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Optimization of a Stimulation Train based on a Predictive Model of Muscle Force and Fatigue

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Abstract: Optimizing stimulation frequency based on a mathematical model that can predict skeletal muscle force and fatigue may improve the effectiveness of functional electrical stimulation systems. Potentially, optimal stimulation patterns can maximize muscle force production while also delaying the onset of muscle fatigue. In this paper, dynamic optimization was used to generate an optimal, frequency varying pulse train that maintains a desired isometric knee extension without unnecessarily fatiguing the muscle. The optimization method employed a predictive mathematical model of muscle force and fatigue. Knee extension experiments were conducted on an able-bodied participant to identify the model parameters. To test the effectiveness of the optimized train to delay muscle fatigue, a second knee extension experiment was conducted to compare the performance of the optimized stimulation train and a 50Hz constant frequency train. The peak force and the force time integral of the optimized stimulation train were found to be higher than the 50Hz constant frequency train. These preliminary results show that optimizing stimulation patterns, based on a subject specific predictive mathematical model, may potentially delay the onset of muscle fatigue while obtaining desired force profiles.

Keywords: Functional Electrical Stimulation, Neuromuscular stimulation, Physiological models, Neuroprosthesis

1. INTRODUCTION

Functional electrical stimulation (FES) is commonly used to induce voluntary-like contractions in skeletal muscles through application of low-level electrical pulses. FES can assist individuals with mobility impairments to achieve functional tasks such as standing and walking (Triolo et al., 1996), drop foot correction (Lyons et al., 2002), grasping (Smith et al., 1998; Prochazka et al., 1997), and bladder control (Popovic et al., 2004). However, application of FES is limited by the rapid onset of muscle fatigue. This is because FES recruits motor units in a non-selective, spatially fixed, and temporally synchronous pattern, compared to the voluntary recruitment in which motor units are asynchronously activated at lower frequencies (Bickel et al., 2011).

Effective fatigue management is very relevant to FES applications because it is always desirable to maintain muscle force for a longer period of time. Factors such as the stimulation method, muscle fiber composition, state of training of the muscle, and the duration and task to be performed have been observed to affect fatigue during FES. Researchers have proposed different stimulation strategies to delay the onset of fatigue such as choosing stimulation frequency and pattern, sequential stimulation, and size order recruitment. During FES, constant frequency trains (CFT) are generally used to activate skeletal muscles. Recently, variable frequency trains (VFT) and doublet frequency trains (DFT) have been shown to significantly improve the force production from the fatigued muscles (Ding et al., 2000). The CFT is a pulse train with equally spaced pulses, the DFT is a pulse train with doublet pulses spaced equally, and the VFT is a CFT with a doublet for the initial pulse.

We are motivated to determine optimized stimulation patterns based on a mathematical model that can predict skeletal muscle forces and fatigue in response to electrical stimulation. This would enable FES systems to deliver custom stimulation patterns that produce a desired muscle force while delaying the onset of muscle fatigue. This paper employs a Hill/Huxley-type nonlinear model, developed by Ding et al. (2002b,a, 2003), to optimize stimulation frequencies for tracking a force reference. Among numerous muscle models, this model is one of the few muscle models that can accommodate a variety of stimulation trains. In an experimental comparison made by Law and Shields (2006), the Hill/Huxley-type nonlinear model predicted muscle force time profiles most accurately. The other models considered in the comparison were a second-order nonlinear model proposed by Bobet and Stein (Bobet and Stein, 1998) and a simple linear differential equation relating force with stimulation trains modeled as dirac delta functions (Law and Shields, 2006). The Hill/Huxley nonlinear model predicts muscle response from a wide range of frequencies and pulse patterns (CFT, DFT, and VFT) (Ding et al., 2002b,a, 2003).

This paper presents the predictive mathematical model that was used to optimize the stimulation frequency to track a pre-defined force reference. The proposed method is shown to be effective in calculating an optimal series of FES pulses that maintains a constant muscle force while limiting muscle fatigue. The optimization was performed by minimizing a cost function that contains both the predicted error from the force reference and the number of stimulation pulses in the delivered

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train. The results suggest that this model may be implemented for use in a model based control scheme. The key contribution of the paper is that the muscle fatigue was shown to be lower when the optimized pulse train was delivered in comparison to a constant frequency train. The paper contains discussion on how parameters for the model were identified, how these parameters were used to define an optimized pulse train, and compares muscle fatigue caused by a computed optimized pulse train to muscle fatigue caused by a constant frequency train.

2. MODEL

The model discussed in Ding et al. (2003) was used to predict muscle response in this paper. The model consists of 2 sets of differential equations that define a force model and a fatigue model. The force that the muscle generates is modeled as:

$$\begin{aligned}\frac{dC_N}{dt} &= \frac{1}{\tau_c}\sum_{i=1}^{n} R_i \exp\left(-\frac{t-t_i}{\tau_c}\right) - \frac{C_N}{\tau_c},\\ R_i &= 1 + (R_0 - 1)\exp[-(t_i - t_{i-1})/\tau_c, \\ \frac{dF}{dt} &= A\frac{C_N}{K_m + C_N} - \frac{F}{\tau_1 + \tau_2\frac{C_N}{K_m+C_N}}.\end{aligned} \tag{1}$$

The muscle fatigue is modeled as:

$$\begin{aligned}\frac{dA}{dt} &= -\frac{A - A_{rest}}{\tau_{fat}} + \alpha_A F,\\ \frac{dKm}{dt} &= -\frac{K_m - K_{m,rest}}{\tau_{fat}} + \alpha_{K_m} F,\\ \frac{d\tau_1}{dt} &= -\frac{\tau_1 - \tau_{1,rest}}{\tau_{fat}} + \alpha_{\tau_1} F.\end{aligned} \tag{2}$$

The parameters in (1) and (2) are defined in Table 1. Parameters sub-scripted “rest” in (2) denote the parameter of the muscle when it is in a non-fatigued state. Note that (2) is made up of a force-based component, F, and a recovery based component, τ_{fat}. The force based component predicts muscle fatigue, and the recovery based component predicts muscle recovery based on the state of the muscle. Corrections to the model parameters in Ding et al. (2002b,a, 2003) are discussed in the Appendix.

3. MUSCLE PARAMETER IDENTIFICATION

Parameter identification experiments were conducted on a leg extension machine fitted with a load cell aligned to measure isometric knee extension force, as shown in Figure 1. The load cell was placed 13 inches from the fulcrum of the knee. Straps were used to securely hold the subject’s leg in place. The extension arm was locked in place such that the subject’s knee angle is approximately 90 degrees. The quadriceps muscle was stimulated using an FNS-8 channel stimulator [CWE Inc., PA USA] to produce an isometric knee extension. Force was measured with a U9C bidirectional force transducer [HBM Inc., Hesse, Germany]. All trials were performed on a healthy 25-year-old male subject.

Prior to recording the test data for model identification, stimulation pulses were standardized to the same amplitude and pulse width. The subject was asked to produce a maximum voluntary isometric contraction (MVIC). To confirm the subject was at his MVIC, an 11 pulse, 100 Hz stimulation was delivered during

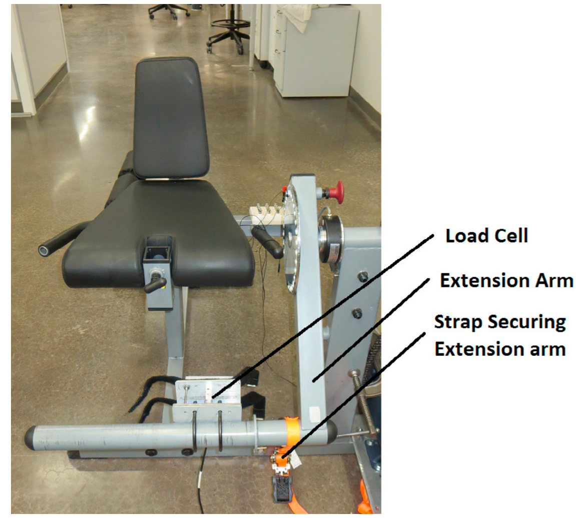

Figure 1. The leg extension machine fitted with a bidirectional force transducer.

the contraction to see if the measured force did not increase by more than 10%. After measuring MVIC, the stimulation current was adjusted such that a six pulse, 100 Hz pulse train produced a muscle force of approximately 20-30% of the MVIC magnitude. The stimulation magnitude of the standardized pulse used for this subject is 35000 µA. Pulse width was maintained at 900 µs. This method is described in Ding et al. (2002b,a, 2003). The muscle was then rested for 10 minutes.

Following the definition of the standardized pulse, the muscle was potentiated using a series of 35 14 Hz CFT trains, where each train was composed of 12 pulses and spaced five seconds from the end of the previous train. The potentiating sequence activates the muscle and prepares it for further stimulation by delivering short pulses that will not significantly fatigue the muscle but will warm it up.

In Ding et al. (2003), subjects are fatigued with a 50 Hz CFT and a 12.5 Hz VFT pulse train followed by 13 CFT pulse trains. 33 Hz is identified as the best frequency to stimulate at for the 13 CFT pulse trains. The purpose of the 50 Hz CFT and 12.5 Hz VFT pulse trains is to monitor changes in muscle parameters over the fatiguing trial. The fatiguing protocol used in this paper is identical to the protocol identified in Ding et al. (2003). Fatiguing was performed using a pulse train sequence of a 20 pulse, 50 Hz CFT followed by a 14 pulse, 12.5 Hz VFT followed by 13, 33 pulse, 33 Hz CFT pulse trains. The series of pulse trains were repeated eight times to fatigue the muscle. The 33 Hz CFT was used because it was determined to be the most effective train for fatigue model parameter identification in Ding et al. (2003).

Model parameters were identified using the results of the fatiguing protocol in 2 stages. First, only the dynamics in (1) were modeled and the parameters for the non-fatigued muscle were identified using a mean-squared-error cost function. The function was evaluated over the first fatiguing series (first 15 pulse trains). In this stage, the optimization tunes only A_{rest}, $\tau_{1,rest}$, τ_2, and $K_{m,rest}$ using the interior-point algorithm. The obtained optimal solution was recorded as the non-fatigued force model parameters. Next, the fatigue dynamics in (2) were included back into the model, and the optimization was re-performed with all force parameters bounded at $\pm 10\%$ of the value obtained in the first stage. All of the fatigue model pa-