Evoked Electromyography-Based Closed-Loop Torque Control in Functional Electrical Stimulation

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***Abstract*—This work proposed a closed-loop torque control strategy of functional electrical stimulation (FES) with the aim of obtaining an accurate, safe and robust FES system. Generally, FES control systems are faced with the challenge of how to deal with time-variant muscle dynamics due to physiological and biochemical factors (such as fatigue). The degraded muscle force needs to be compensated in order to ensure the accuracy of the motion restored by FES. Another challenge concerns the fact that implantable sensors are unavailable to feedback torque information for FES in humans. As FES-evoked electromyography (EMG) represents the activity of stimulated muscles, and also enables joint torque prediction as presented in our previous studies, here we propose an EMG-feedback predictive controller of FES to control joint torque adaptively. EMG feedback contributes to taking the activated muscle state in the FES torque control system into account. The nature of the predictive controller facilitates prediction of the muscle mechanical response and the system can therefore control joint torque from EMG feedback and also respond to time-variant muscle state changes. The control performance, fatigue compensation and aggressive control suppression capabilities of the proposed controller were evaluated and discussed through experimental and simulation studies.**

***Index Terms*—Joint torque control, evoked electromyography, EMG-feedback predictive control, functional electrical stimulation (FES).**

I. INTRODUCTION

SInce functional electrical stimulation (FES) was proposed for motor function restoration in spinal cord injured (SCI) patients, open-loop control has been predominantly used in FES systems, where the stimulation pattern is predefined. The control performance in such systems tends to degrade over time due to various uncertainties in the muscle response. Closed-loop control has been investigated in the laboratory environment but has not yet been widely applied in practice. Regarding lower limb FES control, it is more important in terms of safety and stability comparing with upper limb FES control [1]. In some previous studies, the stimulation onset was modulated adapting to the walking speed, ground surface or the user's intentions through physical sensors such as foot-switches [2], accelerometers and gyroscopes [3], through a built-in algorithm [4] or electromyography (EMG) [5]. In these studies, the sensor information was only used to trigger the stimulation, while the stimulation patterns were predefined empirically or through a trial-and-error process. Such control strategies are not able to compensate for the degraded muscle force/torque caused by muscle state changes and not able to provide a reliable stimulation pattern for desired complex movements (such as stepping up/down stairs with different stair heights, or various sports/exercise movements).

Most other studies regarding FES closed-loop control focus on joint angle feedback to achieve the desired joint angle by adaptively adjusting the stimulation pattern. For example, in [6], a model-based approach was proposed to achieve an efficient and robust FES system, with a nonlinear and physiologically based model describing the dynamic behavior of the knee joint and muscles. An artificial neural network system was proposed to map evoked EMG signal to FES-induced knee joint angle in a knee angle maintaining task [7]. In [8], a sliding model closed-loop control method was proposed to control the knee joint angle. However, the finite-time convergence of the sliding variable could not be guaranteed, and this study did not specifically investigate the performance of the controller facing muscle-state changes. Other studies [9] [10] and [11] led to the development of several adaptive controllers in order to improve joint angle tracking performance in FES. In these studies, the proposed control methods range from neural sliding-mode control to adaptive fuzzy sliding-mode control with joint angle feedback. FES-restored motion always originates from active joint torques and the interaction with environment. Joint angle feedback approaches cannot distinguish the resultant motion elicited by stimulation and that by external forces. Thus, joint torque control is considered to be superior to joint angle control as in humanoid development [12]. The compliance provided by torque control is an important factor especially in the presence of environmental interactions, which is also required for humans in daily activities. In FES, internal joint torque is produced through stimulus-induced muscle contractions. In addition, controlling the variable which is directly affected by FES is straightforward. Therefore, it is important to explicitly control the joint torque elicited by muscle contraction for advanced FES systems. This study is thus aimed at developing a novel FES torque control scheme as an alternative of the

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classical FES closed-loop system. It can also bring adaptive function to muscle time-variant responses.

A torque sensor is required as feedback to achieve closed-loop joint torque control in FES, but existing torque sensors are unsuitable for use in patients' daily lives. Although joint torque control has been studied with respect to unsupported standing [13] [14], torque recording on a specially designed apparatus cannot be applied out of the lab. Therefore, we were motivated to control joint torque from other sensor feedback. A number of methods have been proposed to estimate muscle force or joint torque from EMG signal, and some of them succeeded in tracking muscle fatigue [15] while assuming a time-invariant FES system. In our previous studies, an EMG-based torque prediction method was proposed and validated for time-variant muscle fatigue tracking in SCI patients with surface FES [16] and implanted FES [17]. In addition, this method accounts for actual muscle activities, which can guarantee the stimulation safety and feasibility of FES control. Based on the good performance of torque prediction rendered by EMG signals in [16] and [17], this study was aimed at developing an EMG-feedback closed-loop torque control method so as to achieve the desired FES-induced joint torque. A predictive control strategy was used for our control purpose because of several benefits. For instance, feed-forward prediction and feedback correction are applied to ensure the optimization in predictive control strategies. This is similar to the neural control process, which involves both feed-forward and feed-back strategies to control muscle contraction for a specific task. In the control law of predictive controller, both the control input and output can be easily constrained to avoid both aggressive stimulation and over-stimulation in FES. Moreover, fewer predictive controller parameters need to be adjusted in comparison to other closed-loop control methods, which facilitate hands-on implementation in practice.

This study was aimed at evaluating the feasibility of joint torque control based on EMG feedback in FES context. In section II, the muscle excitation/contraction model and the corresponding state-space representation are introduced. Next, a strategy for FES torque control is proposed in section III. Experimental data from two able-bodied subjects were collected and used to validate the control scheme in section IV. A discussion on this control strategy is given in section V. Finally, section VI concludes the paper.

II. Muscle Excitation and Contraction Model

An FES system delivers electrical impulses to excitable motor neurons, in order to contract a target muscle and produce joint torque and then joint movement. The muscle response can be controlled by adjusting the stimulation parameters, i.e. frequency, amplitude or pulse width (PW), depending on subject's intended tasks. However, the muscle response involves time-variant characteristics like muscle fatigue and reflex, which complicate the control problem in FES.

In a previous work [16], we developed a torque prediction method to provide an accurate torque estimate from EMG signals under isometric conditions. A polynomial Hammerstein model (PHM) was used to represent muscle contraction dynamics, with identification obtained by the Kalman filter (KF) with a forgetting factor. This model structure is able to represent a time-variant nonlinear process and has been used in some biomechanical system identification studies [15].

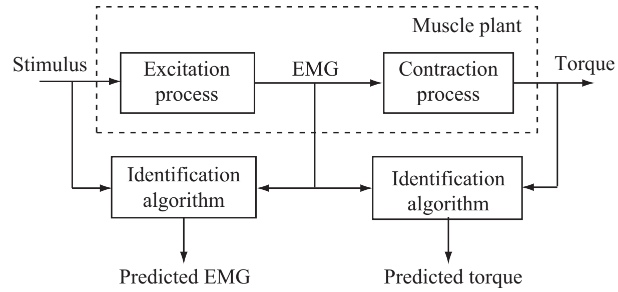

Fig. 1. Model structure of stimulated muscle for model identification. The contraction dynamics model relates EMG to torque. The excitation dynamics model relates stimulation to EMG.

In this study, in order to control FES-induced joint torque based on EMG signals, two PHM cascades were applied to represent the muscle excitation and contraction dynamics, as shown in Fig. 1. EMG served as the output of the excitation model with stimulation as input, as well as the input of the contraction model with joint torque as output. The two PHM models have the same structure, so a generic PHM model structure is recalled and its state-space form is reformulated to decouple the identification process of the linear and nonlinear terms. This decoupling treatment is different from what we did in [16], as it is useful when employing a predictive controller without approximating the nonlinear term.

A PHM model consists of a linear block and a nonlinear block. The linear block of a PHM is modeled by an autoregressive structure with exogenous input (ARX):

$$A(z)y(k) = B(z)h(k) + w(k) \tag{1}$$

where y(k) is the model output, h(k) is the intermediate variable and w(k) is the zero mean and Gaussian white noise. $A(z)$ and $B(z)$ are polynomials in the backward shift operator, z^{-1}, given by:

$$\begin{aligned} A(z) &= 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_l z^{-l} \\ B(z) &= b_1 z^{-1} + b_2 z^{-2} + \cdots + b_m z^{-m} \end{aligned} \tag{2}$$

In the nonlinear block, h(k) is modeled by a polynomial basis function:

$$h(k) = g(u(k)) = \sum_{i=0}^{n} \gamma_i u(k)^i \tag{3}$$

where u(k) is the model input.

Then we get a PHM (l, m, n) model at a given time k as:

$$y(k) = \sum_{i=1}^{l} a_i y(k-i) + \sum_{i=1}^{m} \sum_{j=0}^{n} b_i \gamma_j [u(k-i)]^j + w(k) \tag{4}$$

The state-space form of the generic PHM (l,m,n) model is described as follows:

$$\mathbf{x}(k) = \underbrace{\mathbf{A}(\mathbf{k})\mathbf{x}(k-1) + \mathbf{B}(\mathbf{k})\mathbf{\Psi}\mathbf{u}(k-1) + \mathbf{w}(k)}_{\mathbf{f}(\mathbf{x}(k-1), \mathbf{u}(k-1), \mathbf{w}(k))} \tag{5}$$

where $\mathbf{u}(k-1)$ contains the previous model input as below:

$$\mathbf{u}(k-1) = \begin{bmatrix} u(k-1) & u(k-1)^2 & \cdots & u(k-1)^n \end{bmatrix}^T$$

In (5), the $\mathbf{w}(k)$ is Gaussian white noise vector of the system model. The current state vector $\mathbf{x}(k) = \begin{bmatrix} x_1(k) & x_2(k) & \cdots & x_q(k) \end{bmatrix}^T$, $q = \max(l, m)$. Matrix $\mathbf{A}(\mathbf{k}) \in \mathbb{R}^{q\times q}$ transforms the previous states $\mathbf{x}(k-1)$ into the current states $\mathbf{x}(k)$. Vectors $\mathbf{B}(\mathbf{k}) \in \mathbb{R}^{m\times 1}$ and $\mathbf{\Psi}(\mathbf{k}) \in \mathbb{R}^{1\times(n+1)}$ respectively contain linear and nonlinear coefficients of $\mathbf{u}(k-1)$. Thus, the linear and nonlinear parameter vectors at current time k can be written as:

$$\theta_l(k) = \begin{bmatrix} a_1(k) & \cdots & a_l(k) & b_1(k) & \cdots & b_m(k) \end{bmatrix}^T \quad (6)$$

$$\theta_n(k) = \begin{bmatrix} \gamma_0(k) & \gamma_1(k) & \cdots & \gamma_n(k) \end{bmatrix} \quad (7)$$

With the same model structure representing the muscle excitation and contraction dynamics, the identifications of both models were processed in the same way. The delivered stimulus, the collected EMG and torque signals were provided to identify both the excitation and contraction models. All time-variant states in $\mathbf{x}(k)$ and parameters in $\theta_l(k)$ and $\theta_n(k)$ were identified concurrently by KF with a forgetting factor, as proposed in [16].

III. FES Torque Controller Design

This study was aimed at developing an EMG feedback closed-loop torque control strategy which enables adaptive modulation of the stimulation pattern to achieve a desired torque trajectory. A predictive controller was applied and its control performance can be enhanced by the EMG-based torque estimation method we developed in [16].

In general, the predictive control scheme was developed on the basis of two internal PHM models described above. Accordingly, the controller consisted of two nonlinear generalized predictive controllers (NGPC) in series, as shown in Fig. 2. The control target was generating an optimal stimulation signal u_s to produce the desired joint torque y_d. The main idea was to use the EMG signal for a dual purpose resulting in EMG-feedback predictive control (EFPC), which involved an activation controller and a stimulation controller. The activation controller takes EMG as the control signal m_d to drive the predicted torque, close to the desired torque trajectory y_d, based on the contraction dynamics model. The stimulation controller takes m_d obtained from the activation controller as the desired EMG trajectory, so the control signal, stimulation PW u_s, was computed to drive the predicted EMG (based on the muscle excitation model) close to the EMG reference m_d.

In both the activation controller and stimulation controller, the same model structure–a generic PHM model–was used for process prediction and optimization in NGPC. Therefore, the overall control problem was reduced to resolve two single NGPC problems. The link between these two NGPC controllers is that, at each sample time, the control sequence of the activation controller was used as input reference for the stimulation controller. First, the control solution for a single NGPC is discussed, and then an overall control strategy for torque control is presented.

A. Nonlinear Generalized Predictive Control

As a whole, a single NGPC control problem is resolved in two steps, i.e. finding linear and nonlinear solutions, based on a single PHM model [see equation (1) $\sim$ (4)]. The control problem of the linear part was first resolved by the generalized predictive control (GPC) algorithm, which has been described in a number of publications such as [18] and [19]. Although different methods can be used to obtain the GPC control law, the general idea is to minimize a multistage cost function given by:

$$J = \sum_{j=1}^{N_p} \xi[\hat{y}(k+j|k) - v(k+j)]^2 + \sum_{j=1}^{N_u} \delta[\Delta h(k+j-1)]^2 \quad (8)$$

where $\hat{y}(k+j|k)$ is an optimum j-step ahead prediction of the controlled variable using data up to time k, $v(k+j)$ is the future reference trajectory, and $\Delta h(k+j-1) = h(k+j|k) - h(k)$ is the increment of control action. Then we get:

$$h(k+j|k) = h(k) + \Delta h(k+j-1) \quad (9)$$

In (8), the weighting coefficients ξ, δ respectively penalize the tracking performance regarding $\hat{y}(k+j|k) - v(k+j)$ and the smoothness of the control signal regarding $\Delta h(k+j-1)$. N_p is known as the prediction horizon and N_u is the control horizon; $1 \leq N_u \leq N_p$ implies that all increments of the control action are assumed to be zero for $j > N_u$.

In this study, a simple GPC formulation was applied to resolve the linear control problem, instead of solving recursive Diophantine equations [20]. In short, the optimization problem was computed online in terms of the control sequence $[h(k|k), h(k+1|k), \cdots, h(k+N_u-1|k)]$, so that the predicted controlled variable sequence $[\hat{y}(k+1|k), \hat{y}(k+2|k), \cdots, \hat{y}(k+N_p|k)]$ followed a desired reference trajectory $[v(k+1), v(k+2), \cdots, v(k+N_p)]$. The GPC-computed control sequence was a solution of the linear predictive control problem at step k, which was applied to the linear part of the system and used to solve the nonlinear solution of the NGPC.

After we obtained the linear solution $h(i|k), i = k \sim k + N_u - 1$, the nonlinear solution–the plant input $u(i|k)$–can be resolved from $h(i|k)$ on the basis of function (3). At each time step, the signal sequence $h(i|k)$ was obtained by GPC, the nonlinear model coefficients $\gamma_0, \cdots, \gamma_n$ were known by model identification, so the NGPC control problem was to find the control input signal $u(i|k),\ i = k \sim k + N_u - 1$. This can be resolved by finding the zeros of the following function:

$$p(u(i|k)) = \gamma_0 + \gamma_1 u(i|k) + \cdots + \gamma_n u(i|k)^n - h(i|k) \quad (10)$$

We calculated $u(i|k)$ by finding eigenvalues using the Frobenius companion matrix [21]. Until now, the control problem of a single NGPC has been solved in two steps, first a linear solution and then a nonlinear solution.

In this way, an NGPC has four tuning parameters: N_p, N_u, ξ and δ. The tuning processes of these parameters are not independent of one another but are interactive. Usually, the selection of prediction horizon N_p relies on the sampling time. The selection of control horizon N_u depends on a trade-off between reducing the amount of computation and achieving

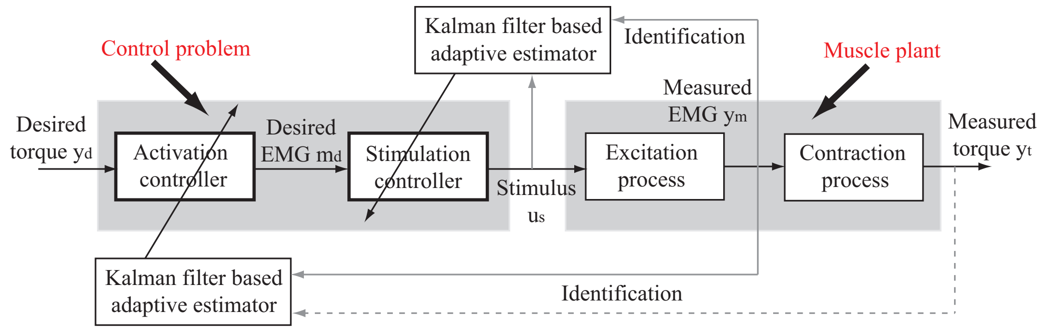

Fig. 2. Diagram illustrating the EMG-Feedback Predictive Control (EFPC) strategy. The control signal obtained from the activation controller was used as the desired reference of the stimulation controller. In each controller, an NGPC algorithm was applied based on a PHM model. The torque measurement y_t and EMG measurement y_m were used for model identification process, as shown by the grey lines. When the torque was suspended for the controller, torque control was achieved only based on EMG feedback, as shown with the grey dashed line.

global optimization [22]. A large N_u may avoid a violation of constraints before they are reached, but it may also result in a substantial amount of computation [18]. The effect of δ is related to suppressing aggressive control actions, while ξ allows the assignment of weight to reduce the trajectory tracking error. The tuning of δ and ξ can be simplified by setting one of them as a constant and tuning the other one.

B. Closed-Loop Implementation of the Dual Predictive Controller

As described above, the proposed EFPC control scheme consists of two NGPC controllers, as illustrated in Fig. 2. Each NGPC works as described in section III-A. Note that, in this EFPC control scheme, the control sequence $m_d(k|k), m_d(k+1|k), \cdots, m_d(k+N_u-1|k)$ obtained in the activation controller is treated as the reference trajectory for the stimulation controller. After the stimulation controller calculation, only the first element of the control sequence $u_s(k|k), u_s(k+1|k), \cdots, u_s(k+N_u-1|k)$ is actually sent to the stimulator during time interval [k,k+1], that is, $u_s(k) = u_s(k|k)$. The procedure is repeated at the next sampling time.

The closed-loop EFPC implementation consists of the following steps periodically, as shown in Table I. Note that, in step 6, the torque measurement can be suspended for the muscle contraction model update. Instead, the EMG-based torque estimate is used in the activation controller as long as the muscle contraction model is preidentified using some initial experimental data.

TABLE I
ALGORITHM DESCRIPTION

Algorithm	Closed-Loop Implementation of the EMG-feedback Predictive Controller
1.	$k \leftarrow 0$
2.	Initialize the KF, and the control parameters for the activation and stimulation controllers: prediction horizon, control horizon, and weighting factors.
3	**while** system is running **do**
4.	$k \leftarrow k+1$
5.	Collect the EMG and torque signals (at current time k)
6.	Update the model parameter estimates by KF for both the muscle excitation model and contraction model. Note that, both the linear parameters in θ_l (6) and the nonlinear parameters in θ_n (7) are simultaneously identified
	// running activation controller (step 7-8)
7.	Calculate the linear solution sequence by GPC (8, 9)
8.	Calculate the control signal sequence m_d in Fig. 2 using (10), and then it is used as reference for the stimulation controller
	// running stimulation controller (step 9-10)
9.	Calculate the linear solution sequence by GPC (8, 9)
10.	The control signal u_s in Fig. 2 is calculated using (10)
11.	Apply u_s to the stimulator
12.	**end**

IV. CONTROL PERFORMANCE EVALUATION

In order to assess the performance of the proposed EFPC, preliminary experiments were conducted on two able-bodied subjects with informed consent. The experimental data were used to verify the control performance and to build virtual subjects for simulation studies.

Surface stimulation was transmitted to induce isometric ankle dorsiflexion in sitting position. The cathode electrode was placed over the common peroneal nerve and the anode one was placed over the proximal Tibialis Anterior (TA) muscle to the knee joint. The stimulus was delivered by a computer-controlled stimulator (ProStim, MXM, France) with PW modulation (PW_{max}=450 us) at a constant amplitude and frequency (40 Hz). Each subject participated in nine test sessions including three different stimulation patterns. In each test session, a sequence consisting of a trapezoidal envelope train (0.4-s ramp-up, 1.2-s plateau, 0.4-s ramp-down) and a 2-s rest were applied for 48 s. Three stimulation patterns—gradual, random and constant patterns—were applied alternatively and repeated three times. The plateau stimulation PW in a gradual session was gradually increased from 20% to 100% of the PW_{max}, while it was randomly determined within 20 $\sim$ 100% of the PW_{max} in a random session, and set at 80% of the PW_{max} in a constant session. Evoked EMG signals from TA muscles were collected and amplified (gain 1000) by a bipolar differential amplifier (Biopac MP100, CA, USA) and sampled at 4 kHz. Isometric ankle dorsiflexion torque was measured using the dynamometer (Biodex 3, Biodex Medical Systems, Inc., Shirley, NY), sampled at 2 kHz, and interfaced with the acquisition system (Biopac MP100). Prior to the experiment, the optimal positions of the stimulation electrodes and EMG recording electrodes were manually determined. The suitable stimulation amplitudes were found to be 26 mA and 35 mA for subjects S1 and S2, respectively.

After the same signal processing as in [16], the relationship between stimulation PW, Mean-Absolute-Value (MAV) of EMG and ankle torque in a gradual test session is plotted in Fig. 3. The amplitudes of these three variables indicate that they are not linear with respect to each other, but they are clearly closely correlated. From the phase viewpoint, the muscle electrical response occurred around 300 ms earlier than the muscle mechanical response, which enabled torque prediction from the EMG signal. The lag between the electrical response and the stimulation event was relatively small (around 3 ms).

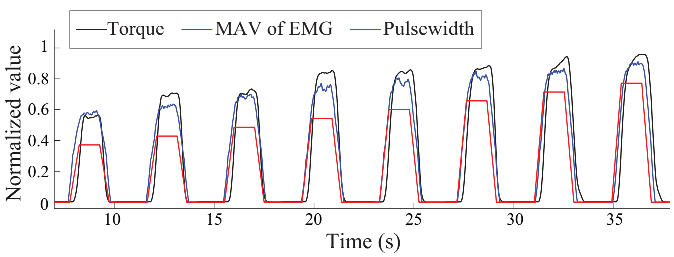

Fig. 3. Relationships between stimulation, muscle electrical response (EMG) and mechanical response (torque). Only part of data were plotted here from a 45-s gradual test. All variables were normalized by their maximum value.

To evaluate the controller performance, the control input signal, torque and MAV of EMG reproduced from the controller were respectively compared with the real stimulation PW, the desired torque and real MAV of EMG. The root mean square (RMS) error and variance accounted for (VAF) were used to determine the control accuracy, where the VAF took the signal variance into account. They were defined as follows:

$$RMS(k) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(y_r(k) - y(k))^2} \times 100\%$$

$$VAF(k) = (1 - \frac{var(y_r(k) - y(k))}{var(y_r(k))}) \times 100\%$$

where N is the number of samples, y_r represents the experimentally measured variable, and y is the variable obtained from the EFPC controller (i.e. the resolved stimulation PW, reproduced MAV of EMG and reproduced torque by the controller).

In the model identification process, model order (3,4,3) was chosen for both the excitation and contraction models as in [16]. The model parameters for both model identification processes are initialized as $a_1 \sim a_3 = 0.2,\ b_1 \sim b_4 = 0.1,\ \gamma_0 = 0.01,\ \gamma_1 \sim \gamma_3 = 1.0$. Both the KF forgetting factors were set at 0.999 as the FES-induced muscle fatigue rate is relatively low in able-bodied subjects. The control sampling time was 0.025 s, i.e. in line with a 40-Hz stimulation frequency. The control signal u_s was constrained within $[0, PW_{max}]$ for each subject, respectively representing non-fiber recruitment and maximal fiber recruitment. For convenience, in each NGPC, the weighting coefficient of the controlled variables was set at $\xi = 1$, while the weighting coefficient of the control signal was adjustable. Therefore, the tuning problem was reduced to tuning the weighting parameter δ_1 in the activation controller and the δ_2 in the stimulation controller. When choosing these two weighting parameters, a tradeoff between the torque tracking accuracy and stimulation PW smoothness should be considered. In order to determine the optimal controller weighting factors, seven weighting factor options with δ_1 and δ_2 within the [0.001,1] range were tested using two test sessions per subject. The RMS errors of both torque tracking and PW matching were calculated. We found that when both of the weighting factors (δ_1, δ_2) were smaller, both the torque tracking and PW matching performance got better. In addition, the controller performance tended to be steady when $\delta_1 = 1.5$, $\delta_2 = 0.01$. Therefore weighting factors $\delta_1 = 1.5$, $\delta_2 = 0.01$ were finally chosen for all of the control problems in this work. The predictive horizon and control horizon in the activation controller and stimulation controller were (40, 30) and (20, 10), respectively, guaranteeing sufficient tracking accuracy as well as efficient computation capacity.

A. Torque tracking performance validation using experimental data

In this section, we verified the EFPC control performance offline with seven experimental test sessions in each subject. The experimentally recorded torque was considered as tracking reference and the control signal was computed by the EFPC controller to track the torque reference. In order to evaluate the control performance of the EFPC controller, we compared the torque reference with the torque calculated by the EFPC, as well as the real PW and the PW calculated by the EFPC. If both of them match well, this indicates that the model identification and control algorithm in EFPC worked correctly to achieve the desired torque trajectory. In the model identification process, the stimulation signal and recorded EMG are always available for model updates throughout the whole test session, as in Fig. 2. Regarding the torque measurement update, we have two phases where one phase named "ON" corresponds to the identification phase for the muscle contraction model with torque update, while the other phase named 'OFF' corresponds to the EMG-feedback torque control phase without torque information. These phases can be switched at an arbitrary time t (t = 10 s in this study). That is, the torque estimate in the activation controller was computed only from the EMG and identified contraction model for the 'OFF' period. This process was illustrated by the grey dashed line in Fig. 2.

Fig. 4 shows the control performance of the proposed EFPC method to track a random torque trajectory in subject S1. The EFPC controller generated control signal and solved muscle activation (dashed line in the bottom and middle plots) to drive the joint torque (dashed line in the top plot) to track the desired torque trajectory (solid line in the top plot). Comparing the control performance between 'ON' and 'OFF' phase, the torque tracking is accurate (RMS = 3.34%) and the control signal also well matches the real experimental stimulation PW (RMS = 7.28%) in the 'OFF' phase, where the torque control was performed only with EMG feedback.

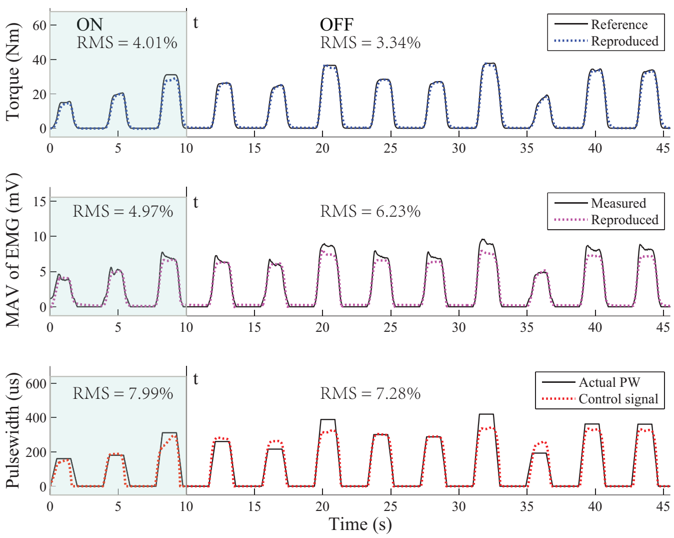

Fig. 4. Evaluation of the proposed EFPC control performance to obtain a randomly changed torque trajectory in subject S1. 'ON': All the stimulation signals, EMG and torque recordings were used for muscle excitation and contraction model identification. 'OFF': The EFPC controller performed torque control only with EMG feedback without using torque measurement. The reproduced torque tracks the desired reference well (top).

Another result in a constant stimulation protocol in subject S2 is shown in Fig. 5. We can clearly find the effect of muscle fatigue in this test session. The same stimulation pattern was repeatedly delivered for 45 s, the joint torque gradually declined indicating the development of muscle fatigue. The reproduced joint torque from the EFPC controller tracks the torque reference well while keeping certain accuracy of the resolved stimulation solution compared with the actual input PW. The small error between the control signal and the real stimulation PW probably comes from the model error, as we did not use the torque measurement for the muscle contraction model update during 'OFF'.

In the same way, the control performance of seven test sessions in two subjects is summarized in Table II. The RMS error and VAF value of the controlled torque, intermediate activation state–MAV of EMG and the control signal–stimulation PW were averaged in seven test sessions (3 gradual, 2 random and 2 constant sessions) in each subject. When the identification with torque update was switched off ('OFF' column), the torque tracking control was still excellent ($< 4.5\%$), both the EMG and stimulation mismatch errors were less than 10.5% against the real values. In addition, all the VAF values were above 90% in 'OFF', indicating close similarity between the values solved by the proposed controller and the real experimental values. These results indicate that the proposed method enables FES torque control while taking the subject-specific time-variant muscle properties into account. Considering the fact that torque is controlled only based on EMG signals in the period of 'OFF' while it is not controllable in any current

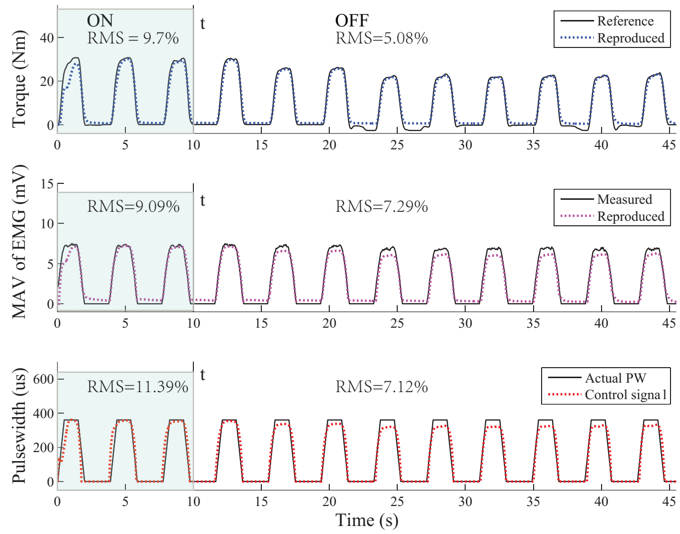

Fig. 5. Evaluation of the EFPC control performance in a constant stimulation test in subject S2. Although the effect of muscle fatigue is quite clear from 15 s, the torque tracking is still good, and the control solution also keeps consistent with the real stimulation PW.

FES systems, this accuracy level is satisfactory.

We may expect that the control errors during 'ON' should be lower than those during 'OFF'. But the results are sometimes opposite, just because the estimator took little time to converge at the beginning resulting in the higher averaged error in 'ON' period. However, the convergence time was actually short (less than 5 s). It is usually supposed to get higher control accuracy when more experimental data contribute to the model identification process. In practice, even we used only 10-s data for model identification, the EFPC controller could produce the desired torque sequence purely using EMG feedback. The reproduced muscle activation and control solution provided by the EFPC also represent the consistency with the actual transitions in the experiment. In addition, the ability to follow the random reference pattern demonstrates the capability of the proposed control strategy to be used for online torque trajectory tracking. Such adaptivity is very important for a practical FES system. The muscle fatigue resulted from repetitive stimulation and the effect of withdrawal reflex in this stimulation protocol were unavoidable, so the control performance also indicates the ability of this control strategy to compensate to some extent for both the muscle fatigue and reflex effect.

B. Simulation Study on Predictive Control Performance

In the previous section, the torque control performance for tracking different torque sequences was demonstrated with experimental data. Here, we try to further investigate the properties of the proposed EFPC controller in simulation studies.

All the simulation studies were conducted based on 'virtual subjects', which were constructed with the models identified by experimental data. That is, the muscle excitation and contraction models were first identified by the experimental data and then used for the following simulation studies of

TABLE II
QUANTIFICATION OF THE CONTROL PERFORMANCE USING TORQUE MEASUREMENT ('ON') AND WITHOUT TORQUE MEASUREMENT ('OFF') (NUMBER OF TESTS = 7*)

Subject	Variable	Averaged RMS error (%)		Averaged VAF (%)	
		ON	OFF	ON	OFF
S1	Torque	5.76	3.81	96.94	98.84
	EMG	6.92	10.52	92.60	91.04
	PW	8.52	10.28	88.45	90.19
S2	Torque	6.66	4.40	96.68	98.64
	EMG	10.22	9.29	89.11	93.80
	PW	9.56	9.55	86.41	91.13

* The seven tests include 3 gradual, 2 random and 2 constant test sessions in each subject. 'ON': Torque update was used to identify the muscle contraction model. 'OFF': EMG-feedback torque control without using torque measurement.

the EFPC controller. The effects of the weighting factor in suppressing aggressive control actions were assessed first. Such simulation study allows us to see the effect of different control parameters keeping the same computational condition and reflecting actual muscle properties. Next, the versatility of the proposed EFPC was evaluated in terms of muscle fatigue compensation and stimulation pattern generation for a given tracking profile.

Suppressing aggressive control actions

A torque reference was prepared as a sequence consisting of a square train and a trapezoidal train. The tracking performance of the desired torque is shown in Fig. 6. Two sets of weighting coefficients were tested, respectively referred to as EFPC1 ($\delta_1 = 0.1$, $\delta_2 = 0.01$), EFPC2 ($\delta_1 = 30$, $\delta_2 = 0.01$). Different weighting coefficients lead to different converging speeds to reach the desired torque, so the controller can be designed to avoid aggressive control actions. Since muscles have physiological limitations in reacting to fast stimulation input variations, and aggressive control action can increase the rate of muscle fatigue [23], it is important for the stimulation controller to provide feasible smooth solutions in FES systems.

When comparing these two torque profiles, the trapezoidal ramp-up period is important to reduce spasticities resulting from sudden step stimulation impulses, while the ramp-down period is important to avoid foot-flap or foot-slap [24]. Hence, the trapezoidal profile is more realistic than the square profile for muscles to follow in practice. Fig. 6 shows that, the transient control actions are smooth when tracking the trapezoidal reference. For the square profile, even it is an inappropriate reference for muscles to follow, if suitable weighting factors are selected, the controller can also provide realistic solutions as in EFPC2. The weighting factor δ in (8) contributes to the function of suppressing aggressive control actions. This result shows that the EFPC can provide physiologically feasible solution even if the unrealistic profile like step torque trajectory is given by mistake.

Complex stimulation pattern generation

It is not trivial to prepare suitable stimulation patterns for complex muscle activation profiles especially considering subject-specific muscle properties in FES. The proposed EFPC is able to generate stimulation pattern which is required to achieve arbitrary torque trajectories for complex tasks. In

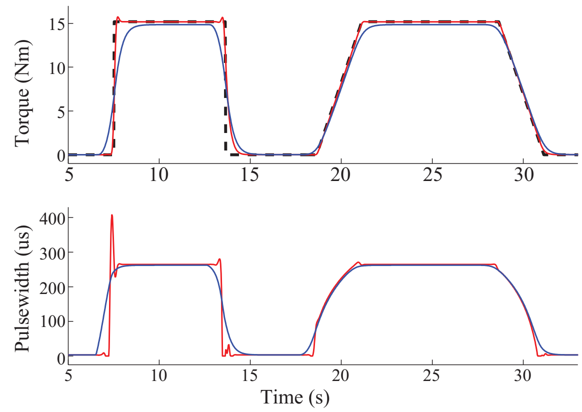

Fig. 6. Two controllers with different weighting factor sets, EFPC1 (red) and EFPC2 (blue), were tested in aggressive control action suppression to track the torque reference (black dashed). The solid lines indicate the solution provided by each controller. Note that the left square profile is an inappropriate reference as the muscle cannot follow due to physiological limitation. The EFPC2 controller provides realistic solutions benefitting from the suitable weighting factor in the predictive control strategy.

[25], the classical trapezoidal stimulation envelop proved to be unsuitable for generating natural gait motion. We have verified if the EFPC strategy allows us to generate the stimulation pattern, resulting in the muscle activity recorded during human natural gait as shown in [25]. A reference trajectory of the ankle joint torque as in Fig. 7 was given to the proposed controller. The EFPC framework could systematically generate the stimulation PW to track the desired trajectory. It is important and convenient to design the required stimulation pattern for any complex intended trajectories, which is superior to the predefined symmetrical stimulation pattern conventionally used in the current FES systems.

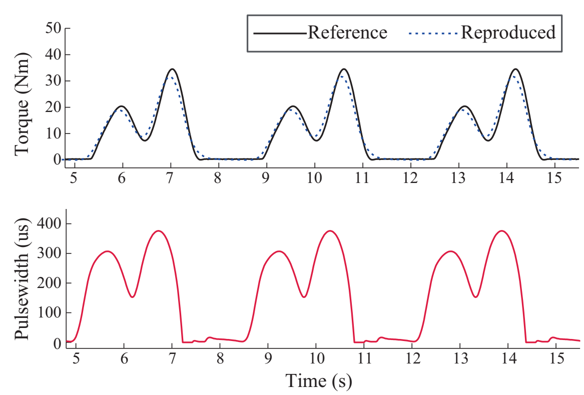

Fig. 7. Natural stimulation pattern generation. The top plot traces the torque trajectory (black) and the reproduced torque from the controller (blue dot). The bottom plot traces the stimulation pattern generated by the EFPC for the joint torque profile.

Muscle fatigue compensation

Another goal of this study was to assess the ability of the EFPC to compensate for fatigue effects. A constant torque trajectory was designed for tracking under muscle fatigue. The EFPC works to generate suitable stimulation PW to maintain the torque level as shown in Fig. 8. The stimulation input was automatically generated and the provided input solution gradually increases to compensate for the torque decrease due to muscle fatigue. The average torque tracking RMS error was approximately 2.18 Nm. Even though this result was obtained by simulation, the muscle models were identified with experimental data representing the actual muscle states. Thus, this result is significant for advanced FES control allowing torque control with adaptive muscle fatigue compensation.

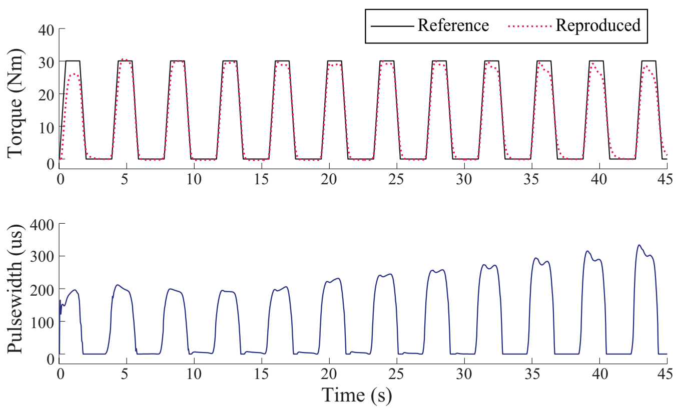

Fig. 8. Muscle fatigue compensation. The reference torque (black solid) was designed to maintain a constant maximum level. The PW required to obtain this torque trajectory was computed by the proposed EFPC and represents the fatigue compensation effect.

V. Discussion

In this study, we newly proposed an EFPC strategy for FES control involving closed-loop torque control rather than classical position feedback control. The EMG signal recorded from stimulated muscle was used to feedback the actual muscle activity to achieve torque control, which has never been investigated in the FES context. Since an appropriate torque sensor is not yet available for humans to use in daily life, torque control based on EMG feedback is meaningful to improve the FES performance in terms of accuracy, safety and adaptability to time-variant muscle state. As muscle mechanical behavior is associated with muscle electrical behavior with an electromechanical lag, EMG could be used to predict torque generation and to control the torque adaptively corresponding to the time-variant muscle response. In addition, the feed-forward property of the predictive controller enables smooth input transitions by taking the physiological muscle activation limitation into account.

This EFPC strategy has the potential to enhance the FES system in several ways. First, it is able to achieve joint torque control based on EMG feedback, which is feasible to be used in daily life, as long as a wireless EMG measurement is used for torque prediction. Second, an appropriate and safe stimulation pattern can be easily generated to produce the desired complex torque also for open-loop use. This is useful when muscle fatigue is not significant or tracking accuracy is not strictly required. Third, the control signal can be explicitly constrained in this control strategy to guarantee stimulation safety. Aggressive input variation can also be systematically avoided. Finally, this control strategy is capable of muscle fatigue compensation benefiting from EMG feedback. The solution of the EFPC mainly consists of a two-step solution with a simple NGPC structure. Consequently, the calculation of each control update takes less than 15 ms in the Matlab environment, which is sufficient for real-time implementation in FES. It also means that the EFPC controller can be driven to tack a torque trajectory given online. The typical drawback of predictive control is that the model inaccuracy may affect the control performance. This issue is covered by KF with a forgetting factor for time-variant and subject-specific model identification, as in [16]. Note that the muscle excitation model (stimulation-to-EMG) can always be updated to overcome time-variances in the muscle excitation process.

The proposed controller was validated using experimental data on two able-bodied individuals, where ankle dorsiflexion was elicited through surface FES under isometric conditions. The EMG signal and ankle torque were recorded for model identification and control performance evaluation. The proposed EFPC enables the generation of a stimulation PW profile to obtain desired torque trajectory reflecting subject-specific muscle properties. The controller performance was evaluated in the torque tracking task based only on EMG signals in the absence of torque measurement updates, as shown in Fig. 4, Fig. 5 and Table II. This result indicates that it is feasible to use the proposed control strategy to control joint torque without a torque sensor in FES. In this preliminary study, we focused on isometric conditions so as to compare the reproduced torque from EFPC with the directly measured torque in order to first validate the control strategy under simple conditions.

VI. Conclusions

This study was aimed at achieving joint torque control from EMG feedback for use in FES. As implantable torque sensors are unavailable yet for torque feedback on human, and EMG was validated for torque prediction in our previous study [16], an EFPC strategy was developed to resolve the torque control problem in FES. EMG signal was used to feedback actual muscle states to track desired joint torque while considering the time-variant muscle dynamics. The EFPC control problem was resolved as a solution of two NGPC problems in series corresponding to activation and stimulation controller, respectively. In practical applications, once the torque deviates from the desired trajectory due to the effects of variations in muscle states or unexpected disturbances, the controller tries to recompute the appropriate stimulation pattern adaptively to achieve the desired torque as long as it does not conflict with the stimulation constraints. This control framework provided satisfactory control accuracy and remarkable torque control performance based only on EMG signals under our experimental and simulation conditions. In addition, the controller was able to generate a suitable stimulation pattern systematically for an arbitrary torque trajectory, which is superior to the conventionally predetermined stimulation pattern. Even when an unrealistic reference was given, the proposed controller could generate the solution which was realistic suppressing aggressive input actions. This model-based torque control framework would be used for various FES applications when considering actual muscle activation through portable noninvasive EMG recordings. In the future, this work will be extended to dynamic motion control in FES, and an appropriate joint dynamics model could be introduced along with the proposed muscle contraction modeling to inversely calculate joint torque from motions as in [6]. Hybrid control of joint torque and joint position would be ideal to meet both kinematic and dynamic requirements.

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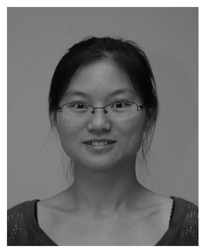

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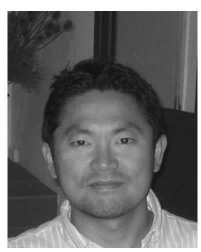

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