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A muscle model for hybrid muscle activation

Abstract: To develop model-based control strategies for Functional Electrical Stimulation (FES) in order to support weak voluntary muscle contractions, a hybrid model for describing joint motions induced by concurrent voluntary- and FES induced muscle activation is proposed. It is based on a Hammerstein model – as commonly used in feedback controlled FES – and exemplarily applied to describe the shoulder abduction joint angle. Main component of a Hammerstein muscle model is usually a static input non-linearity depending on the stimulation intensity. To additionally incorporate voluntary contributions, we extended the static non-linearity by a second input describing the intensity of the voluntary contribution that is estimated by electromyography (EMG) measurements – even during active FES. An Artificial Neural Network (ANN) is used to describe the static input non-linearity. The output of the ANN drives a second-order linear dynamical system that describes the combined muscle activation and joint angle dynamics. The tunable parameters are adapted to the individual subject by a system identification approach using previously recorded I/O-data. The model has been validated in two healthy subjects yielding RMS values for the joint angle error of 3.56° and 3.44°, respectively.

Keywords: Functional Electrical Stimulation (FES); Neuroprosthetic; EMG; Hybrid muscle activation; Neural Network; Muscle Model

DOI: 10.1515/CDBME-2015-0094

1 Introduction

For the rehabilitation of stroke patients it has been found out that a synchronous muscle activation by FES in addition to the voluntary contribution improves motor relearning [7]. It is expected that closed-loop concepts for adjusting the intensity of FES can significantly improve the rehabilitation outcome. However, up to now, most approaches for feedback controlled FES do not incorporate the residual voluntary contribution of the patient. In principle, the estimation of the voluntary activity, even in FES-activated muscles, is possible by means of EMG measurements processed by Digital Signal Processing (DSP) [1]. Despite DSP, the noise level of the estimated volitional muscle activity during active FES is usually higher than during normal EMG recording without FES due to incomplete removal of present stimulation artifacts and the occurring M-Waves (muscle activity caused by FES). Using noisy signals for feedback control usually limit the achievable control performance.

Only few approaches for controlling the stimulation intensity based on the voluntary activity exist; among them are strategies in which the behavior of the stimulation intensity is triggered by crossing pre-defined thresholds for the voluntary activity [1]. The most advanced approach so far is to set the stimulation intensity proportionally to the online estimated voluntary effort of the patient in order to amplify weak residual movements [6]. However, this approach is prone to oscillations (instability) caused by the closed-loop since a low-pass filter must be applied to the noisy voluntary activity.

To improve the estimation of the voluntary activity during FES, we propose the following approach: A model that maps the stimulation intensity and the voluntary activity (hybrid muscle activation) to the occurring joint angle is adapted to the individual person. In a next step, this model can then be used to estimate the voluntary activity by an input observer (an inverse calculation of the voluntary input), whereby measurements of the joint motion and the known stimulation intensity are used.

Previous investigations in modeling muscle behavior based on EMG measurements typically predict the muscle force – commonly only under isometric conditions. A recent example is given in [3], wherein a NARX recurrent neural network model is trained to predict the muscle torque under isometric conditions, however, without considering the voluntary contribution. In [4], a model for describing voluntary muscle activations even without the constraint of isometric conditions is proposed. However, no FES has been applied herein.

2 Experimental set-up

To demonstrate the feasibility of the proposed hybrid model, it is exemplarily applied to the shoulder abduction movement against gravity, as shown in Fig. 1 following local ethical guidelines. Biphasic pulses with 27 Hz were applied the medial deltoid muscle through surface self-
adhesive electrodes (ValuTrode® CF4090 (4x9 cm), Axelgaard Manufacturing Ltd.) using a current-controlled stimulator (Rehastim™, Hasomed GmbH). Using an inertial sensor (MTx, Xsens Technologies B.V.) the shoulder abduction angle was measured. Further, EMG signals were obtained from separate electrodes using the EMG amplifier (Porti 32™, TMS International).

The raw EMG-measurements in-between two stimulation pulses are filtered using the approach described in [2] yielding a normalized estimate \( \gamma^* \) (range [0,1]) for the intensity of the voluntary contribution. For later use in the model, this noisy volitional muscle activity is low-pass filtered by means of a non-causal fourth-order Butterworth filter with zero phase shift and a cut-off frequency of 27 Hz yielding the volitional activity level \( \gamma \) (range [0,1]). The stimulation intensity \( v \) is applied in terms of a normalized charge yielding current amplitude and pulsewidth of the applied bi-phasic stimulation pulses as described in [2].

The real-time implementation is based on a computer system running Linux. Development and evaluation was performed in Scilab 5.5.1 (http://www.scilab.org) using the real-time framework OpenRTDynamics (http://openrtdynamics.sf.net/).

3 Methods

In feedback controlled FES, often Hammerstein muscle models are employed that mainly consist of a non-linear static input function followed by linear transfer function. The input function, also called recruitment function, yields the muscle recruitment (amount of active motor units) depending on the normalized stimulation intensity \( v \) (range [0,1]). The dynamic model part (the transfer function) describes the muscle activation dynamics and the joint motion driven by the muscle recruitment. To consider hybrid muscle activations, we extend the static input function by adding a second input – the voluntary activity estimate \( y \). As shown in Fig. 2, this extended recruitment function is described by an Artificial Neural Network (ANN) that uses Local Linear Models (LLM) weighted by Radial Basis (RB) functions (c.f. Fig. 3). Four normalized radial basis functions

\[
\Phi_i(v, \gamma) = \frac{\mu_i(v, \gamma)}{\sum_{n=1}^{\infty} \mu_n(v, \gamma)}, \quad i = \{1, 2, 3, 4\} \tag{1}
\]

based on standard radial basis functions

\[
\mu_i(v, \gamma) = \exp\left(-\frac{1}{2}\left(\frac{(v - c_{i,v})^2}{\sigma_{i,v}^2} + \frac{(\gamma - c_{i,\gamma})^2}{\sigma_{i,\gamma}^2}\right)\right) \tag{2}
\]

are used. The normalized RB functions are combined with four local linear models to yield the neurons whose outputs are superposed yielding the output of the ANN:

\[
\hat{y} = \sum_{i=1}^{4} (w_{i,0} + w_{i,v}v + w_{i,\gamma}\gamma) \cdot \Phi_i(v, \gamma). \tag{3}
\]
The parameters of the radial basis functions are chosen with respect to [5] and summarized in Tab. 1.

To describe the combined muscle activation dynamics and joint motion, an AutoRegressive model with eXogenous input (ARX) [5] (a linear dynamic transfer function model) is used:

$$\hat{\vartheta}[k] = \begin{array}{l} q^{-m} \\ 1 + a_1 q^{-1} + a_2 q^{-2} \end{array} \hat{y}[k], \quad (4)$$

where $\hat{\vartheta}[k]$ is the joint angle at sampling instant $k$ and $q^{-1}$ is the one-step backwards shift operator ($q^{-1}s(k) = s(k - 1)$). The time delay of $m = 1$ sampling instants matches the typically observed delay in recorded I/O-data. The tunable parameters are combined in the parameter vector $\Theta = [w_1, w_1, w_1, w_1, w_1, w_1, w_1, w_1, w_1, w_1, w_1, a_1, a_2]$. (5)

In order to adapt them to an individual subject and muscle condition, I/O data are recorded during an identification experiment and a successive linear least squares optimization is performed yielding the optimal parameter set $\Theta^*$ that minimizes the cost function

$$J(\Theta) = \sum_{k=0}^{N} \left( \hat{\vartheta}[k](\Theta, \vartheta[k], \nu[k]) - \hat{\vartheta}[k] \right)^2, \quad (6)$$

where $\vartheta[k]$ is the recorded joint angle.

To obtain I/O data, an experimental procedure is proposed in which the stimulation intensity is increased step-wise (five levels, linear increase of the intensity) to the upper well tolerated intensity. During the time periods in which the stimulation intensity remains constant (lasting always 6 s), the subject is instructed to voluntarily elevate his arm to a given joint angle of approximately $50^\circ$ for 2 s.

4 Results

The proposed experimental procedure has been performed twice for two healthy subjects yielding one training and one validation data set for each subject.

The model parameters were identified and the output $\vartheta$ of the obtained model was then simulated (not predicted) for the inputs of the training dataset and compared to the measured output to assess the model fit. The result in terms of the Root Mean Square Error (RMS) is $3.3^\circ$ for subject A and $2.67^\circ$ for subject B.

To validate the model, the inputs of the validation dataset are used to simulate the output of the obtained model. The input signals as well as the simulated and measured output angle are shown in Fig. 4 and Fig. 5 for both subjects. In this validation, RMS errors of $3.56^\circ$ and $3.44^\circ$ for subject A and subject B have been obtained, respectively.

5 Conclusion

For the prediction and simulation of joint angle movements, an ANN-based dynamical model has been developed and tested in two healthy subjects. The obtained
small RMS errors – both for model fit and validation – show the feasibility of the proposed joint angle prediction in the considered joint angle range of about 50 degree. The required time duration of approximately half a minute for the identification procedure is feasible to the time constraints in clinical environments. The observed model accuracy is high despite using a Hammerstein model structure that is usually applied to describe isometric muscle contractions only. A Hill-type muscle model structure can be considered as extension to this approach in case that the accuracy of the proposed model decreases for larger joint angle ranges.

Potential applications include the adaption of FES-support in trial to trial based training procedures. The primary target application will be the estimation of the voluntary activity. Therefor, we propose an input observer using the previously identified model that inversely calculates the input $\gamma$ by using the known stimulation intensity $v$ and the joint angle $\theta$ that can both be measured with low noise amplitude e.g. by means of inertial motion units (IMUs). The obtained model accuracy should be sufficient for the given applications.

Concerning the long-term accuracy, however, we expect difficulties caused by time-variances in the muscle’s behavior. Herein, important factors are the rapidly progressing muscle fatigue under FES and in case of stroke patients, a potential time-variant spasticity. To tackle these issues, we propose a periodic re-calibration of the model in trial to trial based training procedures. Therefor, we expect that I/O data obtained during FES-supported training for motor re-learning are also feasible to allow the parameter estimation. Another approach, worth to be investigated, would be a parameter estimation using Recursive Least Squares (RLS) during training. Both approaches would not require interventions or additional effort to be performed during training sessions.

Future work also considers multiple muscles acting on one joint and, finally, investigations in stroke and incomplete spinal cord injured patients are planned.

**Funding:** The research leading to these results has been funded by the German Federal Ministry of Education and Research (BMBF) within the project BeMobil (FKZ 16SV7069K).

**Author’s Statement**
Conflict of interest: Authors state no conflict of interest.
Material and Methods: Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: The research related to human use has been complied with all the relevant national regulations, institutional policies and in accordance the tenants of the Helsinki Declaration, and has been approved by the authors’ institutional review board or equivalent committee.

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