Design of Optimal Profiles of Electrical Stimulation for Restoring of the Walking

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Abstract— We present a method for the synthesis of electrical stimulation profiles for assisting the walking in hemiplegic individuals. The stimulation profiles are synthesized by combining the joint torques estimated from the simulation that optimizes the tracking errors with a constraint of the minimal coactivation of antagonist muscles and the recruitment of the muscles for the potential user. The predicted electrical stimulation profiles were compared with the EMG recordings of the prime movers of the leg joints. The conclusion is that synthesis of controls should rely on muscle activation profiles determined through simulation, in which the level of coactivation of antagonist muscles are preset to ensure stability of the joints and smooth movements. The example presented uses data from a healthy individual (model parameters), but the methodology is directly implantable for hemiplegic individual just by replacing the model parameters, the EMG and the trajectory of the nonparetic leg.

Index Terms — EMG, Electrical stimulation, Hemiplegia, Optimal control, Walking

I. INTRODUCTION

FUNCTIONAL Electrical Stimulation (FES) is the basic instrument for operation of a motor neural prosthesis (NP). The FES connotes the production of movement that leads to a function. Today, most components of motor NP reached maturity: effective interfaces (electrodes and connectors) have been designed and tested, programmable electronic stimulators are available with powerful microcontrollers, and micromachining technology provides effective sensors [1, 2]. We suggest that the design of an effective controller that guaranties that an FES operates at the level where individuals with paralysis are satisfied would ensure much wider use of NP in daily life [3]. We also suggest that the artificial controller needs to mimic the operation of the sensory-motor systems characteristic for healthy individuals since it must be integrated into the biological control that controls all preserved subsystems.

An appealing method to design stimulation profiles is to record electromyography (EMG) from the prime movers of the joints of interest for movement in healthy individuals, and apply the timing and intensity of rectified and smoothed EMG for the control of paralyzed muscles in an individual with disability. A method that is suitable for implementation is the mapping of the states of the system to the levels of muscle activations [4–6]. Mangold et al. [7] analyzed and compared averaged EMG signals reported in literature for the seven lower extremity muscles during gait of healthy persons with the aim to retrieve the stimulation profiles that can be used in FES for walking. Normal EMG has been used as a template for determining the timing and intensity of stimulation by Kobetić and Marsolais [8]. The stimulation profiles for 48 leg and trunk muscles were estimated by hand-crafting based on EMG recordings to assist walking of individuals with paraplegia. O’Keeffe et al. [9, 10] developed a method for generating a stimulation profile which accurately reproduces the normal EMG of Tibialis Anterior m. during gait of hemiplegics.

Nikolić et al. [11] used inductive learning to generate the rules for predicting Quadriceps m. activity from the EMG recordings. Heller et al. [12] compared one symbolic (inductive learning) and one connectionist (multi layer perceptron type artificial neural network) machine learning technique for reconstruction of Semitendinosus m. and Vastus Medialis m. activity from kinematics data measured during normal human gait at several gait speeds.

However, there are several difficulties in cloning EMG profiles from healthy individuals for external activation of muscles in individuals with disability: 1) external electrical stimulation in paralyzed extremities results with muscle forces outputs that are different from the one found in healthy individuals, 2) modified reflexes limit the individual control of muscles in the manner found in healthy individuals, and 3) sensory information reaching higher levels of central nervous system are greatly modified in individuals with disability compared to healthy individuals [3].

The alternative for control is to generate profiles of muscles activations by customized modeling and simulation [13–15]. Popović et al. [13] presented the simulation based on a reduced model that can be customized for the potential user by using experimentally identified model parameters. Namely, the method considered inertial and muscle parameters that reflected the impairment caused by the lesion. Both planar [15] and 3D models [16] were developed for restoring gait of individuals with hemiplegia and paraplegia, respectively. The optimization was based on optimal control implementing dynamic programming [13], static optimization [14], and dynamic optimization [17]. The method was successfully applied in a clinical study in individuals with paraplegia [16].

Here, we suggest combining these two methods: We apply the simulation for designing stimulation profiles...
since it comprises the activation dynamics of muscles, inertial and physiologic parameters that are characteristic for a given user, and we use EMG recordings for setting of the penalty function to incorporate natural like cocontraction of antagonistic muscles that is characteristic for healthy-like walking. The example presented shows a procedure of selection of the penalty function (constraints). We also show the differences in the stimulation profiles in parallel with the tracking errors with various levels of constraints. The example directly relates to the control of the paretic leg in the stance phase (knee extension, knee bounce at landing, push off) and swing phase (ankle dorsiflexion, knee flexion, controlled terminal extension) by controlling four muscle groups with surface stimulation.

A. Model Based Synthesis of Stimulation Profiles.

Biomechanical model. We used a model that is suitable for the control of walking in individuals with hemiplegia [13]. The adopted reduced planar model of one leg since it is observable and controllable. The remaining parts of the body were replaced by an interface force and torque. The leg [see Fig. 1(a)] is presented with three rigid bodies (i.e., thigh, shank and foot) connected by pin joints (i.e., knee and ankle) allowing the rotations in the sagittal plane (i.e., knee flexion/extension, ankle plantar/dorsi flexion). The joint actuators were assumed as the net results of muscles contractions and resistive torques ($M_{\text{RESK}}, M_{\text{RESA}}$) resulting from soft tissues, ligaments, and stretched muscle-tendon systems [see Fig. 1(b)]. The joint actuators were assumed to be Quadriceps ($M_{\text{QUAD}}$) and Hamstrings ($M_{\text{HAM}}$) acting at the knee, and Tibialis Anterior ($M_{\text{TAL}}$) and Soleus ($M_{\text{SO}}$) acting at the ankle joint. Further details about the model are given in [17].

The model parameters used in the simulation were experimentally identified by applying the techniques described in [21].

Simulation. The goal of the simulation was to determine muscle activation profiles that generate the muscle forces adequate for the tracking of desired trajectories. The simulations were based on optimal control minimizing the following cost function:

$$F(u_i, u_j, u_k) = \left[ \left( \frac{\varphi_i - \varphi_i^*}{\varphi_i^{\text{max}}} \right)^2 + \left( \frac{\varphi_j - \varphi_j^*}{\varphi_j^{\text{max}}} \right)^2 + \sum_{i=1}^{n} u_i^2 \right] dt.$$  

(1)

and minimum muscle activation constraints defined with:

$$u_i(t) + u_j(t) \geq \Omega_i, \quad u_i(t) + u_j(t) \geq \Omega_k, \quad u_i \geq \Omega, \quad i = 1, 2, 3, 4.$$  

(2)

The variables $\varphi_i^*$, $\varphi_j^*$ and $\varphi_i^{\text{max}}$, $\varphi_j^{\text{max}}$ are desired and generated angles, respectively. The parameters $\varphi_i^{\text{max}}$, $\varphi_j^{\text{max}}$ are maximal values of the desired angles. The parameter $T$ is simulation duration. The signals $u_i$ ($i = 1, 2, 3, 4$) are normalized levels of activations for Tibialis Anterior, Soleus, Hamstrings and Quadriceps, respectively. They are constrained to be between zero and one, zero meaning that the muscle is relaxed and one that the muscle is activated at the titanic level. The first two terms in (1) are the sum of the squares of the normalized tracking errors, while the third is the total effort of muscles expressed by their levels of activation. The desired levels of cocontraction of agonist and antagonist muscles were varied by selecting different values of parameters $\Omega_i$, $\Omega_k$ and $\Omega$ ($i = 1, 2, 3, 4$) in (2). The parameters $\Omega_i$ and $\Omega_k$ prescribe minimum values of sums of activations for pairs of antagonistic muscles acting around the ankle and knee. The parameters $\Omega$ ($i = 1, 2, 3, 4$) set the minimum levels of activations of each of the muscles individually. The higher values of these parameters the higher are the cocontractions.

The optimization was done by using two different algorithms. The first, described in [14] and [15] used static optimization (SO) and the second, given in [17], implemented Moving Window Dynamic Optimization (MWDO). Both methods use mathematical model in a discrete form. The SO applies local optimization in which the muscle activations are calculated on a sample by sample basis without considering previous or future values. In contrast, the MWDO applies optimization over the time interval calculating several activation values at once. Moreover, the MWDO takes into account the delay that exists between the onsets of stimulation and the actual muscle activation (muscle activation dynamics [3]). The outputs from SO and MWDO simulations are: 1) the profiles of normalized muscle activations; and 2) the shank and foot segment angles generated when the calculated activations are applied to the model. The MWDO determines muscle excitations in the form of piecewise constant signals. This type of profile is convenient for implementation of pulsatile electrical stimulation and thereby more suitable for practical application compared to the profiles calculated by SO. We simulated in total twenty strides due to the limitations imposed by the number of steps in which ground reaction force (GRF) was measured.

B. Data collection and processing.

Experimental data were collected from a healthy male individual (H=1.75 m; M=73 kg; 26 yrs.). The individual signed a consent form approved by the local ethical committee. The measurements were done in the Gait laboratory at the Center for Sensory Motor Interaction,
Aalborg University, Denmark. The individual walked 20 times at a self-paced gait speed. The average gait speed, stride duration and stride length were 0.95 m/s, 1.51 s and 1.42 m, respectively.

Gait kinematics and kinetics were recorded by a laboratory fixed camera based motion capture system (8 ProReflex MCU240 cameras, Qualisys, SE) and an AMTI force plate (OR6-5, Advanced Mechanical Technology, USA) embedded in the floor at the middle of the walkway. Passive retro-reflective markers were placed on the individual’s right leg according to recommendations for the passive markers. Force plate (OR6-5, Advanced Mechanical Technology, USA) that was used for processing of the acquired motion capture data [18]. Simultaneously, surface bipolar EMG signals were recorded from the following muscles acting around the knee and ankle joints: Hamstrings m., Quadriceps m., Tibialis Anterior m., and Soleus m. Wireless EMG monitor (TeleMyo 2400R, Noraxon, USA) was used for acquisition. High-pass (1st order, 10 Hz cutoff) and low-pass (6th order, 500 Hz cutoff) analog Butterworth filters were implemented at the amplifier inputs (input impedance > 100 MΩ, CMRR > 100 dB). First, the skin was prepared to lower down the impedance and then the pairs of electrodes (Ambu Neuroline 720, Ambu, UK) were placed over the muscles according to the recommendations from the SENIAM committee [19]. Marker trajectories, force plate and EMG data were acquired using a desktop PC compatible computer equipped with the acquisition software (Qualisys Track Manager, Qualisys, SE) and the data acquisition card (PCI-DAS1602/12, Measurement Computing Corporation, USA). Sampling frequencies were set to 100 Hz for the marker trajectories and 1.5 kHz for the force plate and EMG signals.

Data recorded by the cameras and the force plate were processed using the software for human motion analysis. Horizontal and vertical acceleration of the knee (αK, αΩ) and absolute angles of the thigh (ϕT), shank (ϕS), and foot (ϕF) from the horizontal axis were calculated from the marker data. Components (Fx, Fy) of the ground reaction force (GRF) and trajectory of the center of pressure (COP) were determined from the force plate data. The gait pattern signals were low-pass filtered by a 2nd order dual-pass Butterworth filter at a cutoff frequency of 6 Hz [3]. The signals constituted desired trajectory (gait pattern) for the simulations.

The EMG signals were first high pass filtered by a 2nd order dual-pass Butterworth filter at a cutoff frequency of 6 Hz. This was done in order to minimize the movement artifact. The EMG signals were then rectified and low-pass filtered using a 2nd order dual-pass Butterworth filter at a cutoff frequency of 15 Hz [20] to obtain linear envelopes. Finally, the EMG envelopes and GRF data were downsampled to 100 Hz in order to synchronize them with the kinematics data.

II. RESULTS

We illustrate the findings with a representative example that shows the results of simulations for one selected gait stride. The results for other strides over the complete set of data were similar.

![Figure 2: Results of simulation implementing SO without prescribing minimal level of cocontractions. The parameters Ω_i, Ω_e and Ω_i (i = 1,2,3,4) were all set to zero. Notice that the periods of major muscle activity as predicted by the simulation coincide with the EMG activity. Tibialis Anterior is active at the beginning of the stance and throughout the swing. The activation of Soleus gradually increases during the stance phase and reaches maximum at the push off. Similarly, the overall agreement between the simulation-determined activity and EMG is evident for the Quadriceps and Hamstrings as well. However, there are also noticeable differences between the two profiles both in timing and normalized levels of activations. The EMG shows variable level of cocontraction of antagonistic muscles during the gait stride. The simulated muscle activations show no coactivation at all due to the optimization that minimizes the muscle efforts.](image1)

![Figure 3: Results of simulation implementing SO with minimal level of cocontractions. Vertical axes in upper plots are normalized muscle activations (SIM) superimposed to normalized recorded EMG. Lower plots show desired joint angles (DES) and simulation-generated joint angles (GEN). The plots show one gait stride starting with the heel strike. The toe off is at 58% of the gait stride. The periods of major muscle activity as predicted by the simulation coincide with the EMG activity. However, the EMG shows cocontraction of antagonistic muscles while there is no coactivation in the simulation-determined activations. Notice that the periods of major muscle activity as predicted by the simulation coincide with the EMG activity. Tibialis Anterior is active at the beginning of the stance and throughout the swing. The activation of Soleus gradually increases during the stance phase and reaches maximum at the push off. Similarly, the overall agreement between the simulation-determined activity and EMG is evident for the Quadriceps and Hamstrings as well. However, there are also noticeable differences between the two profiles both in timing and normalized levels of activations. The EMG shows variable level of cocontraction of antagonistic muscles during the gait stride. The simulated muscle activations show no coactivation at all due to the optimization that minimizes the muscle efforts.](image2)
setting the parameters heuristically to the following values: \( \Omega_i = 0.2 \) and \( \Omega = 0.05 \) (i = 1,2,3,4). Notice that simulation-determined activations for antagonistic muscles now exhibit coactivation. The calculated activations and recorded EMG became more similar. However, the quality of tracking is very similar in both cases (compare lower plots in Figs. 2 and 3). Maximal tracking errors in both simulations are less then 2.5°.

Figure 4: Results of simulation implementing MWDO without prescribing minimal level of cocontractions. Vertical axes in upper plots are normalized muscle activations (SIM) superimposed to normalized recorded EMG. Lower plots depict desired (DES) and simulation-generated (GEN) joint angles. Notice the tracking error and oscillations in the generated trajectory for the ankle joint angle between 45 % and 55 % of the gait stride.

The results of simulations by using MWDO are given in Figs. 4 and 5. Fig. 4 shows the simulation in which the cocontractions were not imposed (i.e., \( \Omega_i = \Omega = 0 \), i = 1,2,3,4).

Although the optimization minimizes the cocontractions, the calculated activations still exhibit short periods of low-level coactivations, particularly during the phases in which the activity was transferred from a muscle to its antagonist. Regarding the quality of tracking, generated trajectory for the ankle joint angle is lower compared to Fig. 4. Furthermore, there are no oscillations in the generated ankle angle.

The goal of the study was to learn about the constraints that need to be implemented in order to ensure good tracking but also similarity with the biological control. When analyzing the profiles of EMG and simulation results the obvious difference can be seen at the beginning of the gait cycle (loading phase after heel contact).

The EMG recorded from the knee extensor was high compared with the muscle activation level obtained through simulation. We carefully analyzed this behavior, and the finding is that the actual projection of the GRF is operating as the knee extensor in the model; hence, no muscle activity is required to guarantee almost perfect tracking and the condition is the minimization of the muscles efforts. The likely reason that the EMG is high is the readiness of the biological control to respond to...
potential perturbations. The loading is the critical phase, since the gravity is the major force acting at the body, and it is concentrated in the GRF during the loading phase. In the case that the knee does not provide support during the loading the catastrophic effect will follow (falling down). Importantly, the optimizations that we developed are flexible enough to consider this fact. This is illustrated in Fig. 6 that shows the results of SO in which the level of coactivation for the knee muscles was further increased but only in the selected section of the gait stride. This selective boost in coactivation makes the calculated profiles for the knee muscles even more similar to the recorded EMG.

In normal gait of healthy individuals, coactivation of antagonistic muscles at the ankle joint varies throughout the gait cycle, being higher during the weight acceptance and transition between the stance and swing [23]. Lamontagne et al. [24] suggested that the coactivation is an important adaptive behavior in individuals with disabilities. Reduced coactivation on the parietic side may contribute to poor postural stability and poor locomotor performance of the post-stroke individual with hemiplegia. Therefore, designing the stimulation profiles that include coactivation of antagonistic muscles is of direct relevance for gait rehabilitation. Importantly, both SO and MWDO algorithms allow prescribing the desired level of coactivation and thereby fine tuning the tradeoff between the certain level of joint stiffness (stability) and minimization of muscle fatigue.

Simulation based on SO is relatively fast; in each step, only one activation value is calculated by applying static optimization. Simulation of a gait stride by using SO lasted less than 2 minutes. In the examples shown in Figs. 2 and 3 the muscles were strong enough (healthy individual) to generate the selected gait pattern. Due to this fact and because the simulation was done off-line, we obtained an excellent tracking of the desired trajectories. Moreover, the introduction of cocontractions did not affect the tracking. The activations of antagonistic muscles did increase. However, the change was proportional and the net joint torques (driving the model) stayed essentially unchanged.

MWDO uses dynamic optimization that computes several activation values at once. Simulation of a gait stride by using MWDO lasted between 8 and 15 minutes. Importantly, MWDO includes additional constraints that make the simulation more realistic and closer to the real-life application. MWDO calculates piecewise constant excitations which are similar to stair-like stimulation profiles typically used in FES. Muscle activation dynamics are modeled. Therefore, the muscles are not ideal torque generators; instead, they are activated gradually. Making the model more similar to the real system has several consequences. The activity can not be transferred abruptly between the antagonistic muscles. As a result, the simulation generates certain level of coactivations even in case when the coactivations were not prescribed (Fig. 4). The tracking error and oscillations can emerge (Fig. 4). However, introduction of cocontractions stabilizes the ankle (Fig. 5). Due to spring-like properties of the muscles, coactivation increases the joint stiffness, and thereby reduces the oscillations. Therefore, an important conclusion is that introduction of cocontractions not only generates the profiles which are more similar to EMG, but significantly increases the quality of tracking as well.

The other important reason for applying the simulation is the use of the customized model. The importance comes from the fact that the simulation considers a model characterized by parameters of an individual with disability. The characteristics of motor systems in individuals with disability are very different from the ones typical for healthy individual (e.g., weaker muscles, spasticity, altered viscoelastic joint properties, etc.). This is to say, that the method could be used to test the feasibility of various walking patterns (trajectories); thus, in the case that one trajectory shows to be unfeasible, the different set of trajectories could be tested and the one feasible selected for implementation [14, 16].

REFERENCES


