 13(4): P. 433–447

[5] K. Sekihara and S. S. Nagarajan, *Adaptive Spatial Filters for Electromagnetic Brain Imaging*: Springer, 2008.

[6] B Wodlinger, D Calvetti, and DM Durand, "Localization of Neural Activity in Peripheral Nerves: A Modeling Study", BMES 2008, St. Louis MO

[7] HJ Park and DM Durand Motion control of ankle-subtalar joint systems using flat interface nerve electrode on the sciatic nerve, Meeting of the Biomedical Engineering Society (BMES), St.
Louis, USA, 2008.