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Nonlinear Model Predictive Control of Joint Ankle by Electrical Stimulation For Drop Foot Correction

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Abstract— **In this paper we investigate the use of optimal control techniques to improve Functional Electrical Stimulation (FES) for drop foot correction on hemiplegic patients. A model of the foot and the tibialis anterior muscle, the contraction of which is controlled by electrical stimulation has been established and is used in the optimal control problem. The novelty in this work is the use of the ankle accelerations and shank orientations (so-called external states) in the model, which have been measured on hemiplegic patients in a previous experiment using Inertial Measurement Units (IMUs). The optimal control problem minimizes the square of muscle excitations which serves the overall goal of reducing energy consumption in the muscle. In a first step, an offline optimal control problem is solved for test purposes and shows the efficiency of the FES optimal control for drop foot correction. In a second step, a Nonlinear Model Predictive Control (NMPC) problem - or online optimal control problem, is solved in a simulated environment. While the ulitmate goal is to use NMPC on the real system, i.e. directly on the patient, this test in simulation was meant to show the feasibility of NMPC for online drop foot correction. In the optimization problem, a set of fixed constraints of foot orientation was applied. Then, an original adaptive constraint taking into account the current ankle height, was introduced and tested. Comparisons between results under fixed and adaptive constraints highlight the advantage of the adaptive constraints in terms of energy consumption, where its quadratic sum of controls, obtained by NMPC, was three times lower than with the fixed constraint.**

This feasibility study was a first step in application of NMPC on real hemiplegic patients for online FES-based drop foot correction. The adaptive constraints method presents a new and efficient approach in terms of muscular energy consumption minimization.

I. INTRODUCTION

One of the major disabilities caused by hemiplegia, usually due to a cerebro-vasucular accident (CVA), is the drop foot syndrome. It consists on an inability of the foot to perform a dorsiflexion (moving upward) during the swing phase of walking gait. As a consequence, hemiplegic patients adapt their walking gait to avoid dragging the toe on the ground. Excessive hip and knee flexion as well as an extreme lifting motion of the hip are applied for compensation, leading to a non natural and highly inefficient gait.

The drop foot correction (DFC) gathers techniques and solutions to overcome these problems. The most classical one is the use of Ankle-Foot Orthosis (AFO), which ensures a rigid fixation of the ankle at a given position permanently [1]. This solution is simple and commonly used, however it presents some issues related to the non-natural behavior of the foot. A new generation and more complex powered AFO has recently been developed [2] to overcome the passivity problems of the previous version. Both solutions don't offer any therapeutic benefit to hemiplegics patients in terms of dorsiflexion recovery and are cumbersome for them.

Functional Electrical Stimulation (FES) was used in several application to restore the functional behavior in the paralyzed limbs [3]. It was also applied for DFC by contracting artificially the tibialis anterior (TA) muscle, which is responsible of the dorsi-flexion of the ankle [4]. Afterward, several FES-based systems for DFC were proposed and applied, as reviewed in [5]. A hybrid system combining AFO and an FES controller was also proposed [6].

A foot-switch it is usually used as a on/off sensor that detects the heel-off, in order to start the stimulation and activate the TA muscle. The applied stimulation patterns are classically predefined as a trapezoid shape [4]. A system which allows a dynamical adjustment of the stimulation intensity was proposed in [7], where the clinician can specify graphically the shape of the stimulation intensity envelope.

One drawback of FES applications is the induction of muscular fatigue and these predefined stimulation shapes induce more muscular fatigue due to their empirical aspect and the fact that they don't include any information about the ankle-foot system behavior or patient specificities. In addition, the application of predefined stimulation suffers from the lack of adaptability to changes of the musculo-skeletal system behavior (muscle fatigue) and of the environment (stairs, slopes etc.).

The authors in [8] showed the inconsistency of the trapezoidal simulation shapes by comparing the FES-induced EMG with the natural EMG profile. Healthy activation patterns are characterized by two main phases of activity during walking, which was applied by [9], [8] to produce more natural stimulation in FES. However, this method requires the use of cumbersome and bulky equipment and sensors, which is not well accepted by patients. Therefore, an adaptive control stimulation system for DFC is required. Then, a new generation of sensor system is jointly used as an alternative to a foot-switch sensor [10], [11], [12], [13]. These easy-to-use sensors are the Inertial measurement Units (IMUs), which mainly provide accelerations and gyroscopic data. A neural network has been combined with the fuzzy feedback controller [14] or with the PID feedback controller [15] to adjust the optimal electrical stimulation.

Optimal control strategies, based on models of tibialis anterior muscle and ankle joint, have been proposed and tested in [16], to calculate the optimal stimulation which satisfies

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some objectives for the DFC. Several objective functions for optimization have been investigated, such as a quadratic criterion of muscle excitation. It could be shown that precisely tracking a given reference trajectory for walking without a controlled antagonistic muscle is impossible. But the use of an antagonistic muscle to track a reference trajectory is very energy consuming in presence of co-contraction phenomena [17], and it is not necessary to perform the swing phase of a gait. Thus, the definition of realistic goals to achieve an efficient DFC remains an open question.

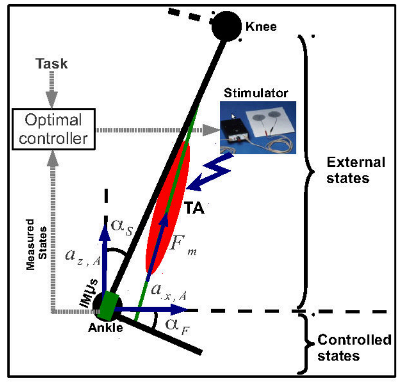
In the current research, we apply a model-based optimal control strategy for the DFC during swing phase gait. The novelty of this work is that the used model includes ankle accelerations and shank orientations, measured using IMU sensors, which were placed on hemiplegic patients in previous experiments. Offline optimization and then Nonlinear Model Predictive Control (NMPC), based on the minimization of he square of the muscle excitation under a set of physiological and kinematic constraints instead of applying a trajectory tracking objective, have been tested. For these computations, a set of fixed constraints were initially applied. Afterwards, original adaptive constraints of the foot orientation taking into account the foot height were proposed and tested in the optimal control formulation. Our optimization uses the model (§-II) of the ankle joint actuated by the TA muscle and uncontrolled states, observed by IMUs (Fig. 1). Offline optimization and online NMPC methods and their implementation details are presented in §-III. The results are presented and discussed in section §-IV and conclusions and some perspectives of this work are presented in §-V.

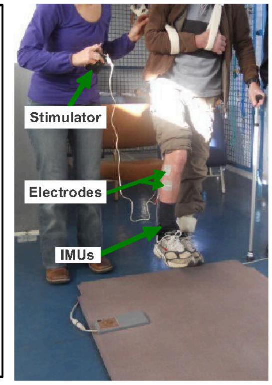
II. MODELING

The global model during the swing phase includes the controlled model and the external states (i.e. uncontrolled from the perspective of this model, but of course controlled by processes outside the scope of this model). They describe the movement of the ankle and the orientation of the shank, which are measured using the IMUs. We assumed that the contact forces are negligible at the beginning of the swing phase, since there is no activation of the antagonistic muscles which could be activated during the push off.

A. Model of ankle-TA muscle

The ankle-TA muscle is modeled in 2D as presented in Fig. 1-(a). The relative orientation of the foot with respect to the shank is controlled by an electrically stimulated TA muscle which produces the force F_m. The absolute orientation of the foot is defined with respect to the horizontal axis with the angle α_F, while α_S defines the absolute orientation of the shank with respect to the vertical axis. Both angles are positive in counter-clockwise direction. The state vector of the system is $\mathbf{x} = [x_1, x_2, x_3] = [f_{act}, \alpha_F, \dot{\alpha}_F]$, where f_{act} is the dynamic activation level of the muscle (with, $0 \leq f_{act} \leq 1$) and $\dot{\alpha}_F$ is the absolute rotational velocity of the foot. The system is controlled with the input vector $\mathbf{u} = [u_1] = [\varepsilon]$, where ε represents the muscle excitation (with, $0 \leq \varepsilon \leq 1$). The system also depends on the external states vector





(a) (b)

Fig. 1. Experimental setup of the FES-based DFC. (a) Optimal control prototype for DFC and model of ankle joint controlled by electrically stimulated Tibialis Anterior (TA) muscle and influenced by external states ($\mathbf{x}^{ext}$). (b) Hemiplegic subject and equipments used in experiments for inertial data acquisition.

$\mathbf{x}^{ext} = [x_1^{ext}, x_2^{ext}, x_3^{ext}, x_4^{ext}] = [a_{x,A}, a_{z,A}, \alpha_S, \dot{\alpha}_S]$, where $a_{x,A}$, $a_{z,A}$ are linear accelerations of ankle in horizontal and vertical axis respectively (Fig. 1-(a)) and $\dot{\alpha}_S$ is the absolute velocity rotation of the shank. They are called external states since they are outside the system actually considered (investigating the control of the relative angle of the foot) and are also determined by controls outside this system. Then, the state equations that model the system behavior are presented below [16]:

$$\begin{cases} \dot{x}_1 = (u_1 - x_1)\left(\frac{u_1}{T_{act}} - \frac{1-u_1}{T_{deact}}\right) \\ \dot{x}_2 = x_3 \\ \dot{x}_3 = \frac{1}{J}(F_m(\mathbf{x},\mathbf{u})d + T_{grav}(x_2) + T_{acc}(x_1^{ext}, x_2^{ext}, x_2) \\ \qquad + T_{Ela}(x_2) + B(x_4^{ext} - x_3)) \end{cases} \tag{1}$$

where, $T_{grav} = -m_F c_F \cos(x_2) g$ is the gravity torque of the foot around the ankle and m_F, c_F denote the mass of the foot and its center of mass location w.r.t the ankle. g is the gravity acceleration and J the inertia of the foot around the ankle. T_{acc} is the torque induced by the movement of the ankle. It is calculated using external states x_1^{ext}, x_2^{ext} as presented in the following equation:

$$T_{acc} = m_F c_F (x_1^{ext} \sin(x_2) - x_2^{ext} \cos(x_2))$$

The experimental set-up for external states measurements and their post processing are more discussed in §II-B.

T_{Ela} is the passive elastic torque around the ankle due to different passive muscles and tissues. Its model is based on works of [18], where the elastic torque depends on the ankle position and also on the knee position. However, in the current work we assumed that the effect of knee angle variation is not significant in the ankle angular range investigated here. Then, the knee angle is set to zero and the model became $T_{Ela} = \exp(a_1 + a_2 x_2) - \exp(a_3 + a_4 x_2) + a_5$, where the values of parameters $[a_1, ..., a_5]$ are resumed in Table II. B is the viscosity parameter and $(x_4^{ext} - x_3)$ represent the relative angular velocity of the joint ankle. d is the moment arm around the ankle joint of the TA muscular force

F_m, induced by the electrical stimulation and defined by a classical three component model [19], as below:

$$F_m = x_1 F_{max} f_{fl}(x_3^{ext} - x_2) f_{fv}(x_4^{ext} - x_3) \tag{2}$$

where, F_{max} is the maximal isometric force of the TA muscle. $f_{fl}(x_3^{ext} - x_2) = \exp\left(-\left[\frac{l_{CE} - l_{CE,opt}}{W l_{CE,opt}}\right]^2\right)$ is a non-linear relationship which links the generated force to the length of the muscle and therefore to the ankle joint angle. $l_{CE,opt}$ is the optimal length of the fiber at which the maximal force can be generated and W is the shape parameter, which defines the range of muscle displacement where a force still remains perceptible. By assuming a constant tendon length l_T, we obtain the length of the muscle fibers as $l_{CE} = l_{MT} - l_T$. l_{MT} is the length of the muscle-tendon complex for the TA that depends linearly on the ankle joint angle: $l_{MT} = l_{MT,0} + d(x_3^{ext} - x_2)$ where $l_{MT,0}$ is the rest length of the muscle-tendon complex, which is reached when the ankle joint is at a right angle (i.e. $x_3^{ext} - x_2 = 0$). The derivation of the of muscle-tendon length equation, allows to obtain the contraction speed of the muscle $v_{CE} = d(x_4^{ext} - x_3)$. f_{fv} is a non-linear force velocity relationship that models the dependency of the muscle force on the contraction speed of the muscle v_{CE}. It is described by two hyperbolic relationships, which ensure a continuous first derivative at the connection point between them (i.e. when $v_{CE} = 0$):

$$\begin{cases} f_{fv}(x_4^{ext} - x_3) = \dfrac{1 - \frac{v_{CE}}{v_{max}}}{1 + \frac{v_{CE}}{v_{max} f_{v1}}} & \text{if } v_{CE} < 0 \text{ (contraction)} \\[2ex] f_{fv}(x_4^{ext} - x_3) = \dfrac{1 + a_v \frac{v_{CE}}{f_{v2}}}{1 + \frac{v_{CE}}{f_{v2}}} & \text{else (extension or isometric)} \end{cases} \tag{3}$$

The maximal contraction speed v_{max} as well as the factors f_{v1}, f_{v2} and a_v are subject-specific and muscle-specific parameters. Names, values of the whole parameters involved in the current model are gathered in Table II.

B. Experimental set-up for inertial data acquisition

The external states $\mathbf{x}^{ext}$ can not be computed or estimated using the current model, but are required as an input for this model and should be observed using the IMUs measurements. For an implementation of a feedback control scheme, these states should be measured online, in a real time directly on the patient. In the current work, we investigated the feasibility of the optimal control strategies (offline and online) before the real application on the patients. In order to simulate the treatment of this real time measurement for the estimation of the external states data in the optimal control procedures, we used experimental IMUs data obtained previously from walking measurements on three hemiplegic patients, but fed it sequentially as if it were actually measured at that time. It would not be possible to use data from patients with drop foot syndrome and without stimulation since the patients in this case adapt the motions of the rest of the leg in order to avoid dragging the toes on the ground, and such leg trajectories do not compare to leg motions of healthy subjects or of stimulated patients. We therefore use data from experiments with drop foot patients which receive a classical stimulation (trapezoidal shape) during the walking gait observe using a peroneal nerve stimulator, as presented in Fig. 1-(b). We assumes that the variation in the external states (uncontrolled limbs) between applying a non optimal stimulation and optimal one is negligible, while a stimulation-based DFC is applied.

These experiments have been performed in Grau-du-Roi rehabilitation center (CHU Nimes- France) on hemiplegic patients, where an agreement from the local ethical committee and a consent from the patients were obtained. The patients were walking on a treadmill when the inertial measurements are acquired through the IMUs sensors. The IMUs, placed in the bottom of the shank and close to the ankle joint (Fig. 1), includes 3 axis Accelerometers, 3 axis Magnetometers and 3 axis Gyroscopes. Due to the well known sensitivity problems of Magnetometers [20], their data are not used. Gyroscopes provided the absolute velocity orientation of the shank $\dot{\alpha}_S$. These data were filtered and integrated to get the orientation of the shank α_S. Then, the orientation information were used to obtain the two accelerations $a_{x,A}$ and $a_{z,A}$ in the global frame, from the accelerations measured in the frame of the accelerometer sensors and after removing the gravity acceleration [20]. Data were filtered using 5^{th} order moving average filter [21]. It is well known that the integration of the inertial data results in drift problems as shown in Fig. 2 for some cycles, however, since we used only the first swing phase (from the Toe-Off (TO) to the Hell Strike (HS)), the problem of drift is not as dominant.

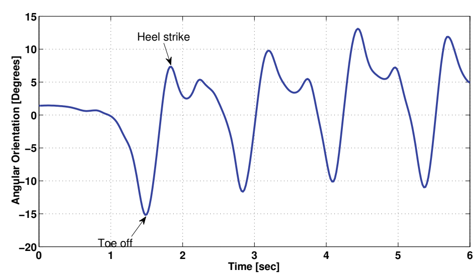


Fig. 2. Absolute shank orientation obtained by integration gyroscopic measurements.

III. OPTIMAL CONTROL STRATEGIES

We use optimal control techniques to generate optimal trajectories for the foot respecting the dynamics of the system as well as other constraints. The goal of the optimization problem is not to track a desired motion for the foot (i.e. mimic the behavior of a healthy foot which may not be desirable for a patient) but rather to optimize a criterion linked the energy consumption or fatigue associated with the walking motion. In this study, we have considered two different types of optimal control problems, namely:

- Offline optimal control problems that determine the whole solution over the whole duration (in this case the swing phase time) based on the system model without taking feedback of the environment into account

- online optimal control problems - or better nonlinear model predictive control problems - which consist of repetitive re-optimizations of the system over a short horizon based on the system model, but taking current state estimations into account as new starting values.

A. Offline optimal control

The aim of this offline optimal control problem to determine the best possible motion for the musculo-skeletal model of the lower leg, according to the criterion specified below. The same approach was already used in [16], but as outlined above, the model and the type of data used are different. We study the result of optimal control trajectories for the shank angle and the ankle position prescribed by external data, leaving the the relative angle of the foot free for optimization. Here we only optimized the the swing phase, but the same approach could be used for the full step if the full multi-phase model was considered. We minimize the integral over the squares of the muscle excitation u_1, i.e. $\min \int_0^T u_1^2 dt$ which results in an optimal control problem of the following form:

$$\min_{\mathbf{x},\mathbf{u}} \quad \int_0^T \mathbf{u}^T W \mathbf{u} dt \tag{4}$$

$$\text{s. t.} \quad \dot{\mathbf{x}}(t) = f(t, \mathbf{x}(t), \mathbf{u}(t)) \tag{5}$$

$$\mathbf{x}(0) = \mathbf{x}_0, \quad \mathbf{u}(T) = \mathbf{x}_e \tag{6}$$

$$\mathbf{r}(t, \mathbf{x}(t), \mathbf{u}(t)) \geq 0 \tag{7}$$

In these computations, the total time T of the swing phase is fixed to the time set by the data ($T = 0.36\,\text{sec}$), but it can also be left free, as we have shown in [16] . Constraint (eq.(5)) takes into account the dynamic model of the foot, and eq.(6) denotes the initial and final conditions for the trajectory (foot position at the beginning and end of the swing phase which in these computations are fixed to reference values). Eq.(7) describes different types of inequality constraints on the motion, such as upper and lower bounds on state and control variables as well as constraints guaranteeing foot clearance which is one of the major objectives of FES drop foot correction. For the solution of the optimal control problem we use the powerful optimal control code MUSCOD developed at Heidelberg University [22], [23] which uses a direct method, discretizing the control variables based on functions with local support, and a multiple shooting parameterization for the state variables. The large but structured nonlinear programming problem resulting from these two discretizations is solved using specially tailored SQP (sequential quadratic programming) methods.

B. Nonlinear Model Predictive Control

The offline optimal control computations described above serve as a preparation for the actual goal of this study which is to optimize FES stimulation online. Nonlinear model predictive control (NMPC) is a form of online optimization taking into account real world information in form of state estimations at a given sampling rate and uses a repeated solution of off-lie optimal control problems. At each sampling point, an optimal control problem is solved for the model for a selected short horizon from the present state, and the solution determines the next control action. This control sequence is executed until a more recent optimal control problem solution is available at the next sampling point (see [24] for more details). The problem that we solve in the online optimization context is similar to the one in the previous section (4) -(7), except for the facts that the time is adjusted to the prediction horizon (0.18 sec), instead of the full swing phase, that the start value is always equal to the current estimated state, and the final constraint is removed since it is not valid for the horizons ending before touchdown. Instead a term punishing the deviation from this end constraint is added as a least squares term to the objective function with some smaller weight.

The NMPC problems arising in this study are solved by the online version of the code MUSCOD mentioned above which is based on the efficient real-time iteration scheme [25]. It is based on the strategy of not finding exact, but only approximate solutions of the individual open-loop optimal control problems and efficiently splits the required computations into those that can be done beforehand, and those that must be done online based on the feedback. In this study, we do not yet perform online optimization in the loop on a real subject, but perform real-time optimization based on previously collected data of external states in order to demonstrate the feasibility of the concept.

IV. RESULTS AND DISCUSSIONS

In this work, optimal stimulations for drop foot correction have been investigated through the most relevant criteria and constraints of the optimization problem. In addition, the feasibility of an online optimal control was tested. Thereafter, some optimal control results are presented.

In the first test, we investigated the optimal control as an offline optimization problem without using a predefined trajectory of the foot orientation. Indeed, we minimized here a quadratic criterion of the control u_1 during the whole swing phase under a the following set of constraints:

$$\begin{cases} x_1(T) = 5^\circ & \text{the final angle} \\ x_2(T) = 0 & \text{the final velocity} \\ x_1(t) \geq -15^\circ & \text{angles each time} \end{cases} \tag{8}$$

Results of the first test are presented in Fig. 3, where controls (Fig. 3-(a)) and muscle activation levels (Fig. 3-(c)) highlight two peaks of activity at the beginning and at at the end of the swing phase and a medium activation somewhere else. These two activity peaks of the muscle are comparable to the shape of two activities established in [9], although the time of swing phase is shorter here. The foot angle trajectory (Fig. 3-(b)) and velocity trajectory (Fig. 3-(d)) respects perfectly the fixed constraints in the very short time of the swing phase and with the imposed external states. This demonstrates the capability of the optimal stimulation to correct the drop foot syndrome using an efficiency-based objective function and avoiding a foot angle trajectory tracking. This offline optimization can be useful to provide a ready-to-use optimal stimulation for a DFC, instead of the classical trapezoidal shape. However, it must be expected that there is a - more or less drastic -

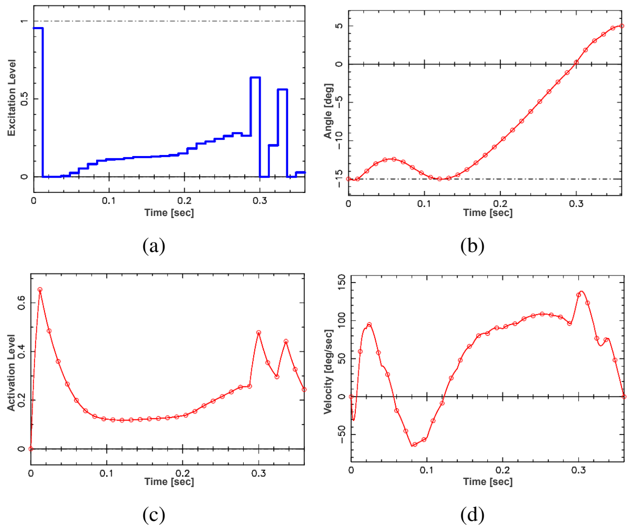


Fig. 3. Offline optimization results with a fixed constraint of foot orientation. (a) The muscle excitation (u_1); (b) The foot orientation angle (x_2); (c) The dynamic activation of TA muscle (x_1); (d) The foot orientation velocity (x_3).

mismatch between the model and the reality, since on the one hand the model is quite simple and on the other hand the external data used as input may be quite far off from the real motion of the external states. If optimal control is performed offline (i.e. the whole computation is done before the motion or at least the step starts), the external states are obviously not determined from current measurements but are guessed based on older information or data that goes back at least to the previous step. All this makes online optimal control a necessary tool for this problem. In the next test case, we therefore applied an NMPC method to control online a simulator of the real ankle-TA system. The horizon of prediction was chosen equal to 18 steps which correspond to 0.18 sec. Results of the online NMPC method are presented in Fig. 4-(a). It shows high and oscillating excitation levels at the beginning of the swing phase. These controls applied to the simulator highlights however a smooth foot angle trajectory as presented in Fig. 4-(b). This excitation levels oscillation is however acceptable since the ankle angle is smoothed by to the natural filtering of the musculoskeletal system. The foot angle trajectory (Fig. 4-(b)) shows that the foot inclination inequality constraint is respected, except before 0.05 sec, where angles are under $-15°$. In the real-time iteration scheme, a lot of efficiency is gained by the fact that no full convergence of the SQP method is achieved in every open-loop optimal control solution, since it is only used for the computation of the next control action. This however implies that not all constraints are always satisfied, since SQP methods only guarantee feasibility at convergence and not for every iterate. However, these foot inclinations still remain acceptable to avoid the drop foot problem, so no other actions have to be taken to avoid infeasibility. Fig. 4-(b) shows also that the final foot angle target was well reached, but a bit quicker than actually required, which made the optimal control results more energy consuming. This is due to the combination of the control and the least square error in the objective function. Further increasing of the control weight may decrease the accuracy of the final foot inclination target. Other formulations for the final ground contact will be investigated in the future. The formulation of the swing

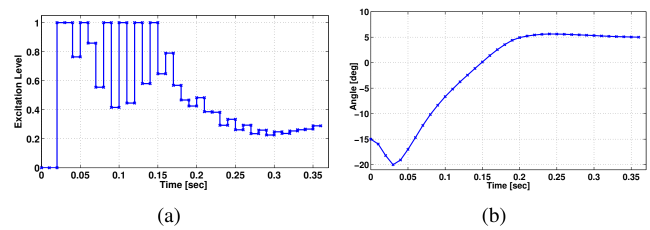


Fig. 4. NMP control results with a fixed constraint of foot orientation. (a) The muscle excitation (u_1); (b) The foot orientation angle (x_2).

foot clearance which is important for the drop foot syndrome was not straightforward with the current model. Since only accelerations of the ankle and no positions are measured and used in the model, the height of the toes can not be directly described for the constraints as it was done in [16]. Instead, a constraint based on the foot ankle is formulated using some heuristics. In the first test, the foot inclination constraint could not be bigger than -15 since it is the start angle. On the other hand, the foot angle constraints is not the same during the swing phase and depends on the height of the foot. Thus, an adaptive inclination constraint is more efficient and required. In the next test case, we have tested an original adaptive inclination constraints based on the model of the ankle-foot and using the online position of the ankle. If the ankle position in Z axis $x_{z,A}$ (height) is known, the minimum allowed foot orientation $\alpha_{F,min}$ present an adaptive constraint, which the model is illustrated by Fig. 5-(a).

To prove the feasibility and to test the relevance of our adaptive foot orientation constraints method, an ankle height trajectory (see Fig. 5-(b)), obtained on valid subject with motion capture system, was for instance used. It has the same swing phase duration. Based on the model of Fig. 5-(a), It is easy to establish a function of the minimum allowed foot orientation $\alpha_{F,min} = -\arcsin\left(\frac{x_{z,A}-\Delta h}{L_{Foot}}\right)$. Where L_{Foot} is the foot length and Δh is a safety distance. It should be chosen carefully to avoid an excessive constraint which increase the activation and then the muscular energy consumption. From the real ankle trajectory (Fig. 5-(b)), the trajectory of $\alpha_{F,min}$ is calculated for $\left[\ L_{Foot} = 26cm, \quad \Delta h = 3cm\ \right]$ as presented in Fig. 5-(c). Therefore, the adaptive constraint, that we used in the next optimal control strategies, consist on the condition $\alpha_F \geq \alpha_{F,min}$. This adaptive constraint model is realistic since it ensure a positive final constraint foot orientation, which is appropriate for the heel strike. In this last test, the new adaptive foot orientation constraint (Fig. 5-(c)) was tested in the NMPC method, described in the second test. Therefore, the fixed inequality foot orientation constraint was replaced by the adaptive one. While the minimized objective became a quadratic criterion of the control u_1, since the adaptive constraints ensure intrinsically a positive final foot orientation from 0.225 sec. Results of this adaptive

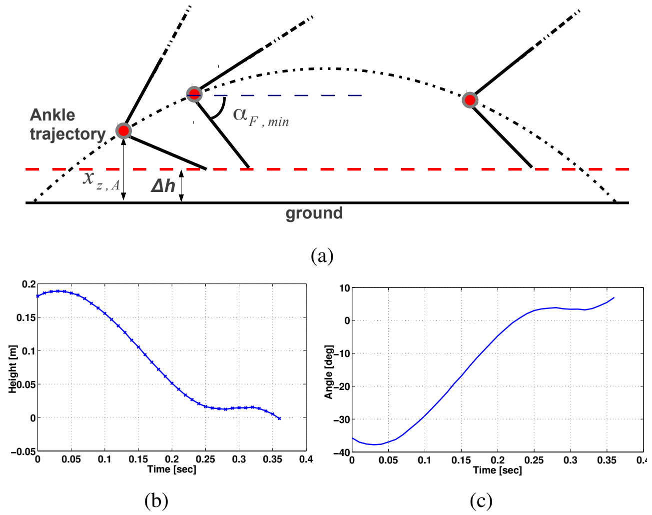


Fig. 5. Model of foot orientation adaptive constraints (a), real data of ankle heights (b) and the calculated adaptive minimal foot orientation $\alpha_{F,min}$ (c).

constraint-NMPC method are resumed in figure 6. Optimal controls, shown in Fig. 6-(a), exhibit clearly a lower muscle excitation than in the results of the NMPC method with a fixed constraint (Fig. 4-(a)). In addition, the foot orientation constraints were perfectly respected, since foot angles (Fig. 6-(a)) are all the time above the minimum foot angles (Fig. 5-(c)).

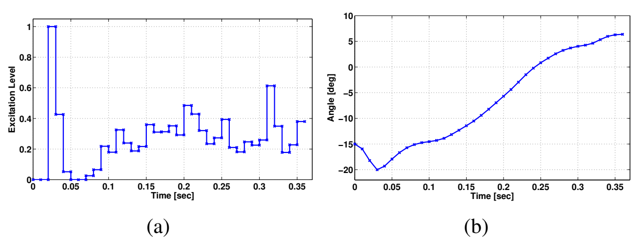


Fig. 6. NMP control results with an adaptive foot orientation constraint, which depends on the position of the ankle (real data); (a) The muscle excitation (u_1); (b) The foot orientation angle (x_2).

The quadratic sum of controls obtained for each method are summarized in Table I. It highlights three times lower quadratic sum of controls with adaptive constraints (0.04) than with fixed constraints (0.12). This comparison shows even lower level of quadratic controls with the first method (0.027). This is due to the fact that this offline optimization considers the global movement, unlike the NMPC method which optimizes online, and thus is more suitable for DFC application.

TABLE I

QUADRATIC SUM OF CONTROLS OBTAINED IN EACH METHOD

Methods	Quadratic sum of controls
Offline optimization with fixed constraints (Fig. 3)	0.027
NMPC with fixed constraints (Fig. 4)	0.120
NMPC with adaptive constraints (Fig. 6)	0.040

When the patients have different tones of drop foot symptoms, this method still remain applicable since the model is close enough to each patient behavior. For that, a parameters identification procedure is required and planned in future works. Application of NMPC-based drop foot correction on a real patients requires to solve following critical points, which are planned in the future works. From muscle excitations u_1 of each results, the pulse width or intensity of stimulation pulses can be directly obtained through the recruitment function [26]. Real foot orientation measurements will be acquired online using an additional IMUs placed on the foot. Thereafter, ankle heights should be obtained online using a double integration of the IMUs accelerations $a_{z,A}$. However, due to the well known drift problems, this method requires specific powerful filtering techniques [20], which will be investigated. In addition, in NMPC application on a real patient, the external states can not be measured on the future horizon but only at the current time. Thus, prediction of these external states based on previous steps or other previous information will be investigated. The start of the stimulation control should be done automatically. Therefore, an automatic gait phase detection based on the Inertial data [13] is planned as well.

V. CONCLUSIONS

In the current work we have investigated the optimal control of ankle joint for the drop foot correction (DFC) in hemiplegic patients through Functional Electrical Stimulation (FES) applied on the tibialis anterior muscle. To satisfy the goal of a energy consumption minimization, no trajectory of the foot orientation was predefined or tracked. Instead, several constraints (fixed and adaptive) of the foot orientation have been investigated, where the objective criteria were mainly a quadratic criterion of controls. Firstly, the optimal control problem has been investigated in the offline mode. Then, Nonlinear Model predictive control (NMPC) was tested online using a simulator of the real ankle joint-tibialis anterior system. This feasibility study allowed the preparation of NMPC application for a real drop foot correction. Test results highlight the efficiency of our approaches for the drop foot correction. Energetic comparisons of results show that the adaptive constraints method is more appropriate than the fixed constraints method, even if both reach the objectives of the drop foot correction.

The NMPC-based application for drop foot correction on a real hemiplegic patients is planned in future works. It requires to solve several critical issues mainly related to online measurements, their availability in the horizon of prediction and their post processing online and in real time.

APPENDIX

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TABLE II

MODEL PARAMETERS AND THEIR VALUES, WHOSE SOME ARE ESTIMATED FOR AN AVERAGE SUBJECT ($75kg - 1.75m$)

Parameters	Signification	Values [unit]
T_{act}	Activation constant time	0.01 [sec]
T_{deact}	Relaxation constant time	0.04 [sec]
J	Inertia of the foot around ankle	0.0197 $[kg.m^2]$
d	Moment arm of TA w.r.t the ankle	3.7 $[cm]$
B	Viscosity parameters	0.82
c_F	COM location w.r.t the ankle	11.45 $[cm]$
m_F	Mass of the foot	1.0275 $[Kg]$
a_v	First force-velocity parameter	1.33
f_{v1}	Second force-velocity parameter	0.18
f_{v2}	Third force-velocity parameter	0.023
v_max	Maximal contraction speed (shortening)	-0.9 $[m/\sec]$
F_{max}	Maximal isometric force	600 $[N]$
W	Shape parameter of f_{fl}	0.56
l_T	Constant tendon length	22.3 $[cm]$
$l_{MT,0}$	Muscle-tendon length at rest	32.1 $[cm]$
$\begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{pmatrix}$	Parameters of elastic torque T_{Ela}	$\begin{pmatrix} 2.10 \\ -0.08 \\ -7.97 \\ 0.19 \\ -1.79 \end{pmatrix}$

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