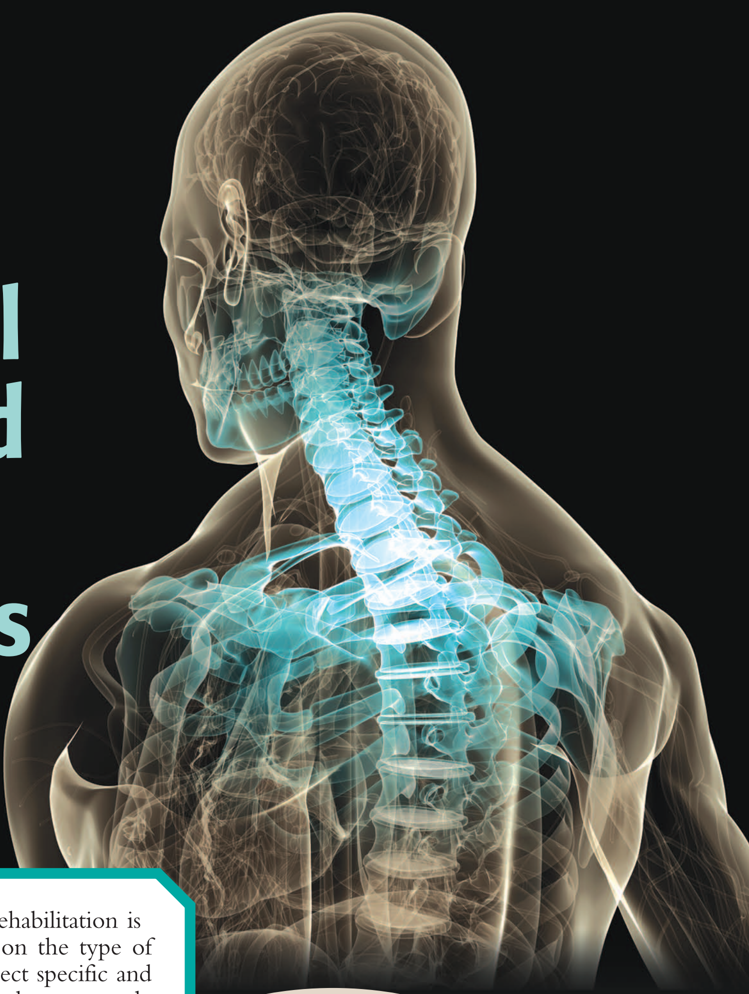
Muscle Fatigue Tracking with Evoked EMG via Recurrent Neural Network: Toward Personalized Neuroprosthetics



***Abstract*—One of the challenging issues in computational rehabilitation is that there is a large variety of patient situations depending on the type of neurological disorder. Human characteristics are basically subject specific and time variant; for instance, neuromuscular dynamics may vary due to muscle fatigue. To tackle such patient specificity and time-varying characteristics, a robust bio-signal processing and a precise model-based control which can manage the nonlinearity and time variance of the system, would bring break-through and new modality toward computational intelligence (CI) based rehabilitation technology and personalized neuroprosthetics. Functional electrical stimulation (FES) is a useful technique to assist restoring motor capability of spinal cord injured (SCI) patients by delivering electrical pulses to paralyzed muscles. However, muscle fatigue constraints the application of FES as it results in the time-variant muscle response. To perform adaptive closed-loop FES control with actual muscle response feedback taken into account, muscular torque is essential to be estimated accurately. However, inadequacy of the implantable torque sensor limits the direct measurement of the time-variant torque at the joint. This motivates the development of methods to estimate muscle torque from bio-signals that can be measured. Evoked electromyogram (eEMG) has been found to be highly correlated with FES-induced torque under various muscle conditions, indicating that it can be used for torque/force prediction. A nonlinear ARX (NARX) type model is preferred to track the relationship between eEMG and stimulated muscular torque. This paper presents a

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NARX recurrent neural network (NARX-RNN) model for identification/prediction of FES-induced muscular dynamics with eEMG. The NARX-RNN model may possess novelty of robust prediction performance. Due to the difficulty of choosing a proper forgetting factor of Kalman filter for predicting time-variant torque with eEMG, the presented NARX-RNN could be considered as an alternative muscular torque predictor. Data collected from five SCI patients is used to evaluate the proposed NARX-RNN model, and the results show promising estimation performances. In addition, the general importance regarding CI-based motor function modeling is introduced along with its potential impact in the rehabilitation domain. The issue toward personalized neuroprosthetics is discussed in detail with the potential role of CI-based identification and the benefit for motor-impaired patient community.

I. Introduction

Computational intelligence (CI) techniques have the potential to play an active role in promoting the quality of life for disabled individuals. Recently an application of the CI-based technology to the rehabilitation field is drawing more attention for researchers and engineers. In terms of homologous mechanism of injury/disease, rehabilitation can be benefited from the community-centric clinical environment by sharing the information of the patient specificity and tendencies among the patient group, which is undergoing the similar neurological disorder in motor function. Meanwhile, personalized neuroprosthetics should compensate for the intersubject variance due to individual physiological properties such as the muscle strength and fatigue level, as it is still patient-specific even if patient groups share the same neurological disorder mechanism. It reveals that we may exploit a general CI-based rehabilitation framework not only for model-based categorization of the motor impaired subjects in community-centric circumstance but also for subject-specific motor function modeling on each individual.

CI methodologies can be helpful to simplify the complex motor modeling by extracting some unrevealed physiological features. Extracting synergies by such CI algorithms transfers the complicated higher dimension (or, higher number of degrees of freedom) modeling problem to a lower dimension (or, lower number of degrees of freedom) simplified task. This dimension reduction paradigm offered by CI opens a shortcut pathway to observe the motor function in a different but insightful manner as compared to the conventional empirical modeling, which actually keeps high dimensional multi-variables and features. As a representative series of pioneering works [1]–[3] concerning using CI algorithms for motor/motion analysis, the non-negative matrix factorization (NMF) algorithm is considered to find muscle synergies among human and animals, as a supplementary tool aiming at detecting physiological motor patterns generated by the central nervous system (CNS) [4]. The matrix factorization algorithms are investigated for identifying muscle synergies [5], and the performance of these algorithms [i.e., principal component analysis (PCA), factor analysis (FA), independent component analysis (ICA), ICA applied to the subspace defined by PCA (ICAPCA), and probabilistic ICA with nonnegativity constraints (pICA)] [5] is compared showing that the extracted synergies by those different methods demonstrate consistent results.

Many clinical rehabilitation modeling problems tend to be complicated so that traditional modeling approaches often become insufficient to handle, and CI can provide an efficient solution to functional motor modeling. As one of the primary direction of CI, neural networks have been investigated for able-bodied or injured subjects' motion or motor modeling, especially in forward dynamics modeling since the relationship between human kinetics and muscle activities could be of high nonlinearity [6]. For example, feed-forward neural network models are presented aiming at estimating human movement at joint level from muscle activities [7]. Back-prorogation (BP) type neural network is used for joint torque estimation in isokinetics condition [8]. BP feed-forward neural network is established to assist the Hill-type muscle model for predicting the joint moment [9]. In [10], a neural network is applied to train the controller to obtain desired (virtual) evoked muscle activations for upper limb neuroprosthesis.

To distinguish different motor functions toward functional categorization during rehabilitation, CI-based classification is essentially required to automatically identify the common features of the patients in similar neurological problems to promote community-centric therapies. One main benchmark is focused on surface electromyography (EMG) pattern based motor/motion modeling and classification. For instance, the probabilistic neural network classifier is addressed for improving EMG-motion pattern classification [11]. A parallel Bayesian based classifier is introduced for simultaneous movement classification under multiple degrees of freedom tasks [12]. In contrast to the rehabilitation which promotes purely voluntary muscle activations, functional electrical stimulation (FES) is one of the existing solutions to partially restore the lost motor functions in people with spinal cord injury (SCI) or after stroke, by means of artificially driving muscle contraction using FES [13], [14]. In a recent work [15], a patient with complete SCI could regain some motor functions by applying FES to the spinal cord. In the article, the authors mention that each of his responses of muscle groups induced by multichannel electrodes is very complex and difficult to predict accurately because of the complex spinal networks and inherent high nonlinearity of the neuromuscular dynamics under FES. They are developing a machine learning algorithm to predict the muscle response to improve stimulation patterns, which is tested on the paralyzed rat, not yet tested on human subjects. Thus, the personalized neuroprosthetics is starting to have much attention [15], [16], and CI would be able to definitely contribute for such purpose as described in the next section.

II. Toward Personalized Neuroprosthetics

Around 90 million people currently suffer from SCI worldwide, and 85 thousand people each year survive the traumatic SCI and prepare to spend an average of 40 years or more in a wheelchair [17]. Advances in treatment have resulted in an increasing number of people with SCI surviving and living decently with their disability. Patients in need of rehabilitation, prosthetics and assistance are usually supported by social welfare and have difficulties in reintegrating a normal life after their accident. The social cost in terms of work force and medical care is thus becoming higher every year [18]. Therefore, developing efficient tools to support those clinical activities such as medical diagnosis and rehabilitation support is highly needed. Reducing the expected cost for the health care of ageing society is really a critical problem [17]. There is a significant meaning for the technology of CI to be applied more actively in this domain. Thus our society is demanding advanced neuroprosthetics which can help restoring movement and mobility to persons with severe motor disabilities. However, one of the challenging issues in neuroprosthetics is to take into account the type of neurological disorder, and their history regarding fitness. Unfortunately, recent technical advances in neuroprosthetics remain confined to sophisticated laboratory environments [16]. The concept of human-centric approaches can improve quality of life, especially by providing personalized modeling and identification of the patient-specific motor property toward tailored neuroprosthetics.

For example, heart pacemaker is one of the most successful neuroprosthetic systems, which use electrical impulses to regulate the beating of the heart. However, the local dynamics regarding the control of heart pacemaker is similar between the patients. That is why results are excellent for a large number of patients. Besides, normally they have static settings along time. In contrast, in the case of motor neuroprosthetics, the local dynamics of neuromuscular system is quite different from patient to patient. This is a reason why motor neuroprosthetics have not reached the level of standard and vastly worldwide uses like pacemaker and cochlear implants. In our opinion, the difficulties for motor prosthetics are:

1) The system is complex and there are many parameters to be considered.
2) The characteristics of the system are largely different among individuals.
3) The parameters of the system are time-variant.
4) The dynamics of the system is nonlinear and cannot be controlled with linear approximation.

In order to address the aforementioned characteristics, a robust bio-signal processing and a precise model-based control which can manage the nonlinearity and time variance of the system, would bring break-through and new modalities in neuroprosthetics.

Muscle fatigue phenomenon and inadequacy of implantable force sensor limit the application of neuroprosthetics. In case of FES, muscle fatigue can drastically change the contraction dynamics and the maximum produced force even when the same set of stimulus parameters is applied. To perform adaptive FES closed-loop control of muscle contraction, the actual force or torque of muscle is preferred to be known accurately first [19], [20]. It is thus essential to monitor muscle state and assess the generated force to personalize the patient muscle response and compensate for the fatigue. One of our final purposes is online monitoring muscle state and assessing the muscle force to achieve accurate FES control.

Evoked EMG (eEMG) offers a way of studying the myoelectric features of the neuromuscular activation associated with stimulated muscle contraction. The eEMG signal was found to be highly correlated with FES-induced muscular torque under various stimulation situations [21]–[24], and the similar phenomenon was found in the implanted FES SCI subject as well [25]. Moreover, Mwave extracted from the eEMG can be an effective detector for tracking potential muscle fatigue [26]. Accordingly, the electrical stimulation configurations can be adaptively modulated by monitoring the recorded eEMG signals [27], [28], and closed-loop muscular torque control by tuning stimulus pulse width according to time variation of eEMG would benefit from modeling between electrical stimulation and eEMG [19]. Exploiting EMG-based estimator for torque estimation could be feasible as well, since the muscle torque highly correlates with both voluntary EMG and eEMG. The nonlinear dynamic models are summarized for EMG-based torque estimation by regression methods [29]. Principal components of EMG signals are extracted to stabilize torso torque estimation [30]. Moreover, in non-volitional situations, a lot of evidences have revealed that the explicit relationship between eEMG and muscle torque is time-varying and highly nonlinear, which implies that adopting non-stationary type estimating approaches [31] would not be enough for stimulated muscle state estimation. To remedy current issues for estimating stimulated muscle torque and tracking fatigue, a Kalman filter with forgetting factor was applied to estimate the FES induced muscular torque with eEMG based modeling in SCI subjects [32].

In Fig. 1, a concept of personalized neuroprosthetics design and patient-community database administration by means of CI based identification is represented. Based on the known dynamics between those signals, we should have the parametric model and estimate its internal parameters using adaptive identification techniques. Based on the online probabilistic identification, optimized FES signals are calculated from the updated model with adaptively identified parameters. This architecture brings high flexibility and precision to

FES control. We believe that it can contribute to the adaptive computation as a new function of personalized neuroprosthetic system. At the same time, considering human-centric modeling, those identified models can be registered into the motor-impaired patient-community database. The model identified through experimental data is effective to extract the motor functional information of each patient for clinical diagnosis. A classification approach would help to make quantitative diagnosis systems which do not exist in the actual rehabilitation community, and it would finally contribute to community-centric purposes as well.

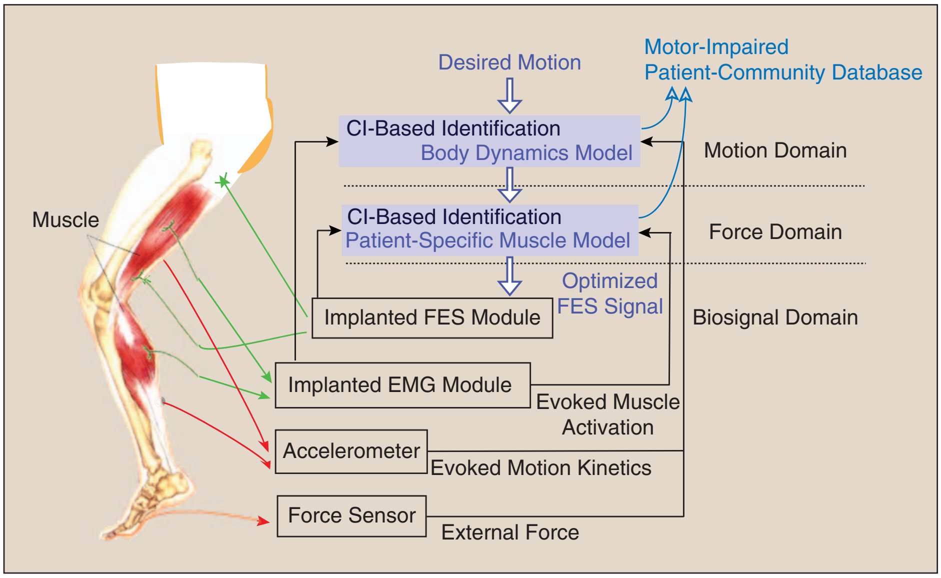

FIGURE 1 Personalized neuroprosthetics design and patient-community database administration by means of CI based identification.

This paper introduces recent results regarding patient-specific muscle modeling and adaptive identification via recurrent neural network, which can correspond to the time-variant muscle property in clinical situation. Our previous work [32] showed promising prediction results with the latest identified model if the forgetting factor can be appropriately selected in a trial-and-error manner. However, empirically selecting the optimal but static forgetting factor for Kalman filter can be a time-consuming task, and the improperly selected one may result in oscillatory behaviors of the model output after identification. As a result, novel CI methodologies are in great demand to automatically enhance the performance of solving such muscle dynamics estimation problems. Taking advantage of CI approaches may enhance modeling precision and reduce the complexity of model tuning, which can promote their real-time implementations. From this point of view, in order to improve the muscle fatigue tracking performance, in our preliminary study verified on two SCI patients [35], a NARX-type recurrent neural network (NARX-RNN) has been reported to model between FES-induced muscular torque and eEMG. In this paper, such NARX-RNN is applied to predict the stimulated muscular torque and track muscle fatigue based on five SCI subjects. Different from the previous work [32], the proposed NARX-RNN is described in a NARX form but supplemented with eEMG and torque coupled terms. Such NARX-RNN can help achieve robust FES modeling and get rid of computing the inversion of online-updating coefficient matrices of the Kalman filter, with enhanced computational efficiency.

The rest of the paper is outlined as follows. The experimental materials and data processing are addressed in Section III. The proposed NARX-RNN model, together with the identification approach for FES-induced muscular torque dynamics with eEMG, is introduced in Section IV. In Section V, the muscular torque prediction results by the NARX-RNN model on five SCI patients are compared with the performance of our previous method [32]. Conclusions and future work are remarked finally.

III. Experimental Materials and Data Processing

The experiments were conducted on five SCI subjects in PROPARA rehabilitation center, Montpellier, France. The subjects were all recruited from the pool of previously screened subjects who had agreed to participate in research studies at the

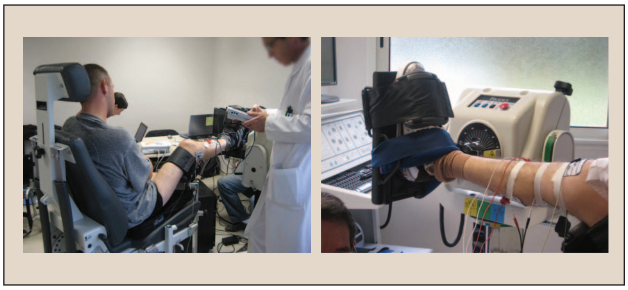

FIGURE 2 Experimental setup for electrical stimulation and ankle torque measurement.

TABLE 1 Patient configurations.

EXPERIMENT SUBJECT	AGE (YEARS)	WEIGHT (kg)	HEIGHT (cm)	LEVEL OF INJURY	MONTHS AFTER INJURY
P1	26	64	192	T6	36
P2	48	76	177	T6	18
P3	39	50	169	T6	3
P4	22	54	172	C7	30
P5	32	61.5	177	C5	8

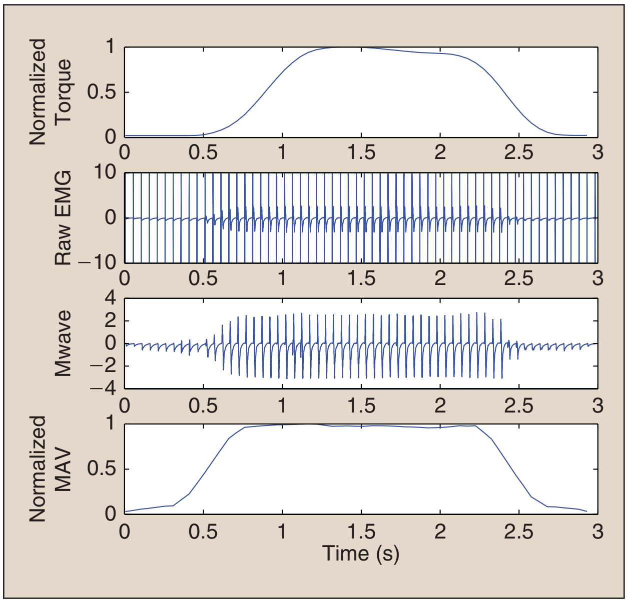

FIGURE 3 An example of processed data [32]. Normalized torque, eEMG raw signal, Mwave extracted by blanking window and normalized MAV were prepared for model identification. The muscle mechanical response (torque) occurs later than muscle electrical response (eEMG) due to so-called electromechanical delay (EMD).

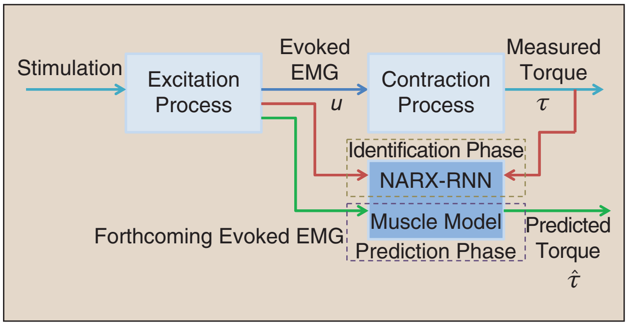

FIGURE 4 NARX-RNN based muscular torque estimation: the RNN model is identified with eEMG and measured torque as input and output respectively; after identification, torque is predicted only with the eEMG.

PROPARA (Montpellier, France). The study was approved by the ethics committee for human protection of Nîmes, France (#2008-A00068-47/1, 2008). The experimental setup is depicted in Fig. 2 and subjects' profiles are shown in Tab. 1. T6 means that 6th thoracic vertebra is damaged for their injury, while C7 and C5 represent 7th and 5th cervical (neck) injury respectively. The subjects were seated on the chair with the ankle joint at 90 degrees, while the joint center was aligned with the axis of a calibrated dynamometer (Biodex 3, Shirley corp., NY, USA). The shank was adjusted to be horizontal to the ground with the knee joint at 40 degrees. Electrical pulses were delivered to the right triceps surae muscle group via surface electrodes (10cm×3cm) to induce muscle contractions and to plantarflex the ankle joint. One electrode was placed 5 cm beneath the popliteal cavity and the other beneath the insertion point of the medial and lateral gastrocnemius on the Achilles tendon. The muscle group was stimulated with amplitude modulation at a constant frequency (30 Hz) and constant pulse-width (450 µs), under isometric conditions, by a portable stimulator (Cefar physio 4, Cefar Medical, Lund, Sweden). eEMG activity of soleus in triceps surae muscle group was recorded, amplified (gain 1000) and sampled at 4 kHz by an acquisition system (Biopac MP100, Biopac Systems Inc., Santa Barbara, CA, USA). The bipolar AgCl EMG electrodes were positioned over the muscle belly in the direction of muscle fiber with 20 mm interelectrode spacing. Isometric ankle plantar-flexion torque was measured using the dynamometer, sampled at 2 kHz, and interfaced with the acquisition system (Biopac MP100).

For each subject, the experiment mainly consisted of two test sessions [32]: a fatigue-inducing test and a random test. The maximum stimulation amplitude was found for each subject at the beginning, by gradually increasing stimulation amplitude until torque saturation. The fatigue-inducing test included several sequences. Each sequence contained five trapezoidal trains with each trapezoidal train consisting of 4s stimulation (1 s ramp-up, 2 s plateau and 1 s ramp-down) and 2 s rest. The stimulation amplitude during plateau was chosen at 50% of the maximum stimulation amplitude. At the end, a sequence including several trapezoidal trains with randomly-generated plateau amplitudes was applied.

eEMG signal was contaminated by stimulation artifacts recorded by the eEMG amplifier, and Mwave (actual muscle response) signals were detected from the raw eEMG and extracted by removing stimulation artifacts. Mwave signals are specific for SCI patients since no voluntary muscle activities are generated. For the preparation of model identification and torque prediction based on eEMG, the measured eEMG and torque were processed in the following procedures [32]. 1) A lowpass filter was applied to measured ankle torque (6th order, cutoff frequency 100 Hz) and measured eEMG (6th-order, cutoff frequency 300 Hz). 2) The filtered eEMG signal was divided into epochs with each epoch containing one Mwave, and the mean absolute value (MAV) of eEMG was calculated every five epochs. 3) The average torque was calculated within the same time window. The MAV and average torque were normalized with respect to their maximum values. An illustrative example of the processed data is shown in Fig. 3.

IV. NARX-RNN for FES-Induced Muscle Modeling and Estimation with Evoked-EMG

The processed eEMG $u(t)$ and muscular torque $\tau(t)$ are introduced into the ensuing NARX-type RNN model as the input and output targets for learning/training respectively. At a given

$$\tau(t) = \sum_{k=1}^{l} v_k(t)\,\tau(t-k) + \sum_{i=1}^{m}\sum_{j=1}^{n} w_{ij}(t)\,u^j(t-i) + a(t)\,u(t-m)\,\tau(t-1) + b(t)\,u(t-1)\,\tau(t-l) \tag{1}$$

$$\hat{\tau}(t) = \sum_{k=1}^{l} v_k^*(t_{id})\,\hat{\tau}(t-k) + \sum_{i=1}^{m}\sum_{j=1}^{n} w_{ij}^*(t_{id})\,u^j(t-i) + a^*(t_{id})\,u(t-m)\,\hat{\tau}(t-1) + b^*(t_{id})\,u(t-1)\,\hat{\tau}(t-l)$$

time instant t, the NARX-RNN model is represented as the muscle contraction dynamics as shown in (1) in the box at the bottom of the previous page. The coefficients $v_k(t)$, $w_{ij}(t)$, $a(t)$ and $b(t)$ are (weights) parameters needed to be determined from the recorded eEMG and measured muscular torque within a period of time $t \in [0, t_{id}]$. Corresponding to NARX-RNN model (1), the structure diagram of FES-induced muscle model with eEMG is shown in Fig. 4. The stimulus pulses elicit the muscle contraction, and then the eEMG signal and torque can be detected and measured. The estimated time-varying parameters for NARX-RNN model (1) are optimally obtained by so-called direct learning at time instant t. As time t evolves, the parameters $v_k(t)$, $w_{ij}(t)$, $a(t)$ and $b(t)$ are updated by training of NARX-RNN model (1) as well.

By exploiting directly-learning method [34] to identify the NARX-RNN model (1) during time interval $t \in [0, t_{id}]$, we can complete the training process and obtain the latest estimated parameters $v_k(t_{id})$, $w_{ij}(t_{id})$, $a(t_{id})$ and $b(t_{id})$. As measured torque $\tau(t)$ is not available if torque sensors are not equipped (or when eEMG based torque prediction only is desired) after time t_{id}, the parameters aforementioned can not be updated anymore. In this case, the latest optimally-estimated parameters $v_k^*(t_{id})$, $w_{ij}^*(t_{id})$, $a^*(t_{id})$ and $b^*(t_{id})$ are used to make prediction after time t_{id}, and the predicted torque $\hat{\tau}(t)$ is expressed as shown in the box at the top of the page. Here note that the torque is predicted only based on the eEMG.

To accelerate identification of the aforementioned NARX-RNN model, we employ the directly-learning pattern in order to identify parameters of NARX-RNN model (1). The direct learning or related methods in machine learning and neural network areas were already verified in nonlinear system identification issues [34]. In this work, we employ such learning method instead of using other traditional methods such as gradient-descent iterative methods [8].

During the time interval of identification $t \in [0, t_{id}]$, we obtain and store the measured torque $\tau(t)$ and eEMG signals $u(t)$. To identify NARX-RNN model (1), we firstly define the following batch squared error function from 0 to t_{id},

$$\begin{aligned} E(t) = \frac{1}{t_{id}}\sum_{t=0}^{t_{id}} [\tau(t) - \sum_{k=1}^{l} v_k(t)\,\tau(t-k) - \sum_{i=1}^{m}\sum_{j=1}^{n} w_{ij}(t)\,u^j(t-i) \\ - a(t)\,u(t-m)\,\tau(t-1) - b(t)\,u(t-1)\,\tau(t-l)]^2, \end{aligned} \tag{2}$$

or in matrix-vector form,

$$E(t) = \frac{1}{t_{id}}(\tau - D\theta)^T(\tau - D\theta), \tag{3}$$

where torque vector is $\tau = [\tau(0), \tau(1), \cdots, \tau(t_{id})]^T$, parameters of the NARX-RNN to be estimated are

$$\theta = [v_1(t_{id}), \cdots, v_l(t_{id}), w_{11}(t_{id}), \cdots, w_{mn}(t_{id}), a(t_{id}), b(t_{id})]^T$$

and the matrix involving past eEMG and torque information is $D = [Y, X_1, X_2, \cdots, X_m, C_1, C_2]$. During the whole identification phase, τ and D are being stored incrementally as time goes.

Specifically, the matrices $Y, X_1, \cdots, X_m, C_1, C_2$ composing matrix D can be written respectively as follows.

$$Y = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ \tau(0) & 0 & \cdots & 0 \\ \tau(1) & \tau(0) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \tau(t_{id}-1) & \tau(t_{id}-2) & \cdots & \tau(t_{id}-l) \end{bmatrix},$$

$$X_1 = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ u(0) & u^2(0) & \cdots & u^n(0) \\ \vdots & \vdots & \ddots & \vdots \\ u(t_{id}-m) & u^2(t_{id}-m) & \cdots & u^n(t_{id}-m) \\ \vdots & \vdots & \ddots & \vdots \\ u(t_{id}-1) & u^2(t_{id}-1) & \cdots & u^n(t_{id}-1) \end{bmatrix},$$

$$\vdots$$

$$X_m = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \\ u(0) & u^2(0) & \cdots & u^n(0) \\ \vdots & \vdots & \ddots & \vdots \\ u(t_{id}-m) & u^2(t_{id}-m) & \cdots & u^n(t_{id}-m) \end{bmatrix},$$

$$C_1 = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ u(0) \\ \vdots \\ u(t_{id}-m) \end{bmatrix} \circ \begin{bmatrix} 0 \\ \tau(0) \\ \vdots \\ \tau(t_{id}-1) \end{bmatrix},$$

and

$$C_2 = \begin{bmatrix} 0 \\ u(0) \\ \vdots \\ u(t_{id}-1) \end{bmatrix} \circ \begin{bmatrix} 0 \\ 0 \\ \vdots \\ \tau(0) \\ \vdots \\ \tau(t_{id}-l) \end{bmatrix},$$

where operator $\circ$ denotes Hadamard product or Schur product between vectors.

To obtain the optimal estimated parameters $\theta^{\star}$ of the NARX-RNN model, the error function $E(t)$ has to be forced to zero during the learning process. By considering the gradient

∇E of error function with respect to θ using the directly-learning style [34], the optimal identified parameters $\theta^\star$ are

$$\theta^* = D^\dagger \tau,$$

where notation $D^\dagger$ is the pseudoinverse of matrix D. This estimation equation provides a more straightforward way to obtain the accurate parameters for identifying NARX-RNN models. In the procedures above, we can observe that many zeros appear in the aforementioned matrices and vectors, which implies that computational time consumption for solving pseudoinverse of matrix D could be rather low. That is to say, the time cost for identifying the parameters of NARX-RNN model (1) describing the relationship between FES-induced torque and eEMG can be low. This is important for online predictive FES control of muscle to establish the predictive model instantly after the identification phase.

As the torque sensors may not be available in practice for patient's daily life, so as to perform better predictive control of muscle activity, we need to predict the muscle torque based only on eEMG. In this case, real-time identification of muscle dynamics is switched off after time instant t_{id} and thus muscle model updating is stopped. We use the latest identified parameters $\theta^\star$ till $t = t_{id}$ to predict the muscle torque, and measured torque is never considered afterwards. According to equation (1), the predicted torque is as follows.

$$\hat{\tau}(t) = \theta^{\star T}[\hat{\tau}(t-1), \cdots, \hat{\tau}(t-l), u(t-1), \cdots, u^n(t-m), u(t-m)\hat{\tau}(t-1), u(t-1)\hat{\tau}(t-l)]^T. \quad (4)$$

It is worth noting here that Kalman filter with forgetting factor for predicting muscular torque has to be with a properly-chosen fixed forgetting factor, which usually distributes within the range [0.9, 1] [32]. Otherwise, Kalman filter may encounter instability and unsatisfactory output results since the forgetting factor may sensitively affect its stability. Compared with Kalman filter with forgetting factor, the proposed NARX-RNN model with its directly-learning estimator, may be regarded as a more robust alternative.

V. Verification Based on Experimental Data

In this section, we focus on the verification of the proposed NARX-RNN model with data from five SCI subjects. For the purposes of comparison, Kalman filter with forgetting factor [32] is also applied for the muscular torque identification and prediction, based on the NARX-type muscle model used in [32].

As in Fig. 5, identification is terminated at time instant t_{id} and then prediction is started afterwards with the latest estimated parameters from time instant t_{id} and ended at time instant t_{pr}. The process cycle is repeated periodically. During the first time period $[t_{id},\ t_{pr}]$, the NARX-RNN model shows similar prediction results as those of Kalman filter. However, as observed from

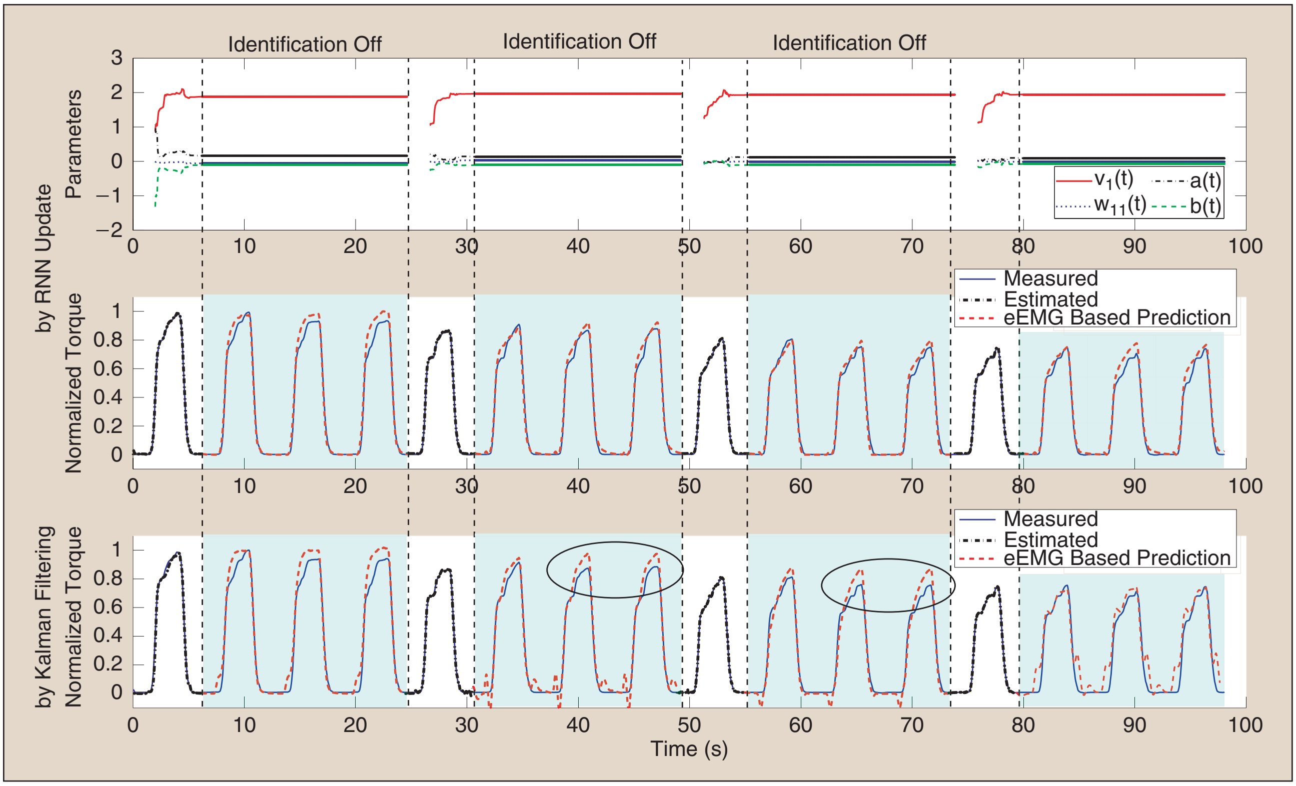

FIGURE 5 Performance of NARX-RNN model and Kalman filter with forgetting factor with eEMG for periodic torque estimation. Identification was switched off for 18s (with blue background color in middle and lower plots). From top to bottom: updated parameters $v_1(t), w_{11}(t), a(t)$, and $b(t)$ of NARX-RNN model; identification and prediction synthesized by NARX-RNN; identification and prediction results synthesized by Kalman filter with forgetting factor $\lambda = 0.965$.

Fig. 5, with the same model order $(l, m, n) = (3, 4, 3)$, NARX-RNN produces better prediction results than those of Kalman filter with forgetting factor $\lambda = 0.965$ as the experiment progresses while having muscle fatigue. As indicated by Fig. 5, the error remains over time in Kalman filter, which requires the model update to follow the time variance caused by the muscle fatigue. This implies that NARX-RNN model can also provide an adaptive identification as Kalman filter. Thus, the proposed method has interesting features of identification while prediction accuracy is maintained keeping its adaptive tracking capabilities. The main reason for the performance difference may lie in two factors: 1) The NARX model architecture embedded in NARX-RNN additionally possesses eEMG-torque-coupled information; 2) NARX-RNN exploits the entire history of information of eEMG and torque to optimally estimate parameters at the end time instant of identification phase, but Kalman filter with forgetting factor uses these information locally with higher priority on recent data in a recursive manner.

Monitoring muscle state and assessing the generated force is essential to personalize the patient muscle modeling and compensate for potential fatigue.

Torque measurement equipment can not be always available in the daily life of the patients, because such device is not portable and implantable sensors are not yet available. In this scenario, we evaluate the performance of NARX-RNN model and Kalman filter in subjects P1-P5 for full eEMG based torque prediction. To investigate the prediction horizon of both approaches, we stop identification within the same time identification period for each patient respectively and start to make prediction without updating muscle models. The average root mean square (RMS) errors at different prediction horizons 10s, 20s, and 30s (for P4, "——" means that 30s is beyond the maximum session time period for testing average horizon RMS error) are calculated. As further illustrated by Tab. 2, under the same length prediction horizon, the RMS error of NARX-RNN model is lower than that of Kalman filter (with optimally selected forgetting factor $\lambda^* = 0.997$) for all the subjects. If the forgetting factor is arbitrarily chosen, the RMS errors can be rather larger due to instability of the filter. This reveals that choosing the proper forgetting factor of Kalman filter affects much on the performance of estimation. It is quite difficult to optimally chose forgetting factor in Kalman filter, since the proper setting depends on the speed of the muscle fatigue. This fatigue speed is unknown in advance and is subject-specific as well. In contrast, NARX-RNN does not have such a tuning problem. All of these imply that the NARX-RNN model possesses superior robustness on prediction of muscle torque with only eEMG signals. In addition, the model identified by Kalman filter with forgetting factor tends to degrade its prediction performance if a longer predictive horizon is requested. From these description, we see that the NARX-RNN method shows the promising prediction performance in all subjects. Since the experimental data contains the torque affected by muscle fatigue which is a major problem in FES control issues, we definitely require the method to predict the time-variant muscle response based on biofeedback signals (i.e., eEMG) in longer prediction horizons.

TABLE 2 Prediction horizon (s) comparison with subjects with the same model order $(l, m, n) = (3, 4, 3)$.

		AVERAGE RMS ERROR UNDER DIFFERENT HORIZONS		
SUBJECT	ESTIMATOR	10s	20s	30s
P1	NARX-RNN	0.04176	0.04656	0.05371
	KALMAN FILTER WITH OPTIMAL λ^*	0.07881	0.08190	0.08735
	KALMAN FILTER WITH RANDOM $\bar{\lambda}$	0.16250	0.16515	0.15704
P2	NARX-RNN	0.04756	0.05295	0.05407
	KALMAN FILTER WITH OPTIMAL λ^*	0.05091	0.05851	0.06231
	KALMAN FILTER WITH RANDOM $\bar{\lambda}$	0.23239	0.22468	0.23184
P3	NARX-RNN	0.04526	0.06081	0.05918
	KALMAN FILTER WITH OPTIMAL λ^*	0.07092	0.08155	0.08044
	KALMAN FILTER WITH RANDOM $\bar{\lambda}$	0.11923	0.09774	0.08642
P4	NARX-RNN	0.08994	0.15989	–
	KALMAN FILTER WITH OPTIMAL λ^*	0.10078	0.18144	–
	KALMAN FILTER WITH RANDOM $\bar{\lambda}$	3.19710	5.10303×10^2	–
P5	NARX-RNN	0.03107	0.03773	0.04045
	KALMAN FILTER WITH OPTIMAL λ^*	0.08037	0.06797	0.06231
	KALMAN FILTER WITH RANDOM $\bar{\lambda}$	0.19158	0.16874	0.16687

VI. Conclusions and Future Work

An FES-induced muscle model represented with NARX-RNN is proposed for muscle fatigue tracking with the eEMG-based estimator. The NARX-RNN is trained by a direct-learning way which guarantees its accurate estimation and lower computational cost. Experimental data obtained from the five SCI subjects were used to verify the proposed NARX-RNN model. For the purposes of comparison, Kalman filter with forgetting factor is also applied with the NARX muscle model addressed in [32] for the torque estimation. The NARX-RNN model demonstrates robust identification performance while keeping its accuracy and stability. Especially, when the muscular/joint torque should be estimated only based on eEMG, eEMG driven prediction synthesized by the NARX-RNN model shows a stable performance even for longer prediction horizons on all subjects. It reveals that the CI based approach may provide an efficient computational solution to identify the subject specificity and to take into account the time variant muscle property during FES. Those functionalities are essential to meet the requirement toward personalized neuroprosthetics. During muscle fatigue under FES, the predicted torque can be further used for adaptive closed-loop FES control to compensate for muscle fatigue [19]. Future work can be extended for adaptive closed-loop FES control for dynamic motion based on eEMG sensing along with joint angle/velocity sensing.

One challenging issue in computational rehabilitation is that a large variety of patient situations exist depending on the type of neurological disorders. To improve the performance of motor neuroprosthetics, subject-specific modeling should be essentially preferred. In addition, human characteristics are basically time variant, for instance, neuromuscular dynamics may vary according to muscle fatigue as presented in this paper. In order to tackle this time-varying characteristics, a robust bio-signal processing and an accurate model-based control which are able to manage the nonlinearity and time variance of the system, can bring break-through and new modalities for computational rehabilitation technologies. Besides, specific individual functional motor modeling, CI-based optimization (e.g., ant colony optimization, differential evolution, swarm intelligence) would contribute to optimally offer motor function assessment and neuroprosthetic motor control for a large population of paralyzed and post-stroke patients, since bio-inspired computational schemes may possess strong capabilities in complex human modeling of motor functions.

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