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# Online Feedback Control of Functional Electrical Stimulation Using Dorsal Root Ganglia Recordings

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***Abstract*—In neuroprostheses that use functional electrical stimulation (FES) to restore motor function, closed-loop feedback control may compensate for muscle fatigue, perturbations and nonlinearities in the behavior of the effected muscles. Kinematic state information is naturally represented in the firing rates of primary afferent neurons, which may be recorded with multi-electrode arrays at the level of the dorsal root ganglia (DRG). Previous work in cats has shown that it is feasible to estimate the kinematic state of the hind limb with a multivariate linear regression model of the neural activity in the DRG. In this study we extend these results to estimate the limb state in real-time during intramuscular stimulation in an anesthetized cat. Furthermore, we used the limb state estimates as feedback to a finite state FES controller to generate rudimentary walking behavior. This work demonstrates the feasibility of using DRG activity in a closed-loop FES system.**

## I. Introduction

FUNTIONAL electrical stimulation (FES) holds great potential to restore motor function after brain and spinal cord injury. Many current FES applications operate in open-loop mode [1], in which the intended function is not automatically regulated. In closed-loop control, however, it is possible to dynamically change stimulation parameters in response to feedback from the limb, enabling compensation for muscle fatigue [2] and corrections to perturbations of the extremity [3]. Continuous feedback control has yet to be fully implemented in FES applications due to challenges in the mounting, positioning, reliability, and inconveniences of external sensors [4], and the need for a wide variety of sensors for adequate detection of multi-joint limb activity [5].

There is a growing effort to incorporate natural neural feedback into closed-loop FES systems [6]. These approaches typically record from a single nerve bundle and are thus constrained to partial information and control of a limb, such as a single joint [7]. Our approach is to record sensory activity from dorsal root ganglia (DRG) to estimate the state of the entire limb.

DRG contain the cell bodies for afferent fibers where they enter the spinal cord. Electrodes inserted into DRG allow extracellular recording of action potentials from individual neurons with a high signal to noise ratio. High density arrays of penetrating microelectrodes allow large numbers of isolated neurons to be recorded simultaneously, for concurrent tracking of muscle spindle (limb proprioception), cutaneous (touch) and Golgi tendon organ (force) afferents [8]. Access to this sensory information at a single location is a significant benefit over recording from multiple peripheral nerve locations or with multiple external sensors. Recent studies have demonstrated that limb position and velocity can be decoded from signals recorded from lumbar DRG in cats [9], [10].

The goal of this study was to extract limb information directly from primary afferent DRG neurons with implanted electrodes and apply the estimated limb state towards online feedback control of FES-controlled walking movements in an anesthetized cat. We were successful at obtaining rudimentary walking patterns with a closed-loop controller that successfully rejected stimulation artifacts and compensated for perturbations to the desired limb path.

## II. Methods

### A. Experiment Setup

All procedures were approved by the Institutional Animal Care and Use Committee of the University of Pittsburgh. Intact adult cats were anesthetized with a ketamine-xylazine mixture and maintained on isoflurane (1-2.5%) for the duration of each experiment. Vitals, including blood pressure, heart rate, respiratory rate, core body temperature, oxygen saturation and end-tidal $CO_2$ were monitored continuously and maintained within normal limits.

A laminectomy was performed to expose the lumbar spinal cord and DRG. The cat was placed in a custom frame, which supported the torso, spine and pelvis while allowing the hind limb to move freely through its full range of motion (Fig. 1). The head and torso were further supported by a stereotaxic frame and vertebrae clamp, and bone screws were place bilaterally in the iliac crests to tether the pelvis with stainless steel wire. Penetrating micro-electrode arrays (90 channel MultiPort arrays, Blackrock Microsystems) were inserted into the left L6 and L7 DRG (10x4 and 10x5

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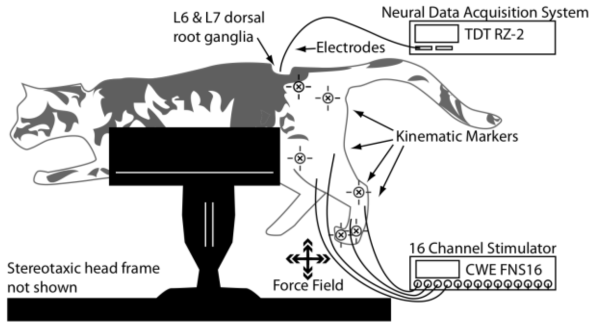


Fig. 1. Experimental setup. Blackrock MultiPort arrays (40- and 50-channels) were inserted in the L6 and L7 DRG for recording neural activity and active LED markers tracked the hindlimb kinematics. Electrodes were placed in muscles spanning the hip, knee and ankle joints. A haptic robot (not pictured) was attached to the foot to generate forces for simulating ground contact.

arrays, respectively).

Neural data from the DRG arrays was sampled at 25 kHz with a real-time biopotential signal processing system (RZ-2, Tucker Davis Technologies) and bandpass filtered (300-3000 Hz). Spike thresholds on each channel were automatically set at a level above the noise floor. Multiple spikes on a channel were discriminated online using a k-means clustering algorithm. Spike events were binned in 50ms windows for each channel on the recording hardware (RZ-2).

LED markers were placed over the left iliac crest and the left hip, knee, ankle and metatarsal-phalangeal (MTP, utilized as endpoint reference) joints. Kinematic data was recorded at 120 Hz with a 6-camera motion capture system (Impulse, PhaseSpace Motion Capture). The hip, knee, and ankle joint angles were computed in real-time using custom developed MATLAB software (The MathWorks, Inc.). The limb segments between each marker were measured and entered into the software so that the endpoint location could be calculated from the joint angles. A haptic robot (Phantom Premium 1.5HF, SensAble Technologies Inc.) was attached to the plantar surface of the left foot and used to create a virtual floor, rendering ground reaction forces during the stance phase of the step cycle (Fig. 1).

A total of nine patch (epimysial) and stainless steel needle (intramuscular) stimulating electrodes were placed in the primary flexor and extensor muscles that span the hip, knee and ankle joints for FES. Suitable locations for electrode placement were found by stimulating each muscle with a mono-polar probe, to test for the approximate motor end-point location, before electrode implantation.

### B. *Real-time Encoding of Firing Rate Models*

We implemented a multivariate linear regression model for on-line decoding of limb position from a population of neurons. The firing rates (FR) were obtained by convolving the binned spike counts with a triangular window spanning 150ms. We employed a joint based reference frame (hip, knee, ankle) and predicted the joint angles by modeling them as a linear function of the observed firing rates, such that

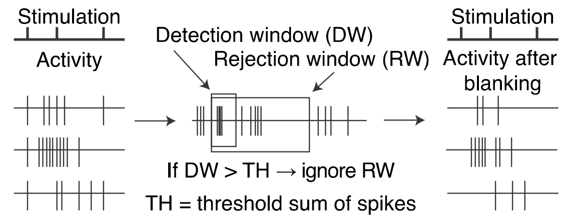


Fig. 2. Stimulus artifact rejection scheme as implemented on the recording hardware (RZ2). If the count of channels with events within a detection window (DW = 400 μs) exceeded the threshold ($TH =$ 60% of all channels), then all recorded spikes within the rejection window ($RW = 2$ ms) were ignored by the real-time controller.

$$X_k = \beta_{k0} + \sum_{i \in S_k} \beta_{ki} \, FR_i + \epsilon_{k}, \tag{1}$$

where $S_k$ refers to the set of neurons that were classified in real-time by the clustering algorithm, and $\epsilon_k$ are uncorrelated random errors. Based on the measured limb segment lengths and the estimated joint angles, the limb endpoint was also estimated.

### C. *Stimulus Artifact Rejection*

We implemented a synchronous event detection algorithm on the RZ-2 real-time processor to eliminate stimulation artifacts from the recorded neural data (Fig. 2). We defined a detection window (400 μs) such that if more than 60% of the channels recorded a threshold-crossing event within it, all events in the corresponding rejection window (RW) were excluded from the calculation of the instantaneous unit firing rates. The RW (2 ms) was chosen to be sufficiently large to eliminate stimulus artifacts. The instantaneous firing rate of each unit was subsequently calculated on the real-time processor (RZ-2) and streamed to the real-time controller described in the next section..

### D. *Finite State Stimulation Controller*

Neural firing rates and limb kinematic measurements were streamed in real-time to a finite state controller implemented in LabView (National Instruments). The controller estimated the limb kinematics in 50 ms windows and generated charge-balanced stimulation commands to a 16-channel stimulator (FNS16, CWE Inc.).

The stimulation channels were synchronized to use a shared constant frequency (30 Hz) and constant pulse-width (200 μs) with independent variable stimulation amplitude, to reduce the impact of stimulus artifact rejection and increase the usable recording time.

States within the controller were associated with 4 phases of the gait cycle: toe strike, toe lift, swing initiation, and end swing (Fig. 3). A set of stimulation channels and amplitudes (0.5-20 mA) was chosen for each state to evoke the desired movement, based on trial and error for the targeted movement path. State transitions were set to occur when the limb endpoint entered and remained in the desired region for at least 200 ms.

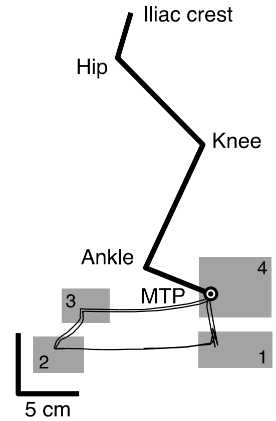


Fig. 3. State space controller diagram and limb schematic. Locations of LED markers on the limb are noted on the schematic (MTP = metatarsal-phalangeal joint; endpoint). The state transition regions were defined in the plane of movement (boxes 1-4, representing toe strike, toe lift, swing initiation, and end swing). After the limb endpoint entered and dwelled 200 ms in a region, the controller changed to the next state. The trace demonstrates an example path of the limb endpoint through two stepping cycles.

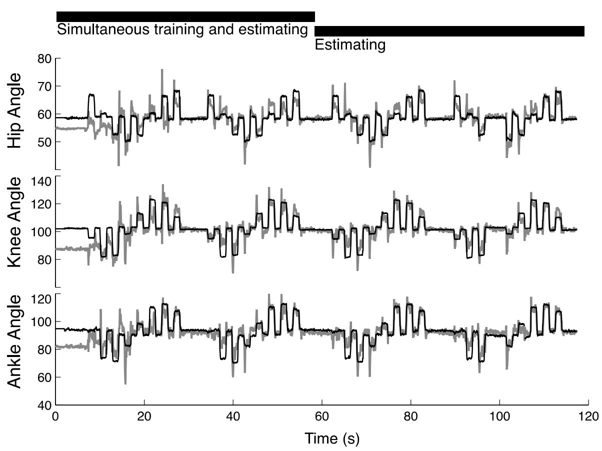


Fig. 4. Example of real-time estimation of joint angles during passive movement. During the training phase, the actual joint angles (black, in degrees) and the neural firing rates were used to continuously update the model. Simultaneously, the decoder used the most recent model to estimate the joint position (gray). After the training phase, the final model was used to estimate the kinematics.

## E. Experimental Testing

The plantar surface of the foot was attached to a robot manipulator (VS-6556E/GM, DENSO Robotics), which passively moved the limb through a series of center-out movements. During this time, the reverse regression model was generated, to estimate the position of the limb. Next the Denso robot was replaced with the haptic robot. Closed-loop FES trials were performed in which either the stimulation controller was unimpeded or perturbations were introduced to hinder progress.

# III. Results

We were able to estimate the limb position in real-time while rejecting stimulus artifacts and demonstrate closed-loop control of a hind limb with FES in one anesthetized cat experiment.

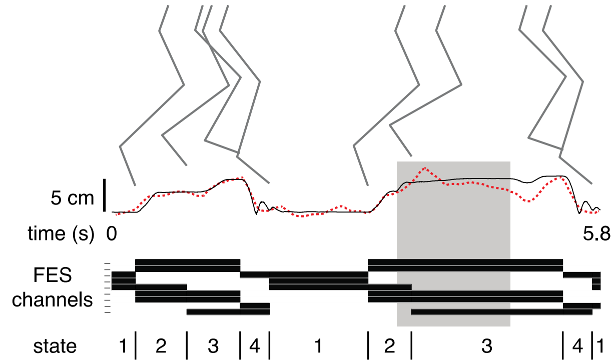


Fig. 5. Example of online feedback control of limb position during two step cycles. The actual limb posture at each state transition is represented by the stick figures at top, with the actual (solid line) and estimated (dotted line) position of the toe indicated. As the controller transitioned between the different states, different stimulator channel combinations were generated (horizontal black bars at bottom). The second step cycle is a perturbation trial in which the limb was manually held for 1.4 seconds (indicated by shaded box) to prevent progression to state 4.

## A. Real-time decoding of primary afferents

An example of real-time decoding using reverse regression is presented in Fig. 4. At the start was a training phase in which the kinematics and instantaneous firing rates were used to create and then continuously update regression models for the kinematic parameters (joint angles). Note that as time proceeds during the training phase, the accuracy of the estimated kinematics improves. At 60 s, the regression models were fixed and subsequently used the observed firing rates to estimate the limb kinematics.

## B. Closed-loop Control of FES

Using the state controller and real-time limb position estimate, we were able to obtain closed-loop control of the hind limb. Fig. 5 presents two step cycles from one trial in which the state controller was able to maintain the limb within the desired trajectory. As the foot moved from end swing to toe strike, there were small oscillations resulting from contact with the simulated floor with forces rendered by the haptic robot (state 4 in Fig. 5). Subsequently, the foot pushed back, lifted up and moved forward before repeating the cycle. The stimulation sequence on the implanted stimulation sites is indicated at the bottom of the figure. Four distinct stimulation channel patterns were responsible for transitioning between the different stages in the step cycle.

We performed seven trials in which the leg was under continuous closed-loop FES control, each lasting 1 min, with 1-2 min between each trial. Starting near the mid-point of each trial, fatigue was observed, leading to a decrease in both step height (2-16%) and speed of motion as the trial progressed. Although the limb endpoint progressively did not step as high at the ends of each cycle within a trial, it was still able to achieve the desired state changes required for successful behavior.

In another scenario, we performed three trials with multiple perturbations by obstructing the movement of the leg during stimulation. This resulted in a prolonged stimulation period in the current state, as the controller correctly identified from the neural activity that the leg had not changed states (second step cycle in Fig. 5). Once the obstruction was removed, the limb moved forward to the desired state and continued through the normal cycle.

## IV. Discussion

In this study we demonstrated the feasibility of using ensemble neural recordings in hindlimb DRG to provide kinematic state feedback for a simple closed-loop FES controller that was able to generate walking-like behavior. Real-time estimation of the limb position from DRG firing rates was performed with successful rejection of stimulation artifacts. The state controller was able to dynamically respond to changes in the limb position and perturbations in the path without manual intervention.

This work presents an advanced form of closed-loop control, as the entire state of the limb was included in the controller. Current approaches for closed-loop FES regulate a single joint [2], [7] or require multiple external sensors [5]. Our approach utilizing DRG afferent recordings presents a significant improvement, as this location provides access to sensory neurons from the entire leg that convey position, velocity, and/or force information for the limb.

As this study presents an initial feasibility demonstration, there are several key opportunities to improve the performance. Although the estimates of limb state were sufficient to drive the state-machine during these closed-loop trials, the accuracy of the estimated limb state feedback could be increased (note that estimated and actual kinematics do not match exactly in Fig. 4 and Fig. 5). Some decoding algorithms, such as state-space regression models, have demonstrated significant improvements over reverse regression models but are not currently tractable in real-time [10]. Other decoding methods, such as Bayesian classifiers or fuzzy neural networks may achieve similar improvements while remaining computationally tractable [11]. As the stimulation parameters are driven by a state-machine, Bayesian classifiers may simply predict the likelihood of the leg being in one of the switching states. Such a method might result in more robust state switching but will lose the ability to track the individual limb-state variables. Furthermore, the finite state controller could be replaced by more sophisticated controller designs that may improve performance and stability of the system. For example, a continuous PID controller may prove to be more robust and would enable reference trajectory tracking for more refined movements [12].

Epimysial and intramuscular electrodes, as we used here, have long been a standard approach for FES control of the lower leg [1]. Although these methods allow for direct activation of muscles, fatigue and incomplete muscle recruitment may occur, as we observed. Alternate electrode interfaces are under development, such as selective stimulation of peripheral nerves for graded muscle recruitment and intra-spinal micro stimulation to activate synergies of muscles, as are improvements in stimulation control algorithms for adaptive compensation [1]. Integration of this feedback controller with an improved FES electrode system may yield improved muscle recruitment and function.

In summary, a closed-loop neural prosthesis comprises a complex system integrating different challenges such as afferent recording, kinematic state decoding, actuating the muscles and the accompanying control algorithms. The results presented here show that with the current technology, it is possible to develop a rudimentary online FES controller with sensory feedback which is able to generate walking like behavior in a closed-loop fashion. Continuing efforts to improve FES control, afferent decoding and interface technology should be pursued to enable the use of closed-loop FES neuroprostheses in the future.


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