APPLICATION OF NONLINEAR MODEL PREDICTIVE CONTROLLER FOR FES-ASSISTED STANDING UP IN PARAPLEgia

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Abstract— Functional Electrical Stimulation (FES) is a method of restoring functional movements in patients of spinal cord injury that electrically induces muscle contractions. Nonlinear dynamics of paraplegics during standing up and limits of the physiological actuators suggest “Nonlinear Model Predictive Control” as a good candidate to follow desired trajectory and maintaining standing no need to learning or tuning many parameters such as many nonlinear controllers that had been used previously. In this work, the theoretical possibility of FES assisted standing up in paraplegic patient is studied using Nonlinear Model Predictive Control approach by computer simulation. The Proposed controller shows good tracking behavior for ankle, knee and hip joint angles in simulated paraplegic standing up and improves patient safety because of considering constraints in control.

I. INTRODUCTION

Devices delivering functional electrical stimulation (FES) are a type of neural prosthesis; they are substituting for a neural function which is damaged or destroyed. FES aims to restore functional movements in patients of spinal cord injury (paraplegias) that electrically induces muscle contractions for standing and walking. A FES system can be considered as a tracking controller. It generates muscle stimulation signals such that the patient can track a determined trajectory to stand up.

Previously suggested controllers have their own benefits and disadvantages. The open-loop procedure proposed by Kralj and Bajd is straightforward [1]. However, the produced motion with this system has unnatural jerk and disturbances can not be compensated. Too high terminal velocity of joints may damage to the insensate tissues. Also, it may cause or exacerbate shoulder pain. A number of closed Loop schemes have been suggested to solve these problems. Tuning of the controller parameters is difficult because the dynamics of standing up is nonlinear, has a high degree of inter-segmental coupling and is affected by the voluntary arm forces. In these studies, the controller parameters were usually designed by trial and error. Ewins [1] used linearized model of paraplegic standing to design PID type closed loop knee controller for FES standing up. These results showed smooth trajectories, however the terminal knee velocities and upper limb loading were not appropriate. Because of nonlinear dynamics, the PID controller doesn't work properly. Davoodi and Andrew [2] used Gain Scheduling PID to overcome the problem. In several points covering performance range of plant, standing dynamics was approximated with linear model. Corresponding with each approximation, a PID controller was designed. Genetic algorithm as an optimization approach was used for tuning controllers' parameters. These tuned parameters are very sensitive to plant model mismatch.

To design FES controller, nonlinear dynamics of paraplegic standing and wide range of joint variation during movement must be considered. Therefore, nonlinear controller schemes are very suitable for this purpose [3]. Davoodi and et al. proposed Fuzzy Logic Controller (FLC) for designing FES controller. This system showed improved performance, in terms of the trajectory smoothness, knee end velocity and the required arm forces, compared with PID control. However, the amount of manual tuning required to optimize the fuzzy controller precluded its practical application. For tuning FLC parameters genetic algorithm was used [4]. Regarding computational burden for genetic algorithm convergent, real-time adjustment of FLC parameters is impossible. Adaptive fuzzy logic controller with reinforcement learning was suggested by Davoodi and Andrew for FES system [4].

In this work, using nonlinear model predictive control FES controller was developed for paraplegic standing up. Towhidkhah and et al. proposed model predictive control scheme for natural human movement control strategy that is exerted by central nervous system [5]. In general, nonlinear predictive control is a good technique for control of nonlinear systems with constrained states or inputs. The performance of suggested FES system was evaluated by computer simulation. Good tracking behavior and model-plant mismatch robustness were observed.

II. VIRTUAL PATIENT

Paraplegic patient model is necessary for design and simulation. We name this model as “virtual patient”. The model incorporates body segments, muscles, passive joint properties and voluntary use of the upper limb [1], [6]. The movement was assumed to be symmetrical. The head and neck were also assumed to remain along the trunk. A four linked rigid body model with three degrees of freedom was used to describe the dynamics of the body and lower extremities in sagittal plane. Links were assumed to be connected by frictionless pin joints. Segmental centers of mass are assumed to lie on the line connecting the two
adjacent joints. Physical parameters were scaled to body mass and height according to Winter's suggestion [7].

The muscles were modeled by first order transfer functions. The moment transmitted by the passive leg joint structures has both elastic and damping term [8]:

\[ \tau_{\text{pass}} = k_s e^{-k_t (\theta - \theta_0)} - k_e \dot{\theta} \]

where, \( \theta \) and \( \dot{\theta} \) are joint angular displacement and velocity. \( \theta_0 \) and \( \theta_2 \) are the final ranges of joint angular movement.

It has been assumed that the chair during the movement exerts forces at the hip joint onto the femur. Thus two nonlinear spring-dashpot pairs were used to model the viscose-elastic characteristic of body chair contact in horizontal and vertical directions [9]:

\[ F_{\text{ich}} = K_{\text{ich}} i - B_{\text{ich}} i \]  \( i = X, Y \)

where, \( i \) is the incremental change of the spring length in X or Y directions, \( K_{\text{ich}} \) and \( B_{\text{ich}} \) are the stiffness and damping parameters of the spring dashpot pairs, respectively.

In arm assisted standing up the function of arms and voluntary movements of trunk has been integrated into the model as external loads at the shoulders which could vary with time during the movement. The horizontal and vertical components of the equivalent force at the shoulder joint were generated by fuzzy logic controllers with the rules defined heuristically based on the fact that these forces primarily provide balance and help in lifting the body [4].

The dynamic equations of the system have been derived by applying Newton-Euler equations to each link [10]:

\[ M(\theta) \dot{\theta} + C(\theta, \dot{\theta}) \dot{\theta} + G(\theta) = J^T \tau \]

where, \( \theta \), \( \dot{\theta} \) and \( \ddot{\theta} \) are joint angular displacement, velocity and acceleration vectors, \( M(\theta) \) is the inertia matrix of system, \( C(\theta, \dot{\theta}) \) is the term comprising the Coriolis and centrifugal forces, \( G(\theta) \) is the gravitational term, \( \tau \) is the total joint torque vector at ankle, knee and hip. \( J_T \), \( J_{ch} \) and \( J_{sh} \) are Jacobians that transform moments and external loads to joint angular space.

### III. Trajectory Planning

Regarding that FES system was treated as a tracking controller, we must determine reference trajectory such that tracking this path lead the patient to stand up. Differences between patient conditions necessitate different appropriate trajectories for each paraplegic patient. The strategy used by central nervous system for path planning is the best way to determine the reference trajectory. Considering mathematical models proposed for human motion planning, the reference path was determined by optimizing a cost function combining the minimum jerk or maximum smoothness criteria and minimum torque change criteria [11]:

\[ C = \frac{1}{T_f} \int_0^{T_f} \tau^T W_E \tau + \dot{\tau}^T W_v \dot{\tau} + \alpha J(t) dt + \text{Pen} \]

Where, \( \tau \) is the joint moment vector, \( W_E \), \( W_v \) are weight matrixes, \( J(t) \) and \( \text{Pen} \) are the jerk and penalty term respectively. Inverse dynamic equations of the system are equality constraints. Inequality constraints are physiological limitations, physical limitation such as stability, geometrical constraints (motion form) and boundary conditions. Using splines on the midway points, search space parameterized and “sequential quadratic programming” was utilized for optimization [12],[13]. Notice that, obtaining the optimal reference path is not the purposes of optimization, we just want to have a reference path to transmit the patient to standing position.

### IV. Nonlinear Model Predictive Control

In General the model predictive control (MPC) problem is formulated as solving online a finite horizon optimal control problem subjects to system dynamics and constraints involving states and controls. Based on measurements obtained at time \( t \), the controller predicts the future behavior of the system over a prediction horizon and determines over a control horizon the input signal such that a performance objective function is optimized. Summarizing the basic MPC scheme works as follows:
1) Obtain measurement or estimation of the states of the system.
2) Compute an optimal input signal by minimizing a given cost function over a certain prediction horizon in the future using a model of system.
3) Implement the first sample of the optimal input control.
4) Continue with 1.

V. CONTROLLER DESIGN

For Implementation of nonlinear model predictive control algorithm a nonlinear programming problem must be solved in each sampling instant to obtain optimal control signal. The online nonlinear optimization imposes a heavy computational burden which requires extensive computing power and a long sampling time. For a system with fast dynamics this problem becomes even more challenging due to the fast sampling requirement. Linearization of nonlinear model around equilibrium operating points involves several shortcomings. The best way to address these difficulties arising in predictive control of nonlinear systems is to pursue an analytic approach, where it is intended to develop a closed form NMPC and online optimization is not required [14],[15]. After approximation of the tracking error in the receding horizon by its Taylor series expansion, an analytic solution to the MPC is developed and a closed form nonlinear predictive controller is presented [14]-[16].

The system described by dynamic equations (2) can be written in the state space representation:

$$
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= F(x_1, x_2) + P(x_1) \tau(t) \\
y &= x_1
\end{align*}
$$

(5)

where, $x=[x_1 \ x_2]^T=[\theta \ \dot{\theta}]^T \in \mathbb{R}^n$ is the state vector, $\tau(t) \in \mathbb{R}^n$ represents the moment vector and $y(t) \in \mathbb{R}^n$ is the output vector (angular positions). Also,

$$
F(x_1, x_2) = (M(\theta) J_\theta^{-1})^{-1} (J_\theta^{T} - 1) (C(\theta, \dot{\theta}) \dot{\theta} + G(\theta) - J_{ch} L_{ch} - J_{sh} L_{sh})
$$

(6)

are bounded matrix and bounded vector function respectively. Approximate nonlinear predictive control was applied to system described by equation (4) and (5). In the predictive control strategy, the following control problem is solved at each $t$ and $x(t)$ [16]:

$$
J = \frac{1}{2} \int_t^{t+h} \left\{ \begin{array}{cc}
0 & e_1(t+T) \\
e_2(t+T) & 0
\end{array} \right\}^T Q \left\{ \begin{array}{cc}
0 & e_1(t+T) \\
e_2(t+T) & 0
\end{array} \right\} dT + \frac{1}{2} u(t+T)^T R u(t+T)
$$

(7)

subject to the state equations (5) and $x(t+h) = 0$ for some $h > 0$, where $Q$ is positive definite and $R$ semi positive definite. Denote the optimal control to the above problem by $u^*(T), T \in [t, t+h]$. The currently applied control $u(t)$ is set to $u^*(T)$. In equation (7), $h$ denotes prediction horizon. To avoid the computational burden as mentioned above, we should approximate the above receding horizon control problem by expanding each component of the predicted tracking error $e(t+T)$ into Taylor series at $e(t)$ and to simplify the relations, the control signal is assumed to be constant over the control horizon. We obtain:

$$
u(t) = - (J_\theta^{T} - 1) M(x_1) \ F^{-1} \left\{ \frac{10}{3h^2} Q_1 e_1 + \frac{5}{2h} (Q_1 + 2Q_2) e_2 + (Q_1 + 4Q_2) (F(x_1, x_2) - \dot{x}_{ref} / 2) \right\}
$$

$$
F = Q_1 + 4Q_2 + 20h^{-4} (J_\theta^{T} - 1) M(x_1) R (J_\theta^{T} - 1) M(x_1)
$$

By La Salle’s invariance theorem, has been proven that the $e(t)$ tends to the origin. We examine this fact with computer simulation.

VI. SIMULATION RESULTS

System schematic is shown in Fig 2. For computer simulation the patient model (virtual patient) and FES controller (NMPC algorithm) was implemented using Matlab® 6.5.1.

A. Standing Maneuver

Controller parameters were selected by trial and error: $Q_1=5 \times 10^4 I_3$, $Q_2=9 \times 10^4 I_3$, $R=1 \times 10^{-6} I_3$, $h=h_c=100 ms$ where $I_3$ denotes the identity matrix with dimension 3 by 3. Reference trajectory and plant outputs (joint angular position respect to horizon direction) are showed in Fig 3. As illustrated tracking error is negligible. For visualizing paraplegic patient sit to stand maneuver, the existent patient model implemented in Matlab® SimMechanics Toolbox.
B. Robustness Evaluation

Inherent robustness corresponds to the fact that nominal NMPC can cope with model uncertainties without taking them into account. This fact stems from the close relation of NMPC to optimal control. The analysis of robustness properties of NMPC scheme must be considered as an unsolved problem in general.

In this work, robustness of NMPC controller in FES system, with respect to model plant mismatch was considered by simulation study. Patient weight loss or gain, slow changes in the voluntary control of upper limb strategy due to the patient becoming more skilled in the maneuver and initial position of patient are common sources of mismatch between patient and its model which used by NMPC algorithm for prediction of future behavior. Simulation results showed that the system is robust to near 30% change in patient weight (loss or gain). Also 25% change in magnitude of voluntary arm forces doesn’t have considerable effect on the controller performance. The controller is robust to 40% changes in patient initial position conditions.

VII. CONCLUSIONS

In this paper, application of nonlinear model predictive control strategy for designing FES system for paraplegic patient standing up was discussed. The proposed algorithm was simulated utilizing paraplegic patient model. After determination reference trajectory sit to stand maneuver was animated and controller robustness to the plant model mismatching was considered. The designed system has showed good tracking behavior and considerable robustness to common mismatching. Despite design simplicity and straightforward implementation, in compare with other FES controllers nonlinear predictive strategy has showed satisfying performance. The proposed method doesn’t need tuning or learning and is a suitable approach for practical application.

REFERENCES


