Optimal Patterns Synthesis Approach for Knee Motion under Functional Electrical Stimulation

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Abstract

This paper concerns the synthesis of Functional Electrical Stimulation (FES) patterns for efficient functional movement. We propose an approach based on a nonlinear optimization formulation. The study considers a biomechanical knee model and the associated agonist/antagonist muscles. The goal of this method is to synthesize optimal patterns which minimize the muscular activities in order to reduce the fatigue. The approach is illustrated with a sinusoidal desired knee joint trajectory. Moreover, The applied optimal FES patterns allow the muscles co-contraction during the movement.

1. Introduction

In healthy subjects, the Central Nervous System (CNS) sends electrical signals to muscular fibres that produce a force, and then a movement. When there is a spinal cord lesion, Functional Electrical Stimulation (FES) may be used to activate the skeletal muscles like in the SUAW's project [2]. However, its application poses some problems in practice. In fact, the applied stimulation patterns are often empirically chosen, increasing the muscular fatigue. For motion synthesis, we use the muscular activities minimization approach. Therefore, our work goal, presented in this paper, is to obtain optimal stimulation patterns based on a nonlinear optimization problem formulation.

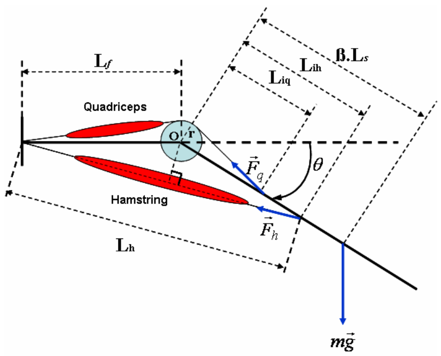

Figure 1 - Knee biomechanical model

It considers a biomechanical knee model and the actuation based on the quadriceps and hamstring muscles. In the next section, the knee biomechanical model, the muscle model, the parameters identification and the optimization problem formulation are presented. In section 3, we will present the simulation results. Section 4 presents the conclusions and discussion.

2. Method

2.1. Biomechanical model

In this first on going study, we consider a 2D biomechanical model with one degree of freedom characterizing the knee joint. It is controlled by two-antagonist muscles, which are the quadriceps and the hamstring. Figure 1 is a simplistic representation of this joint. where, θ is knee joint angle, $\mathbf{L}_f$ and $\mathbf{L}_s$ are the femur and shank+foot lengths, $\mathbf{L}_{iq}$ and $\mathbf{L}_{ih}$ are the distances between the insertion point of each muscle (quadriceps and hamstring) and the rotation point **O**, **r** is the pulley radius. $\vec{F}_q$ and $\vec{F}_h$ are the quadriceps and the hamstring forces applied on the tibia. m is the shank+foot mass and β is the mass distribution coefficient. The geometrical formulation of each muscle length ($\mathbf{L}_q$, $\mathbf{L}_h$) is given in [5]. The dynamics is described by the following second order nonlinear equation:

$$I\ddot{\theta} = \Gamma_h - \Gamma_q + mg(\beta \mathbf{L}_s)\cos(\theta) - F_v\dot{\theta} - K_e(\theta - \theta_r) \quad \textbf{(1)}$$

where, $\dot{\theta}$ and $\ddot{\theta}$ are the knee joint velocity and acceleration, Γ_q and Γ_h are the quadriceps and hamstring torques, F_v and K_e are the viscous friction and elasticity coefficients, I is the inertia of shank+foot group and θ_r is the resting angle of elasticity torque that should be identified.

2.2. Muscle model under FES

The muscle model used in the following is the one proposed in [4]. One of the main aspect of this model is that its input is the FES signal. This model is composed of two parts (figure 2):

- The activation model, that describes the behaviour of muscle fibres under FES and includes the fibre recruitment percentage and the dynamic activation representing mainly the calcium dynamics.
- The mechanical muscle model, that represents the mechanical muscular contraction. It is controlled by the recruitment rate α and the chemical control u_{ch}.

The model input is a square signal (figure 2) described by the pulse width ***PW***, the intensity ***I*** and the frequency ***f***.

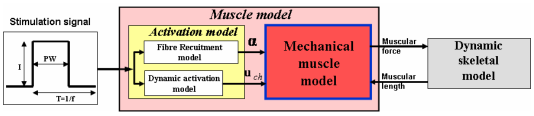

Figure 2 - Complete muscle model

The mechanical model is based on the Hill structure (figure 3). It includes a contractile element E_c controlled by two inputs α and u_{ch}. E_s and E_p are the serial and parallel elements.

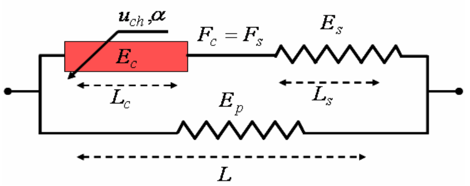

Figure 3 - controlled mechanical muscle model

2.3 Parameters identification

Four groups of parameters have to be estimated for each subject:

1. the anthropometric parameters: the inertia **I**, the mass ***m*** and the shank+foot length $\mathbf{L_s}$. They were estimated from the mass and length of the whole body through the De leva approach [1].
2. The dynamic parameters: the viscous friction F_v and the elasticity coefficient K_e. They were identified using *Eq. 1* by means of passive pendulum tests applied on the joint knee (*i.e.* $\Gamma_q = \Gamma_h = 0$).
3. The geometrical parameters $\mathbf{L_f}$, $\mathbf{L_{iq}}$, $\mathbf{L_{ih}}$ and **r** (figure 1) were identified by using the quadriceps and hamstring lengths estimated from the Hawkins laws [3].
4. The force-length equation is a relationship between muscular maximal force and the muscle length (***Eq. 2***). We identify $\boldsymbol{b_l}$ in the following equation:

$$F(L) = F_{\max}.\exp\left[-\left(\frac{L/L_0 - 1}{b_l}\right)^2\right] \qquad \textbf{(2)}$$

where, ***L*** is the current muscle length and $\boldsymbol{L_0}$ the muscle length at maximal force $F_{\max}$. Methods for the estimation phase are proposed in [5] [6].

2.4. Optimal stimulation patterns

For synthesizing the optimal FES patterns, we optimize the pulse width (PW) and the intensity (I) of the stimulation patterns minimizing the joint trajectory tracking errors and the activation of the two antagonistic muscles (*Eq. 3*). The optimization problem is stated as:

$$\min_{\mathbf{u}} \; J(\mathbf{x},\mathbf{u})$$

subject to, $\mathbf{u}_{\min} < \mathbf{u} < \mathbf{u}_{\max}$

where, $\mathbf{x} = [K_q \;\; K_h \;\; F_q \;\; F_h \;\; \theta \;\; \dot{\theta}]^T$ is the state vector and $\mathbf{u} = [\mathbf{u}_q \;\; \mathbf{u}_h]^T$ the inputs, with $\mathbf{u}_q = [PW_q \;\; I_q]$ the quadriceps inputs and $\mathbf{u}_h = [PW_h \;\; I_h]$ the hamstring inputs. K_i is the muscular stiffness and F_i is the muscular force $(i = q, h)$. $\mathbf{u}_{\max}$, $\mathbf{u}_{\min}$ are the maximal and minimal constraints of inputs. q and h represents respectively the quadriceps and the hamstring muscles.
The optimization criterium is:

$$J = \frac{1}{2}\int_{t=0}^{t_{end}} \mu_1(\theta(\mathbf{u}_q,\mathbf{u}_h) - \theta_d)^2 + \mu_2\alpha_q(\mathbf{u}_q)^2 + \mu_3\alpha_h(\mathbf{u}_h)^2\,dt \qquad \textbf{(3)}$$

where, θ_d is the desired joint trajectory, t_{end} is total duration of the movement and μ_1, μ_2, μ_3 are the cost function weights. The recruitment rate α_q, α_h of quadriceps and hamstring represent their muscular activities depending on PW and I. In the following, we will assume that the frequency f is fixed.

3. Results

Simulations have been performed using MatLab 7.0.0 on a PC platform (*Pentium-IV 3-GHz, 1-Gb RAM*). In the first part of the simulation, we test the minimal number of inputs for obtaining an efficient synthesis. Intensities I_q and I_h of muscle input signals are first fixed. We only optimize the pulse widths PW_q, PW_h for synthesizing a knee sinusoidal motion. We choose 10 degrees of freedom for the motion control in order to decrease the computation duration.

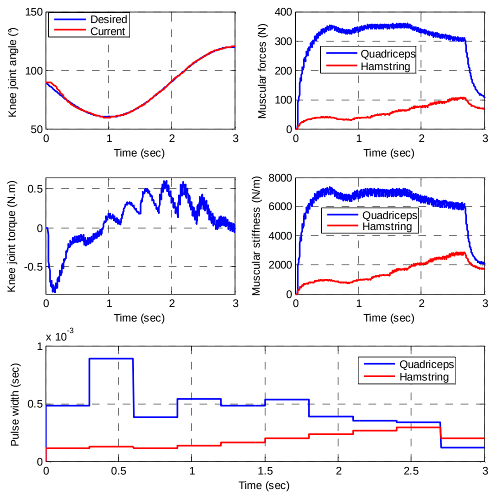

Figure 4 - knee system state, output and inputs (*PW*)

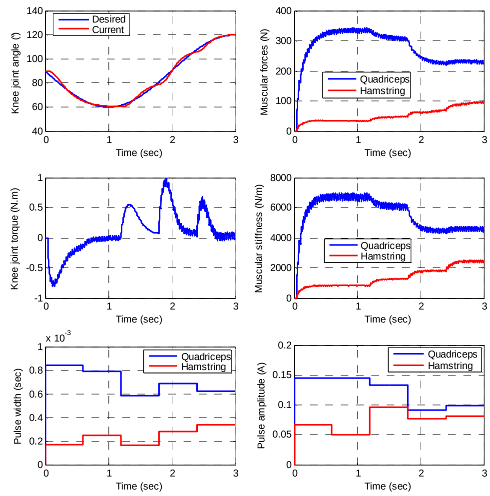

Figure 5 - knee system state, output and inputs (*PW, I*)

The desired motion trajectory starts at rest position (***90°***), makes a flexion to ***60°*** then an extension to ***120°*.** The results are presented on figure 4.

In the second part, we optimize all the stimulation inputs *i.e.* $\mathbf{u} = \begin{bmatrix} PW_q & I_q & PW_h & I_h \end{bmatrix}^T$ for the same sinusoidal motion. We take 5 degrees of freedom such that the number of optimized parameters is the same than before. Figure 5 illustrates these synthesis results. This simultaneous optimization of all inputs may be useful to minimize the charge $Q = PW \times I$ applied on each muscle. It also allows selecting the best recruitment curve sensitivity. Actually, both simulations last around 14*h*. It depends on the number of optimized parameters and the total movement duration t_{end}.

4. Discussion and Conclusions

In the current paper, a nonlinear optimization method was used to determine optimal electrical stimulation patterns. This optimization is based on nonlinear knee and muscle models. The results show the optimization method effectiveness for an optimal electrical stimulation. In the first part of results, we observe good motion synthesis except at the start due to the system delay. The results are less accurate in the second part, although the number of optimized parameters is the same. The increase of degrees of freedom improves the tracking accuracy. However, it increases the optimization duration. The results show the co-contraction occurrence of antagonistic muscles. The co-contraction rate is not explicitly controlled but it appears for the motion stabilization. It depends on the cost function weight μ_1, μ_2 and μ_3. In the future works, the optimal stimulation patterns will be applied to paraplegics for experimental validations. An important part of work will then be the specific parameters identification of each subject.

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