Setup and Procedure for Online Identification of Electrically Stimulated Muscle With Matlab Simulink

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***Abstract*—This paper first describes a laboratory setup for biomechanical experiments that runs within the universal simulation environment Matlab Simulink. The overall system comprises a personal computer, two AMTI (Advanced Mechanical Technology, Inc., Watertown, MA 02472) force plates, Parotec force-sensor shoe insoles, Optotrak system for noncontact three-dimensional (3-D)-position measuring, and a computer-controlled four-channel electrical stimulator. Conceptually, the most important application is implementation of closed-loop electrical stimulation of intact and paralyzed subjects in the laboratory. Second, the system was tested in real-time muscle model identification procedure during a standing experiment. The plantarflexors of three nonimpaired subjects were excited with pseudorandom binary sequences (PRBSs) with small deviations around selected operating points. Electrically stimulated muscles were presented with a linear local dynamic block that was identified with a recursive least-square method (RARX). RARX block was designed with fundamental Matlab Simulink blocks that support real-time operation. Introduced was online estimation of model output, which offers a great manner of instant model validation. Two modes of operation with online validation were tested. In the first mode, the operating point for selected excitation level was identified online. In the second mode, the operating point was measured in preceding experiments. Both procedures resulted in satisfying second-order models that will be used in the adaptive controller design.**

***Index Terms*—Least-square method, model identification, neuromuscular stimulation, time-varying systems.**

NOMENCLATURE

A	Stimulation pulse amplitude.
a_i	Linear model denominator parameter with index i.
b_i	Linear model numerator parameter with index i.
$G_p(z)$	Transfer function of discrete-time systems.
t	Time.
PW	Stimulation pulsewidth.
$u(t)$	Stimulation input.
$y(t)$	Measured muscle output.
$\hat{y}(t)$	Estimated muscle output.
z	Variable of the z-transformation $z = \exp(T_0 s)$.
$\hat{\theta}^T$	Vector of estimated linear model parameters $\big((2n+1) \times 1\big)$.
Ψd^T	Vector of delayed inputs and outputs $\big((2n+1) \times 1\big)$.

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I. INTRODUCTION

ONE of the widely used methods for obtaining body stability in persons after spinal cord injury is restoration of motor function to paralyzed limbs with functional neuromuscular stimulation (FNS). FNS enables controlled neural activation through the application of low intensity of electrical stimulation. While existing simple open-loop FNS systems demonstrate impressive functions, the ease of use, response repeatability, and level of fatigue are expected to improve if closed-loop feedback is incorporated. The entry point for closed-loop utilization would be the FNS single-joint muscles. This study focuses on the ankle joint only. Knee and hip joints can be locked with mechanical orthosis [1]–[3]. An advantage of applying closed-loop control of the ankle joint during standing is also the ankle biomechanics. During standing, the ankle is far from the anatomical limits of extension or flexion. Also, the dorsiflexor-plantarflexor muscle pair acting at the ankle joint is not able to stabilize the body under the conditions of open-loop stimulation [1].

Closed-loop control, in general, allows good disturbance rejection and reference tracking in applications such as FNS where sensors are available. The process of building the FNS closed-loop experimental system involves the following stages.

A. Modeling of the Electrically Stimulated Musculoskeletal System

Electrically stimulated muscle can be observed as a complex nonlinear time-varying actuator with muscle activation at the input, generating output muscle force that moves the limb or segment. The task of modeling, in general, requires both the determination of a particular model structure, which defines the complexity of the model, and the assignment of model parameters. Several types of muscle model have been derived from *in vitro* studies that are advantageous for general understanding of dynamic properties of skeletal muscles [4]–[8]. In contrast, *in vivo* recognition of muscle models (e.g., with paraplegic subjects) can include realistic aspects of spasticity and remaining neuromuscular influence of the intact upper body. This text describes a system for real-time *in vivo* muscle identification, which is also suitable for implementation in adaptive control strategies. Generally, frequency response of various skeletal muscles under isometric conditions is a linear second-order system with double real poles and a pure time delay [4]. The static force-activation relation can be described by a nonlinear monotonic isometric recruitment curve. The second-order transfer function as a linear part of the muscle model follows the nonlinear block. This form is known as Hammerstein model and has been applied to muscle models [2], [8], [9]. In contrast to the Hammerstein model, local models describe muscle dynamic that is specific to selected stimulation region, and enable the observation of changes of the dynamic properties between regions.

B. Real-Time Feedback Control Applications

Several researchers studied adaptive FNS control algorithms and recursive muscle model parameter identification that would efficiently track the changes in muscle properties [9]–[12]. Major property changes are due to fatigue and unexpected spasticity. In order to implement such a closed-loop controller on a computer, appropriate computer software is required. The software must handle complete sensory data, perform controller calculations, and send the calculated FNS parameters to one or more electrical stimulators. In our case, we used Matlab Simulink[1] software, primarily designed for modeling, simulating, and control of dynamic systems.

The introductory part of this paper presents key elements and a configuration of sensory-actuator system for closed-loop FNS applications with human subjects. The system was tested in real-time muscle modeling experiments using Matlab Simulink. The human ankle plantarflexors were described with a local muscle model. A hierarchical musculoskeletal model was then parameterized from the real-time measured subject input–output data. Following are sample identification results for discrete descriptions.

II. Methods—Sensory and Actuator System

The overall system comprises personal computer (PC)-compatible computer, Optotrak system for noncontact position measuring, two force plates, force-sensor shoe insoles, computer-controlled electrical stimulator, and the mechanical rotating frame (MRF). The essential task was to construct Matlab Simulink blocks for each measuring device and for the electrical stimulator in order to describe and run the system. These blocks are connected to various procedures of the original Simulink comprehensive library. By following a set of predefined rules, hardware interface functions in C programming language can be implemented as a Matlab S function. The S functions are incorporated into Simulink models by using the S-function blocks, one of the Simulink choices, which allow custom sampling time and other parameter setting. Furthermore, strict real-time execution is of primary importance for control systems application. Thus, provisions are also made to accelerate the execution. S functions for selected hardware are presented in dual form of target language compiler format to enable real-time mode operation of designed Simulink models [13]. The experimental environment components are described further in text.

A. Computer-Controlled Electrical Stimulator

An FNS system with four stimulation channels and direct PC control via RS-232 line was utilized. The PC-to-stimulator communication protocol enables Matlab Simulink to drive the stimulation parameters. The stimulator and the Simulink presentation with stimulator block are depicted in Fig. 1. The possible block configuration has two inputs for two-channel amplitude (A1–A2) and two inputs for pulsewidth modulation (PW1–PW2). Amplitude inputs to Simulink are binary coded between 0 (0 mA) and 254 (100 mA). Inputs for impulse pulsewidths are unsigned binary values ranging from 0 to 129, which corresponds to 130 values, each representing a 10-μs step. Stimulation frequency is, for ensuring synchronized real-time execution, defined by Simulink and was, in our experiments, always set to 20 Hz. For safety reasons, in case of PC system breakdown, the stimulator itself does not generate any pulses.

B. Parotec Force-Sensor Shoe Insoles[2]

Parotec System force-sensor shoe insoles are used for quantitative estimation of loads under subject's feet [14]. Forty-eight capacity sensors from the left and right insoles are connected to a common control unit transmitter. While the subject wears the shoe insoles, the data collection from sensors is supervised by dedicated microprocessor. In order to send the measured data in real time to the PC, a serial RS–232 connection link between the transmitter and the PC at the standardized speed 57 600 b/s is utilized. Activity is possible at 10-Hz and 50-Hz sampling frequency. Each sensor value is presented with a pressure value in range from 0 to 2550 N/cm^2 in steps of 10 N/cm^2.

C. Optotrak System for Noncontact Position Measurement[3]

The Optotrak system is a noncontact high-speed high-accuracy three-dimensional (3-D) motion measurement and analysis system which provides 3-D data in real time. Sensor cameras track target points defined by up to 256 miniature infrared emitting diodes—markers that can be stuck on the subject. The Optotrak system connects to a standard PC platform via an industry system architecture (ISA) card. A C-language application program interface (API) is provided with the Optotrak system for camera calibration and data collection. Our custom written Optotrak Simulink block includes those API functions that provide online acquisition of the 3-D marker data. The number of Simulink block outputs can easily be changed to the desired number of markers and measuring frequency.

D. ODAU System for Force Plates' Signal Acquisition

The AMTI OR 6-5-1[4] platform simultaneously delivers three force components along the x, y, and z axes, and three moment components around the x, y, and z axes, as analog voltage levels. The ODAU unit used for acquisition of these analog signals is synchronized with Optotrak 3-D motion measurement using the Optotrak system hardware clock.

E. MRF

The MRF was built in the laboratory to study human body stability and its properties in the sagittal plane [3]. The frame braces the knee, hip, and lumbosacral joints in extended positions, and both ankle joints are constrained to a limited and safe

[1]The MathWorks, Inc., Natick, MA 01760 USA.

[2]Paromed Medizintechnik GmbH, 83115 Markt Neubern, Germany.

[3]Northern Digital Inc., Waterloo, ON N2V 1C5, Canada.

[4]Advanced Mechanical Technology, Inc., Watertown, MA 02472 USA.

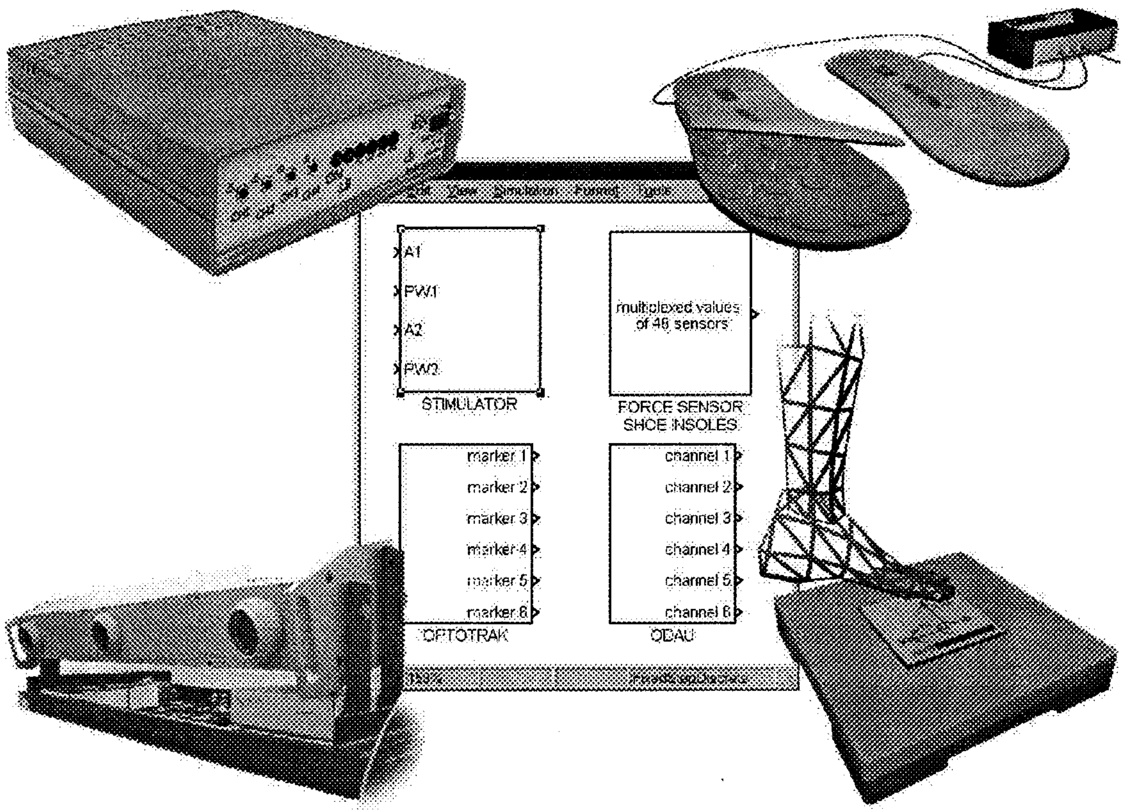

Fig. 1. Simulink scheme with blocks for electrical stimulator, force sensor shoe insoles, Optotrak system, and Optotrak data acquisition unit (ODAU) system for force plate signal acquisition. The stimulator block has two or more stimulation amplitude inputs (A1, A2) and two pulsewidth inputs (PW1, PW2). Shoe insoles block has one multiplexed output for 48 sensor values. The Optotrak block and ODAU block have six marker outputs and six analog channel outputs. In addition to block presentation are pictures of electrical stimulator (upper left), shoe insoles with controller unit (upper right), Optotrak camera device with three sensors (lower left), and AMTI force plate (lower right). The signal inputs and outputs are not connected yet.

range of motion. This enables investigations of control strategies with the ankle muscles as actuators in both intact and paraplegic subjects. Two force plates, independent for left and right feet, are mounted beneath and are separated from the frame. The force plate axes are aligned with the MRF rotation axes being aligned with plantar–dorsiflexion axes of the ankles.

III. Methods—Muscle Model Identification

If online real-time muscle identification is needed, the model transfer function must in practice be presented with a discrete transfer function due to Matlab Simulink real-time mode limitations. A discrete form of a second-order discrete function with one zero and pure time delay z^{-1} was chosen [2], [6]

$$G_p(z) = \frac{z^{-1}\left(b_0 + b_1 z^{-1}\right)}{1 + a_1 z^{-1} + a_2 z^{-2}}. \tag{1}$$

The sampling time was equal to the stimulation rate, i.e., 0.05 s. Parameters $\theta = [a_1, a_2, b_0, b_1]$ can be estimated online in real time with RARX algorithm, where the old values are updated for the current sample time t after the new sample of input $u(t+1)$ and output $y(t+1)$ are available. When observing local models, the inputs $u(t)$ and $y(t)$ represent deviations of the mean values U_{00} and Y_{00}. Operating point U_{00} and Y_{00} can be estimated online with the recursive algorithm or can be estimated with advance measurements. The operating point of electrically stimulated muscle represents here a value that may change with time. The algorithm with online operating point estimation thus needs to estimate the additional parameter K

$$K = Y_{00} + a_1 Y_{00} + a_2 Y_{00} - b_1 U_{00} - b_2 U_{00}. \tag{2}$$

Updated parameter approximations $\hat{\theta}(t+1) = [\hat{a}_1, \hat{a}_2, \hat{b}_0, \hat{b}_1, \hat{K}]$ can be generated with a simple recursive method [15], [16]

$$\begin{aligned}\hat{\theta}(t+1) =& \hat{\theta}(t) + P(t+1)\psi_d(t+1)\Big[y(t+1)\\ &\qquad -\psi_d^T(t+1)\hat{\theta}(t)\Big]\end{aligned} \tag{3}$$

$$P(t+1) = \left[P(t) - \frac{P(t)\psi_d(t+1)\psi_d^T(t+1)P(t)}{1 + \psi_d^T P(t)\psi_d(t+1)}\right]. \tag{4}$$

Here, $\psi_d^T(t) = [-y(t-1), -y(t-2), u(t-1), u(t-2), 1]$ stands for the data set vector including inputs, outputs, and auxiliary constant equal 1, while $P(t)$ stands for intermediate matrices and represents the product $[\psi_d^T(t)\psi_d(t)]^{-1}$. The above recursive method minimizes the square of error between the model estimation and the measured output. The discrete equivalent of the linear transfer function (1) can be written with the difference equation

$$\begin{aligned}y(t) + K =& -\hat{a}_1 y(t-1) - \hat{a}_2 y(t-2) + \hat{b}_0 u(t-1)\\ &+ \hat{b}_1 u(t-2) + \hat{K}.\end{aligned} \tag{5}$$

Based on (3), the recursive algorithm tends to equal the left (measured output) and right (model estimation) sides of (5). For implementation of the algorithm (3) and (4) directly in Matlab

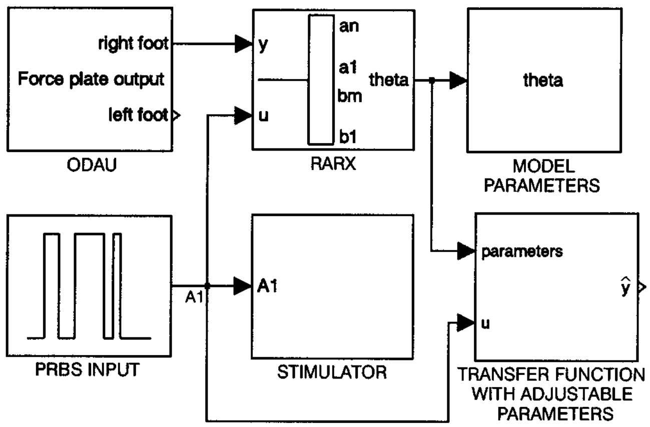

Fig. 2. Matlab Simulink block diagram for recursive identification of muscle model. A1: activation data for muscle in PRBS form. RARX: block for recursive identification. Parameters: parameters of discrete transfer function as a result of the real-time identification procedure. The unconnected output $\hat{y}$ is the online model output estimate used for instant model validation.

Simulink, we used six blocks for matrix multiplications, one block for computation of the matrix transpose, and more signal time delays. These blocks belong to fundamental Matlab digital signal processor library and are coded in real-time workshop (RTW) format to support efficient real-time operation [13]. The RARX block receives required muscle input (the stimulation level) and muscle output (muscle-generated moments), as is shown in Fig. 2, (block RARX). Simultaneously, as parameter estimation $\hat{\theta}$, we may also predict the model generated output $\hat{y}(t)$ online and instantly validate the model quality. This can be done with a discrete transfer function with adjustable numerator and denominator parameters. We designed such Matlab Simulink block with adjustable parameters using programming language C descriptions of (1).

The experiments proceeded as follows. The subject stood in the MRF, which was fixed for isometrical conditions in the upright position with four strings in forward and backward directions. Each foot acted directly on one of two force plates. Force sensor shoe insoles were placed in the casual shoes. In this particular experiment, the subject cannot move in the frame, meaning that the Optotrak is not necessary. However, we still collected Optotrak data for verification purposes. The Optotrak system operated at either 100-Hz or 20-Hz sampling frequencies. The computer-controlled electrical stimulator delivered pulses at 20 Hz. The self-adhesive 50 mm $\times$ 90 mm Axelgaard electrodes[5] were placed on the midlines of the plantarflexor muscles of the subject. Transfer function parameter test inputs in this study were trains of pulses, amplitude modulated with pseudorandom binary sequences (PRBSs). Each pulse took one of two possible amplitudes. The pulsewidth was set constant at 400 μs. Test random sequences of 30 s each were computer generated. PRBSs are necessary to ensure persistent excitation for the muscle dynamics and parameter identifiability. Maximal muscle joint generated moment at maximal stimulation amplitude (50 mA in our trials) was measured prior to identification procedures. PRBS sequences were then generated to excite muscle around the operating point of 62.5% of maximal activation with amplitude deviations of 12%. The selected PRBS amplitude level was used for comparison reasons to other studies [2].

[5]Axelgaard Manufacturing Company, Fallbrook, CA 92028 USA.

IV. Experimantal Results

Three intact subjects, ages 24, 27, and 37, participated in all measurements. Samples of the acquired muscle joint moment and the parameters of muscle model are presented here. Parameters of electrically stimulated muscle are presented as outcome of the online real-time identification procedure. The muscle response to 20-Hz stimulation with PRBS activation envelope show significant moment deviation for two activation levels (Fig. 3). The muscle generated moment was measured with force plates. The upper chart in Fig. 3 shows the measured moment and the estimated model output.

The lower chart in Fig. 3 compares the moment value with the model estimate where constant K from (2) was not identified online. Both the measured moment curve and modeled output are detrended, which means that offset values are substracted from signals. In this case, both the stimulator input and measured moment were detrended online, which requires better knowledge about the operating point. Good overlap of both curves indicates that the mean output moment corresponds to the predicted operating point. The operating point was defined in the stimulation sequence one minute before the identification. Comparison of both identification modes (with and without recursive online operating point estimation, upper and lower Fig. 3) demonstrates slower parameter convergence when the model operating point is identified. Online model output estimations are, in both cases, distorted as a result of worse estimation of model states for past sample times.

The offline simulation of models captured in some particular moment of time offers better model validation. Simulation of the discussed model with operating point estimation taken after 0.5 s and 5 s time of identification periods is presented in Fig. 4. Slowly converging parameter K adapts after approximately 5 s to a correct model output level.

The changes of denominator parameters of model, with operating point estimation time according to (3) and (4), are depicted in Fig. 5. Initial parameter values were set to 0. This presumes that the strength and dynamic response of muscle to electrical stimulation are unknown. Identified values were then used to calculate new estimated output. In the first second of stimulation sequence, the identified parameters varied due to high gradient adaptation values from (4). This affected the estimate of model output, which varied synchronously.

Very similar courses, as shown in Figs. 3–5 for particular subjects, were acquired with other two measured subjects. For all three, the method was found to be convergent. Minor differences encountered within subjects and in day-to-day trials, might be contributed to particular electrode placement and muscle properties. These were not examined in greater detail here because a much larger experimental group would be required to competently discuss the results.

V. Discussion and Conclusion

A nonlinear continuous process sampled at a fixed sampling interval was identified as an equivalent discrete time model.

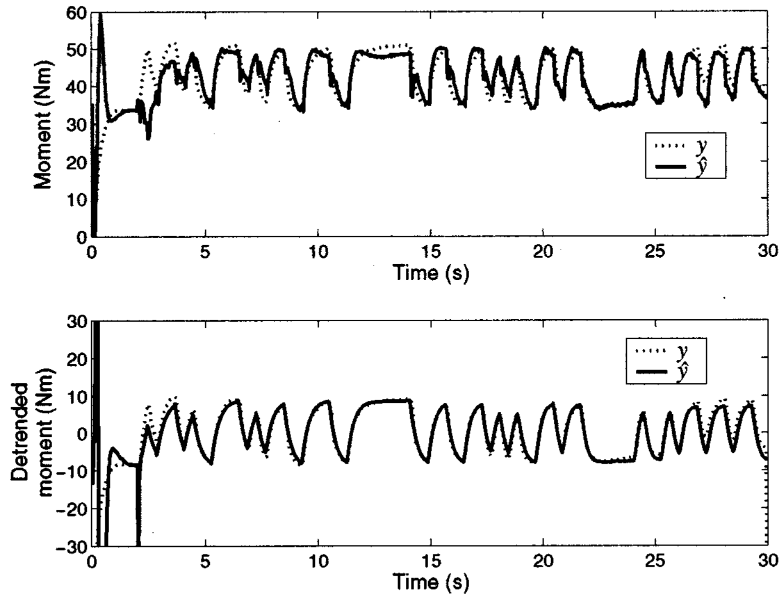

Fig. 3. Upper graph compares measured muscle output y and online estimate $\hat{y}$ for the identification procedure with operating point identification. Lower graph compares detrended muscle output y with estimate $\hat{y}$ with advance operating point measurement and no online operating point estimation. Model output mean level is close to 0 and indicates correct expectation of the operating point.

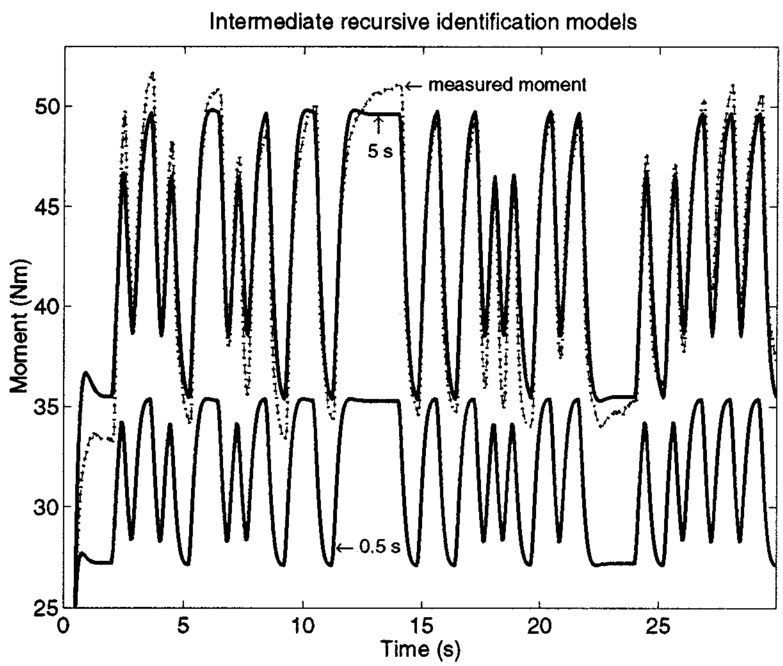

Fig. 4. Subsequent comparison of measured moment and estimated moments for two recursive models with operating point estimation. For the first are taken parameter values as were captured at 0.5 s of previous experimental trial.

This common identification approach has been applied in linear, nonlinear, and adaptive muscle model identification by several authors [2], [5], [6], [11], [12]. We have implemented adaptive parameter identification using a RARX Matlab Simulink subsystem that appeared to behave satisfactorily in an online real-time identification procedure at a sampling frequency of 20 Hz. The subsystem was designed from blocks intended for matrix and signal operations. Introducing block presentation of RARX identification method makes advantageous starting point for modified methods and uses the well-tested real-time code descriptions of Matlab Simulink library blocks. The proven least-squares method was chosen as the cost function because it offers good numerical properties and low computational burden. A very welcome quality of least-squares method is that applying new parameters as additional states can extend the formulation of our models. Based on this and on the flexibility of Matlab Simulink subsystem, we designed two varieties of a classical RARX algorithm. This commonly used algorithm was extended in order to estimate model operating point online. The identification procedure spent approximately 5 s to estimate the operating point of the sample case correctly. The operating point estimation times were similar for all three stimulated subjects. The

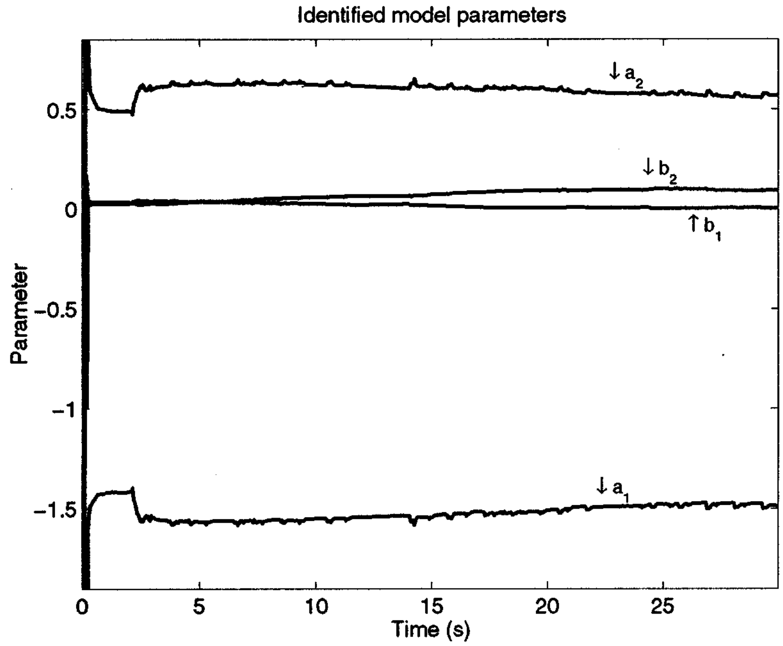

Fig. 5. Denominator $(a_1,\ a_2)$ and numerator $(b_0,\ b_1)$ parameter courses of discrete linear transfer function with operating point estimation.

dynamic properties were estimated faster, as can be seen both in settled parameter values (Fig. 5) and model output course (Fig. 4) after 0.5 s. Assuming that fatigue is a relatively slow process, the RARX method may, thus, be used for efficient identification of local muscle models. If identification procedure is used for short time sequences, the operating point may be estimated with the preceding experiment, which improves the model parameter convergence. The models for various operating points of activation levels for all subjects show that recursive identification may be used in local adaptive controller design. The main disadvantage of all local models are the initial oscillations of parameter values, caused by unknown model states. These can be can be reduced with correct model initial states and can be considered later in the controller design. If the muscle activation changes essentially and the nonlinear muscle properties are emphasized, additional methods of model adaptation must be applied, such as gain scheduling or fuzzy logic switching between many local models.

In future work, muscle models with nonlinear dynamics will be examined and an adaptive muscle moment controller will be designed by using and upgrading the equipment and results that are presented here. The future experiments using described models in closed loop will be able to answer the following questions.

- Are second-order local models accurate enough for control applications?
- Are linearized local models adequate for use in nonlinear control, which may require fast and large changes of muscle activation?
- Is the identification of operating point fast enough for satisfying control with such muscle activation changes?

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