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Nonlinear model predictive control of functional electrical stimulation

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ABSTRACT

Minimizing the amount of electrical stimulation can potentially mitigate the adverse effects of muscle fatigue during functional electrical stimulation (FES) induced limb movements. A gradient projection-based model predictive controller is presented for optimal control of a knee extension elicited via FES. A control Lyapunov function was used as a terminal cost to ensure stability of the model predictive control. The controller validation results show that the algorithm can be implemented in real-time with a steady-state RMS error of less than 2°. The experiments also show that the controller follows step changes in desired angles and is robust to external disturbances.

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1. Introduction

An upper motor neuron disease or disorder impairs an individual's ability to perform functional movements, such as standing, walking, reaching, and grasping. Functional electrical stimulation (FES) is the application of low-level electrical current to the nerves that innervate the muscles to cause functional limb motion. FES has the potential to restore limb movements in individuals with corticospinal impairments. For example, by stimulating specific muscle groups in an appropriate sequential manner a walking motion can be achieved (Bajd, Kralj, Turk, Benko, & Šega, 1983; Granat, Ferguson, Andrews, & Delargy, 1993; Hardin et al., 2007; Kralj & Bajd, 1989; Kobetic, Triolo, & Marsolais, 1997; Marsolais & Kobetic, 1987). Most FES devices, such as the Parastep system (Klose et al., 1997) (Therapeutics Inc.), use electrodes placed on the surface of the skin (transcutaneous electrodes) to enable paraplegics to achieve standing and walking. However, this causes the muscles to fatigue more rapidly than normal, volitional muscle contractions. Muscle fatigue is the decline in the ability of a muscle to produce a force, and typically occurs due to fatigue of the nervous system or metabolic fatigue. In the case of transcutaneous stimulation the manner in which the muscle fibers are recruited differs from how muscle fibers are recruited during a natural, volitional contraction that causes FES-induced muscle contractions to result in muscle fatigue occurring at a significantly more rapid rate. There are two theories as to how the muscle fibers are recruited due to the application of FES, and why it causes rapid muscle fatigue. The first theory is that the muscle fibers are recruited in an inverse manner of Henneman's size principle (Mendell & Henneman, 1971), in other words FES induced contractions recruit the larger motor units (large force and fatigue rapidly) first and then the smaller motor units (low force and fatigue resistant). The second theory is that FES inherently recruits muscle fibers in a repeated and non-selective manner (Bickel, Gregory, & Dean, 2011), which means that unlike volitional contractions that recruit according to the size principle FES has no control over the motor units that are recruited. Regardless of which of these theories are correct, it is apparent that the rapid onset of muscle fatigue greatly limits the duration for which FES-based devices can be used. Error-based feedback control of FES (Ajoudani & Erfanian, 2009; Alibeji, Kirsch, Farrokhi, & Sharma, 2015; Sharma, Bhasin, Wang, & Dixon, 2011, 2009) can compensate for lower force production, due to muscle fatigue, by increasing the amplitude or frequency of electrical stimulation. However, increasing amplitude or frequency of stimulation can further aggravate the rate at which muscle fatigue occurs.

Recent advances in hybrid powered walking orthosis (Farris, Quintero, & Goldfarb, 2011, 2014), or use of orthosis or an exoskeleton (Dollar & Herr, 2008) in general, can reduce stimulation duty cycle of FES because orthosis can be used to share or reduce stimulation of certain muscles during walking. However, stimulation of muscles when orthosis is not employed (e.g., during swing phase of FES + passive orthosis-based walking, Sharma, Mushahwar, & Stein, 2014) or during shared control between a powered orthosis and FES (del-Ama, Gil-Agudo, Bravo-Esteban, Perez-Nombela, Pons, & Moreno, 2015; Ha, Murray, & Goldfarb, 2015, 2012; Quintero, Farris, Durfee, & Goldfarb, 2010, 2012) is still

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a significant problem. Optimal control techniques can be used to produce the minimum amount of stimulation that is required to create a desired limb motion, thus reducing muscle fatigue. In Popović, Stein, Oğuztöreli, Lebiedowska, and Jonić (1999) and Sharma et al. (2014) optimizations of musculoskeletal gait models were used to compute the minimum amount of stimulation required to produce a gait motion. The computed stimulation patterns can be applied in open-loop control to reproduce the desired gait. However, open-loop optimal control techniques are not robust to disturbances or modeling errors due to the lack of feedback. In Wang, Sharma, Johnson, Gregory, and Dixon (2013) a PD controller with an adaptive inverse optimal controller was used to control knee extension through FES. This robust technique incorporates error-based feedback control with a neural network that compensates for uncertainties in the musculoskeletal model. However, this technique did not solve the optimal control problem of an *a priori* cost function.

Unlike inverse optimal control, model predictive control (MPC) can solve the optimal control problem given an *a priori* cost function. Also, unlike open-loop optimal control techniques, MPC uses feedback that makes it more robust to disturbances. An optimal control-based controller when implemented runs in open loop because control inputs are computed for infinite horizon. MPC (also known as receding horizon control) uses a mathematical model of a system to predict how it will behave over a finite time horizon. Then by minimizing a user-defined cost function, control signals over the finite time horizon are numerically computed. The current state of the system is measured at each discrete time step of the control, which MPC uses as an initial condition for the next horizon. These initial conditions also act as feedback for the control. However, only the first element of the computed optimal control sequence is implemented on the system. In the next iteration the measured state is updated, the prediction horizon is shifted one time step forward, and the procedure is repeated.

MPC has been proposed for the control of FES for FES-assisted standing in Esfanjani and Towhidkhah (2005) and for drop foot correction in Benoussaad, Mourad, Mombaur, Katja, and Azevedo-Coste (2013). In Esfanjani and Towhidkhah (2005) MPC was simulated on a musculoskeletal model of the lower extremities and torso to track trajectories that minimize joint torque and jerk, enabling the model to make a sit-to-stand transfer. In Benoussaad et al. (2013) MPC was used in simulations on a musculoskeletal model to compute stimulation to the tibialis anterior muscle that minimizes stimulation and ground clearance of the foot during a step. The nonlinear dynamics of the musculoskeletal system and time-varying muscular response to FES makes MPC of a musculoskeletal system challenging. In Mohammed, Poignet, Fraisse, and Guiraud (2012) MPC was coupled with an input–output feedback linearization controller and simulated on FES control of knee extension. The input–output feedback linearization controller was used to cancel out the nonlinear dynamics of the musculoskeletal systems, thus making the optimal control problem simpler to solve. MPC was then used to control the linearized system instead of the nonlinear system, which resulted in computation times less than 20 ms in simulations. Therefore, the controller developed in Mohammed et al. (2012) can potentially be applied for real-time MPC of FES with a control frequency of no more than 50 Hz. However, its experimental verification remains to be seen.

In this paper, a nonlinear MPC (NMPC) algorithm that controls a nonlinear musculoskeletal system driven via FES is presented. The work presented in this paper is an expansion on the results presented in Kirsch et al. (), which only presented preliminary results for one participant. A gradient projection method was used to solve the optimal control problem, which has sufficiently fast computation times to facilitate real-time implementation of NMPC (Graichen & Käpernick, 2012; Käpernick & Graichen, 2014). This paper also presents a musculoskeletal model with muscle activation dynamics and a procedure for estimating the subject specific parameters of the model that can be used for the implementation of NMPC of FES for knee extensions. Simulations and experimental results obtained from 3 able-bodied individuals illustrated that the NMPC method can be used to control knee extension via FES with approximately 2° of steady-state RMS error. The NMPC algorithm was also shown to be robust to impulsive disturbances during the knee regulation experiments. Because NMPC is an optimal control technique it may reduce the amount of stimulation required to produce a desired motion, thus reducing the effects of FES-induced muscle fatigue. Potentially, the proposed NMPC method may benefit FES-based gait restoration devices by increasing walking durations.

2. Leg extension neuroprosthesis model

The leg extension dynamics during FES can be described as

$$J\ddot{\theta} + G - \tau_p = \tau_{ke}, \tag{1}$$

where $\theta, \dot{\theta}, \ddot{\theta} \in \mathbb{R}$ are the angular position, velocity, and acceleration of the lower leg (shank and foot) relative to equilibrium as illustrated in Fig. 1, J is the moment of inertia of the lower leg, and $G(\theta) = mgl_c \sin(\theta + \theta_{eq})$ is the gravitational torque. In the gravitational torque m is the mass of the lower leg, g is gravitational acceleration, l_c is the distance from the knee joint to the center of mass, and θ_{eq} is the equilibrium position of the lower leg relative to vertical as illustrated in Fig. 1. The passive musculoskeletal torque of the knee joint, $\tau_p(\theta, \dot{\theta})$ in (1), is modeled as

$$\tau_p = d_1(\phi - \phi_0) + d_2\dot{\phi} + d_3 e^{d_4\phi} - d_5 e^{d_6\phi}, \tag{2}$$

where the anatomical knee joint angle and angular velocity, $\phi, \dot{\phi} \in \mathbb{R}$, are defined as $\phi = \frac{\pi}{2} - \theta - \theta_{eq}$ and $\dot{\phi} = -\dot{\theta}$. The parameters d_i $(i = [1-6])$ and ϕ_0 are subject specific parameters that model the stiffness and damping of the knee joint. The exponential terms in τ_p model hyperextension and hyperflexion of the knee joint.

The torque produced by the muscles due to an FES induced muscle contraction, $\tau_{ke}(\theta, \dot{\theta}, a_{ke})$, is modeled using torque–length and torque–velocity muscle relationships as

$$\tau_{ke} = (c_2\phi^2 + c_1\phi + c_0)(1 + c_3\dot{\phi})a_{ke}, \tag{3}$$

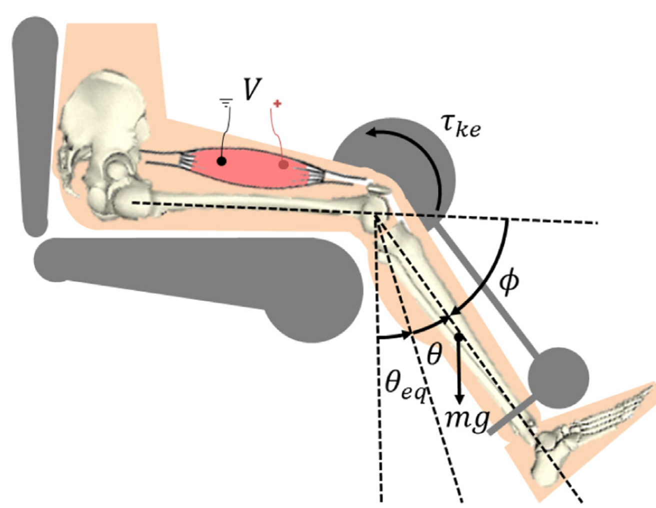

Fig. 1. This knee extension neuroprosthesis uses electrical stimulation of the quadriceps muscles to elicit a knee extension. The angle θ is the angle of the lower leg relative to the equilibrium position of the lower leg, and the angle ϕ is the anatomical knee joint angle.

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