ADAPTIVE PARAMETER SELECTION FOR ASYNCHRONOUS INTRAFASCICULAR MULTI-ELECTRODE STIMULATION

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ABSTRACT

This paper describes an adaptive algorithm for selecting per-electrode stimulus intensities and inter-electrode stimulation phasing to achieve desired isometric plantar-flexion forces via asynchronous, intrafascicular multi-electrode stimulation. The algorithm employed a linear model of force production and a gradient descent approach for updating the parameters of the model. The adaptively selected model stimulation parameters were validated in experiments in which stimulation was delivered via a Utah Slanted Electrode Array that was acutely implanted in the sciatic nerve of an anesthetized feline. In simulations and experiments, desired steps in force were evoked, and exhibited short time-to-peak (< 0.5 s), low overshoot (< 10%), low steady-state error (< 4%), and low steady-state ripple (< 12%), with rapid convergence of stimulation parameters. For periodic desired forces, the algorithm was able to quickly converge and experimental trials showed low amplitude error (mean error < 10% of maximum force), and short time delay (< 250 ms).

Index Terms— Gradient Descent, Neuroprosthesis, Functional Electrical Stimulation, Animal Models.

1. INTRODUCTION

Functional Electrical Stimulation (FES) has been clinically employed to restore lost neuromuscular function due to spinal cord injury or other neural deficits. Electrical stimulation applied to nerves can evoke forceful contractions of paralyzed muscle resulting in functional movement. However, current clinical FES methods to control muscle function rely on high-frequency, single-electrode surface or extraneural stimulation, which has limited force scalability and can lead to rapid fatigue [1].

Recent advances in high-channel-count peripheral nerve interfaces, such as the Utah Slanted Electrode Array (USEA), allow for selective activation of large numbers of motor-unit groups within a single muscle [2]. Graded force production can be achieved by modulating the stimulus intensity delivered to an implanted electrode, thus activating more or less motor-unit groups. Relatively high-frequency muscle contractions are required to evoke smooth tetanic forces [3]. When stimulating via only one electrode, this high-frequency stimulation leads to rapid muscle fatigue. Because multi-electrode arrays allow for selective access to unique populations of motor-unit groups within a single muscle, asynchronous stimulation via multiple independent electrodes at a low per-electrode frequency, but high composite frequency, can evoke smooth, fatigue-resistant muscle contractions [1, 4].

Asynchronous Multi-Electrode Stimulation (AMES) poses unique challenges, especially in the determination of stimulation parameters—per-electrode stimulus intensities and inter-electrode stimulation phasing—that will evoke smooth, precise motor function. Algorithms have been developed that can predict the dynamic muscle response to single-electrode stimulation [5], but these models have not been extended to AMES. Adaptive algorithms have been used to determine optimal inter-electrode phasing for AMES that can evoke smooth static isometric forces [4, 6], and other algorithms have been designed to determine per-electrode stimulus intensities to evoke precise periodic joint torques [7]. Recently, we have investigated closed-loop force-feedback control that modulates per-electrode stimulus intensities to evoke any desired force trajectory, using asynchronous IntraFascicular Multi-electrode Stimulation (aIFMS) [8]. However, we are unaware of any method that can adaptively determine both per-electrode stimulus intensities and inter-electrode stimulation phasing to evoke smooth, precise, arbitrary force trajectories.

Here we present a gradient descent adaptive filtering method that can determine per-electrode stimulus intensities and inter-electrode stimulation phasing by minimizing the difference (error) between any desired force trajectory and an estimate of aIFMS evoked forces. Stimulation parameters were adaptively determined in open-loop simulation and then validated with experimental stimulation, as a first step towards developing a real-time closed-loop method. The simulations and subsequent experimental results show successful production of desired isometric force trajectories.

2. ADAPTIVE PARAMETER SELECTION

Single-pulse stimulation via a single USEA electrode evokes a twitch response in force, Fig. 1a, and graded force production can be achieved by modulating the stimulus

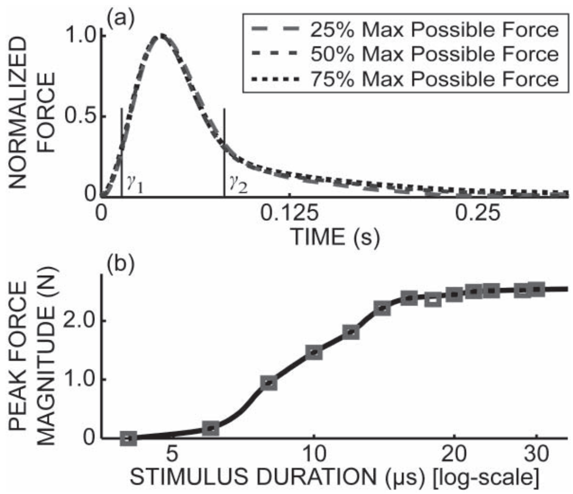

Fig. 1. (a) Stimulation was delivered to a single USEA electrode at a stimulus duration that would evoke 25%, 50%, and 75% of the maximum possible twitch force, as determined from (b). The normalized twitch-force responses show stimulus duration invariant kinetics, which is desirable for this study. γ_1 and γ_2, the cost function bounds, are marked for this characteristic twitch-force response. (b) Typical twitch-force recruitment map, showing the relationship between delivered stimulus duration and evoked peak twitch-force, and the bounds of useable stimulus durations.

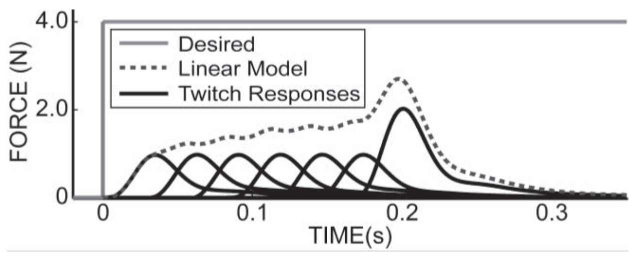

Fig. 2. The first cycle of algorithmic parameter determination is shown for a simulation of 6-electrode, 36-Hz asynchronous stimulation, where all twitch-response kinetics are similar. The desired force was a 4-N step function. The initial cycle of stimulation was estimated. The algorithm then determined the stimulation intensity (increase) and timing (decreased offset) for the second cycle of stimulation via the first electrode by looking backwards in time at the linear model of estimated force during the first stimulation cycle. The second cycle of stimulation via the first electrode with adapted parameters is shown by the larger twitch-response due to stimulation at $t = 0.161$ s.

intensity (i.e., the stimulus duration), Fig. 1b. For stimulation via each utilized electrode, there is a known normalized, characteristic twitch-force response to a single stimulus, $x_i(t)$. Our algorithm uses these characteristic responses in a linear summation model of aIFMS force production:

$$F_e(t) = \sum_{i=1}^{M} \sum_{j=1}^{K} a_{i,j} \cdot x_i(t - \tau_{i,j}), \tag{1}$$

where $a_{i,j}$ is the stimulation intensity for electrode i during stimulation cycle j, $\tau_{i,j}$ is the stimulation time, M is the total number of stimulating electrodes, and K is the total number of stimulation cycles.

For each electrode, we want to determine the stimulation parameters, a and τ, that will minimize the difference (error) between a desired force trajectory, $F_d(t)$, and the estimated evoked forces, $F_e(t)$, where

$$e(t) = F_d(t) - F_e(t). \tag{2}$$

For each stimulation, the cost function to be minimized is set as

$$L(t) = \int_{T_1}^{T_2} \left[e(\lambda) \right]^2 d\lambda, \tag{3}$$

where the interval of interest is between the time when the twitch-force response initially rises above 25% of the maximum response, T_1, and the time when the twitch-force response drops below 25% of the maximum response, T_2. These bounds are used because this is the time window when the majority of the twitch-force response occurs, and when the majority of changes in $F_e(t)$ are due to stimulation via the corresponding electrode, Fig. 1a. For each stimulation, T_1 and T_2 are set as

$$T_1 = \tau_{i,j} + \gamma_{i1} \text{ and } T_2 = \tau_{i,j} + \gamma_{i2}, \tag{4}$$

where γ_1 and γ_2 are as shown in Fig. 1a.

Gradients of the cost function based on stimulation intensity, a, and stimulation time, τ, are determined:

$$\nabla_{a_{i,j}} \left[L(t) \right] = \int_{T_1}^{T_2} \left[-2 \cdot e(\lambda) \cdot x_i(\lambda - \tau_{i,j}) \right] d\lambda \tag{5}$$

$$\nabla_{\tau_{i,j}} \left[L(t) \right] = \int_{T_1}^{T_2} \left[2 \cdot e(\lambda) \cdot a_{i,j} \cdot \frac{d}{d\tau} \left[x_{i,j}(\lambda - \tau_i) \right] \right] d\lambda. \tag{6}$$

The parameters for the subsequent cycle of stimulation are updated as

$$a_{i,j+1} = a_{i,j} - \eta_a \cdot \nabla_{a_{i,j}} \left[L(t) \right] \tag{7}$$

$$o_{i,j+1} = o_{i,j} - \eta_\tau \cdot \nabla_{\tau_{i,j}} \left[L(t) \right] \tag{8}$$

$$\tau_{i,j+1} = \tau_{i-1,j+1} + o_{i,j+1}, \tag{9}$$

where $o_{i,j}$ is the offset time between stimulation via the prior electrode (i-1) and the current electrode (i), and η is the rate of adaptation, independently set for each stimulation parameter, a and τ. The stimulation parameters for each electrode are iteratively determined for each subsequent cycle of stimulation by looking backwards in time at the bounded estimated force response during the previous cycle of stimulation, Fig. 2. After the subsequent cycle of stimulation parameters are updated for each stimulating electrode, the force estimation model is updated, Fig. 2.

3. METHODS

Experiments were conducted on an adult male feline using procedures approved by the University of Utah Institutional Animal Care and Use Committee. The initial experimental methods are fully described in [8], and are briefly described below. The feline was anesthetized and mechanically ventilated. Vital signs were monitored and recorded to assess the depth of anesthesia and animal status.

A 100-electrode USEA was implanted in the left sciatic nerve. The animal was placed in a prone position in a rigid trough with its hind limbs suspended. The metatarsal-phalangeal joint of the animal's left foot was secured to a six degree-of-freedom load cell (model Gamma-US-15, ATI, Apex, USA) via plastic ties. Bone pins were inserted in the left tibia and fixed to the surgical table, to ensure that all forces generated by plantar-flexor muscles were isometric. The magnitude of the evoked ground reaction force vector was used as the force response for all experiments.

Monophasic electrical stimulation was delivered using a custom-built, multi-channel, constant-voltage stimulation unit [9] at a voltage of -4 V, using stimulus durations between 0.2 μs and 512 μs with 0.2-μs resolution. Twitch-force recruitment maps were generated for all electrodes that generated a peak force greater than 0.5 N in response to a single 256-μs stimulus, Fig. 1b. The pair-wise level of axonal activation overlap was measured for all electrodes whose stimulation evoked fast-twitch plantar-flexion [1].

Six electrodes were chosen for simulation and experimental stimulation from those having the smallest pair-wise overlap, low activation thresholds and strong maximum peak twitch force as determined from recruitment maps (Fig. 1b), and from those having similar normalized force response kinetics at all possible stimulus durations (Fig. 1a). For each of these six electrodes, the normalized, characteristic twitch-force response, $x_i(t)$, was determined as the normalized twitch-force response to the stimulus duration that evoked 50% of maximal twitch-force.

Simulations were performed using MATLAB software (The Mathworks, Natick, USA). Initial stimulation intensities were set to $F_d(0)$/M, where M was the total number of stimulation electrodes, and initial inter-electrode timing offsets were set to $1/f_c$, where f_c was the desired composite frequency in Hertz. Both intensity and offset were bounded. The minimum allowable stimulation intensity was zero, and the maximum allowable stimulation intensity via each electrode was determined from initial twitch-force recruitment mapping, Fig. 1b. The minimum and maximum allowable offset times were set as 0.5 times and 1.5 times the initial offset ($1/f_c$). The derivative in (6) was numerically determined from a smoothed model of the characteristic twitch-response, $x_i(t)$.

Adaptation gains, η_a and η_o, were tuned through iterative simulations to find the gains that produced steps in force with adequate response characteristics (short time-to-peak, low overshoot, low steady-state error, and low steady-state ripple), which are defined as follows. Time-to-peak, *Tp*, is the time from force step onset to peak evoked force. Percent overshoot, *%OS*, is the percent difference between the peak evoked force and the mean evoked steady-state force, measured during the last 0.25 s of stimulation. Steady-state error, *SSE*, is the difference between the desired force and the mean evoked steady-state force. Steady-state ripple, *SSR*, is the difference between the peak-to-peak evoked force during the last 0.25 s of stimulation and the mean evoked steady-state force. The *SSR* metric is important for multi-electrode stimulation because it is a characteristic of the smoothness of the evoked forces.

For periodic desired forces, the adaptation gains were tuned to produce forces with minimal amplitude error, E_A. To determine E_A, the evoked forces were shifted backwards in time until the sum of the squared per-sample difference between the time-shifted forces and desired force trajectory was a minimum. E_A is the square-root of this squared per-sample difference. The time shift was also measured as a time delay metric of the response, T_d.

After parameter sets were determined in simulation, stimulus intensities were converted to useable stimulus durations via recruitment maps (Fig. 1b). This was necessary because the recruitment map for each electrode is a nonlinear function with varying characteristics. Because stimulation via the chosen electrodes did not activate completely independent motor-unit groups, and because muscle contractions do not combine linearly [10], an additional gain factor of 0.6 (determined experimentally) was applied to the stimulus intensities prior to stimulus duration conversion (see Discussion). Electrical stimulation was delivered via the six chosen USEA electrodes through custom MATLAB software. Experimental responses were evaluated on the same metrics as simulations.

4. RESULTS

All experimental stimulations were conducted using six electrodes with an initial composite frequency of f_c = 36 Hz. In simulation, desired steps in force were achieved with short *Tp* (425 ms), low *%OS* (7.5%), low *SSE* (-1%), and low *SSR* (10%), Fig. 3. Experiments, using the stimulation parameters determined in simulation, evoked similar results (*Tp* = 445 ms, *%OS* = 7.6%, *SSE* = 3%, *SSR* = 11%), Fig. 3. The maximum instantaneous per-electrode stimulation frequency was 6.9 Hz, and the steady-state converged composite frequency was 40.2 Hz.

Periodic force trajectories were achieved in simulation with low amplitude error (E_A = 0.06 ± 0.04 N, mean ± SD) and short time delay (T_d = 215 ms), Fig. 4. Experimental stimulation evoked periodic forces with slightly larger amplitude error than simulation (E_A = 0.28 ± 0.21 N), but similar time delay (T_d = 224 ms), Fig. 4. The maximum instantaneous per-electrode stimulation frequency was 7.2 Hz. Higher frequency desired force trajectories were achieved with similar amplitude errors and time delays (data not shown).

More complex time-varying force trajectories were also achieved in simulation with low amplitude error (E_A = 0.11 ± 0.08 N) and short time delay (T_d = 208 ms), Fig. 5. Experimental stimulation evoked forces with slightly larger amplitude error (E_A = 0.34 ± 0.22 N), but similar time delay T_d = 222 ms), Fig. 5. The maximum instantaneous per-electrode stimulation frequency was 7.1 Hz.

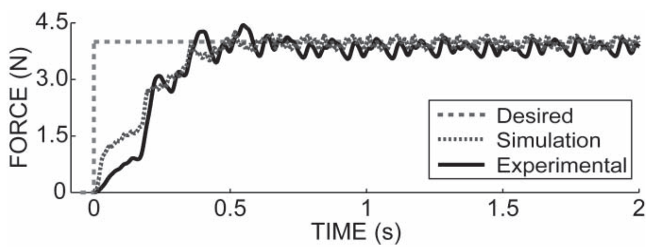

Fig. 3. A 4-N desired step in force was successfully evoked in simulation and with experimental stimulation.

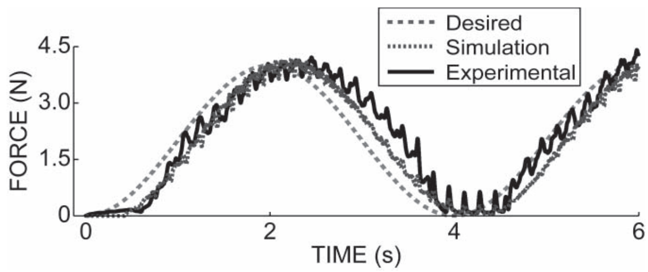

Fig. 4. A 4-N, 0.25-Hz sinusoidal desired force trajectory was successfully evoked in simulation and with experimental stimulation. Experimental results had slightly larger amplitude error than simulation results.

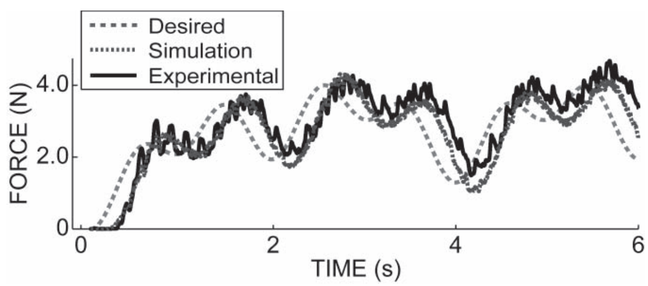

Fig. 5. A 4-N composite of sinusoids, desired force trajectory was successfully evoked in simulation and with experimental stimulation. Again, experimental results had slightly larger amplitude errors than simulation results.

5. DISCUSSION

Experiments described in this paper demonstrated that complex isometric force trajectories can be successfully achieved with aIFMS. Other algorithms may be able to evoke smooth static muscle forces or periodic joint torques [4, 6, 7], but our approach has the benefit of being able to determine all stimulation parameters for any desired forces, including completely arbitrary trajectories.

One difficulty with this method is the offline tuning of adaptation gains, η_a and η_o. It would be beneficial to have automated gain parameterization to determine optimal stimulation parameters. Experimental stimulation required an additional stimulation intensity gain factor of 0.6, which was determined experimentally. Contractions of multiple motor-unit groups do not combine in a completely linear manner [10], and we are unaware of a good model for the specific interaction of stimulation via multiple intrafascicular electrodes. Although aIFMS can evoke fatigue-resistant force, fatigue will eventually occur in muscle fibers even at low stimulation frequencies [1]. Long term stability of the algorithm has not yet been experimentally evaluated. Real-time implementation of the algorithm with closed-loop feedback of the force error signals [8] should enhance the ability of the algorithm to compensate for modeling errors and time-variations in the force generation mechanism. Future work will investigate better force generation models as well as closed-loop adaptation of the stimulation parameters in the experiments.

6. ACKNOWLEDGMENT

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