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ISOMETRIC MUSCLE CONTRACTION INDUCED BY REPETITIVE PERIPHERAL MAGNETIC STIMULATION [1]

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Abstract: Repetitive peripheral magnetic stimulation (*RPMS*) is an innovative approach in treatment of central paresis, e.g. after stroke, by inducing muscle contractions and relaxations. The therapeutic effect can be increased by a closed loop control to induce coordinated movements in the forearm and the fingers. An appropriate model of muscle contractions induced by *RPMS* provides the basis for the controler design. In the presented paper a model based on a Hammerstein–structure for the contraction of the biceps brachii will be established. This model also builds the basis for a nonlinear system identification which is used to individualize the model to a single subject.

Keywords: Magnetic stimulation, muscle contraction model, parameter identification

1. INTRODUCTION

A central paresis of the arm and/or hand, e.g. after stroke, reduces the quality of life dramatically. Nevertheless, studies on large clinical cohorts, using standard therapeutic methods, showed that approximately 45 % of patients with completed stroke have persistent hemiparesis [Gresham and Stanson 1998]. This data indicates the importance of innovativ approaches in rehabilitation of central paresis.

Cortical reorganization probably forms the basis of relearning lost motor functions. Morphological and functional investigations due to central paresis revealed that the sensorimotor cortex retains a great capability to adapt to altered afferent input [Ziemann *et al.* 1998]. The adaptation to changes in input or output can occur quickly, first only as a functional modulation [Classen *et al.* 1998], later as a lasting reorganization [Nicolelis *et al.* 1998]. Therefore the integrity of both the executive motor structures and the afferent sensory loop for motor recovery is important.

In order to activate a beneficial reorganization process, the lost (reduced) proprioceptive input should be compensated. Currently physiotherapy aims to achieve such a compensation through externally applied movements. When the lost movements are induced by muscle stimulation, the proprioceptive input is much higher and corresponds closer to the lost voluntary action patterns which increases the therapeutic effectiveness [Struppler *et al.* 2003]. In this context the functional electrical stimulation (fES) is a well–known method for muscle stimulation. However, the fES not only activates somatosensory nerve fibers, also cutaneous receptors are activated which causes pain. Therefore the usability of fES for rehabilitation purposes is limited [Conforto *et al.* 2002, e.g.].

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As a new, deeper penetrating, focused and painless stimulation method repetitive peripheral magnetic stimulation (*RPMS*) is used. As depicted in fig. 1 the proprioceptive inflow to the CNS is elicited by magnetic field impulses in two ways: a direct part by the depolarization of the terminal sensory nerve branches and an indirect part by the depolarization of the terminal motor nerve branches and a physiological activation of the muscle-length receptors.

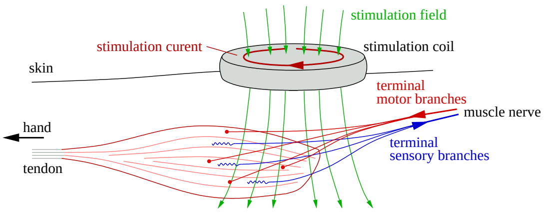

Fig. 1. Schematic of the *RPMS* application

The repetitive applied field impulses are sinusoidal half-waves with a fixed duration of $100\,\mu$s and a variable amplitude called stimulation intensity. The maximum stimulation intensity of 100 % corresponds to a magnetic flux density of approx. $2.0\,$T. The field impulses are generated by a self-built stimulation device [Schmid *et al.* 1993].

The therapeutic concept of *RPMS* is the activation of a reorganization processes by inducing a proprioceptive input to the CNS physiologically corresponding to the lost input during active movements [Struppler *et al.* 1996, e.g.]. In clinical experimental studies [see Struppler *et al.* 2004] on spasticity, cognitive functions, cerebral activation, stiffness around the elbow joint and goal-directed motor performances it could be shown, that the sensorimotor dysfunctions due to brain lesions can be remarkably improved by *RPMS*.

In this paper a model for the isometric muscle contraction of the biceps brachii based on experimental data will be presented. Since this is a qualitative model which does not encounter individual parameters like muscle fatigue, a nonlinear system identification presented in [Angerer *et al.* 2004] will be used to adapt the model to a single subject. This is illustrated by the identification results for two different subjects and a parallel stimulation of the biceps and the triceps brachii.

2. ISOMETRIC CONTRACTION MODEL

The muscle contraction behavior has already been investigated with functional electrical stimulation (fES) (overview in [Veltink *et al.* 1992]). Since compared to *RPMS* there are fundamental differences in pulse shape and pulse propagation also the muscle response induced by fES might differ from that induced by *RPMS*. The modelling approach introduced in the following sections will describe the nonlinear control path and its structure qualitative on one hand, and on the other hand the necessary adaptation of the main parameters to a individual patient will be taken into account.

In the following the force generated by a muscle stimulated with magnetic pulses under isometric conditions (no movement in the elbow joint, see fig. 2) will be modelled. According to the approaches used with fES the dynamic behavior (activation dynamics) as well as static behavior (recruitment characteristics) will be analyzed. In order to investigate on the contraction dynamics an experimental setup as depicted in fig. 2 is used. A stimulation coil is placed above the innervation area of the biceps brachii muscle, and the force resulting from stimulation is measured with a force sensor attached to the subject's wrist. In order to compare *RPMS* with fES, all experiments concerning the activation dynamics have been accomplished with electrical stimulation as well.

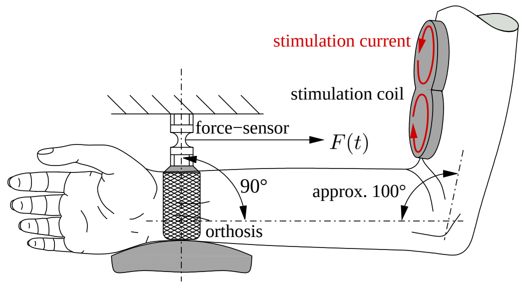

Fig. 2. Experimental setup

2.1 *Activation dynamics*

As a first parameter the latency T_l between the peripheral stimulus and the mechanical muscle response is considered. In [Popovic and Jaukovic 2000] the typical latencies of electrical stimulation are $T_l = 20 - 50$ ms. In order to determine the latency for *RPMS* the force response to a single magnetic pulse as shown in fig. 3 is considered. The raw force signal F_{raw} shows an artefact due to the strong magnetic pulse. The maximum of this artefact is taken to determine the particular time of stimulation. The time derivative $\dot{F}$ is obtained by numerical differentiation of the filtered signal F (moving average filter without phase shift). The latency in fig. 3 is $T_l = 1.75$ ms. In order to determine the average latency $\overline{T}_l$, 3698 data sets of 8 healthy subjects (aged from 20 to 32 yrs) with different stimulation intensities and pulse widths have been evaluated. The result is summarized in tab. 1. A dependency of T_l on the stimulation intensity or the stimulation pulse width could not be shown.

Table 1. Latency T_l and its mean value over all subjects, and standard deviation $\overline{s}_{T_l}$

	electr. stim.	magnetic stim.
T_l in ms	20.83 - 28.24	2.52 - 3.85
mean value $\overline{T}_l$ in ms	24.4	3.45
s_{T_l} in ms	3.05	0.93

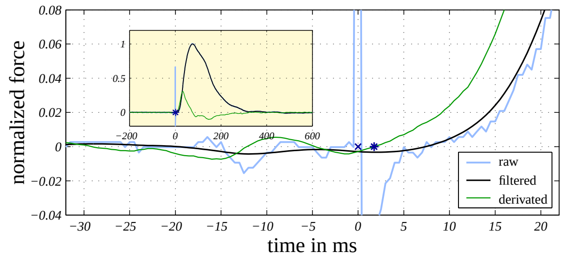

Fig. 3. Typical force responce due to a single magnetic stimuli (small window: entire force response)

Secondly the dynamics of the muscle twitch caused by a single peripheral stimulus (see fig. 3) is analyzed. In fES related work [Veltink *et al.* 1992, e.g.] the dynamics are mostly modelled as a second order transfer function with two identical real poles at $-1/T_a$. Hence the transfer function is

$$G_a' = K\frac{1}{(1+sT_a)^2} \quad . \tag{1}$$

For a more appropriate modelling in [Havel 2002] a third order transfer function with three identical real poles has been proposed. Since there is no oscillation in the muscle twitch (fig. 3), the poles have to be real. In the following a transfer function of n^{th} order and its time-domain equation will be considered:

$$K\frac{1}{(1+sT_a)^n} \;\bullet\!\!-\!\!\circ\; \frac{K}{T_a^n(n-1)!}t^{n-1}e^{\frac{-t}{T_a}} \tag{2}$$

By calculating the gain K so that the peak value of the time domain eq. (2) is 1, and with the time discretisation $t = kT_s$ follows the modelled force response

$$y_a(T_a)[k] = \frac{(kT_s)^{n-1}e^{-(kT_s)/T_a}}{((n-1)T_a)(n-1)e^{-(n-1)}} \quad . \tag{3}$$

Thus, $y_a[k]$ can be compared with the normalized force response $F[k]/\hat{F}$, whereas $\hat{F}$ is the respective peak value. In order to evaluate the approximation of eq. (3), the quadratic error

$$E(T_a) = \sum_{k=0}^{N}\left(\frac{F[k]}{\hat{F}} - y_a(T_a)[k]\right)^2 \tag{4}$$

is defined, whereas N is the length of the truncated force response. The optimal time constant $T_{a,\mathrm{opt}}$ is computed by minimizing the quadratic error $E(T_a)$ with a recursive search algorithm. 3143 data sets have been evaluated. First it could be shown that neither with fES nor with *RPMS* the pulse width of the applied stimuli has any significant effect on T_a, which is not explicitely explained in this paper. Fig. 4 shows the minimized quadratic errors $E_{\min}$ dependent on the normalized peak value $\hat{F}/\hat{F}_{\max}$, whereas $\hat{F}_{\max}$ is the peak value of the force response generated with a maximum stimulation intensity.

From fig. 4 it can be seen that a transfer function with identical real poles models the muscle twitch generated by *RPMS* better than the muscle twitch generated by fES. In both cases the 4^{th} order transfer function doesn't yield significant improvement compared to

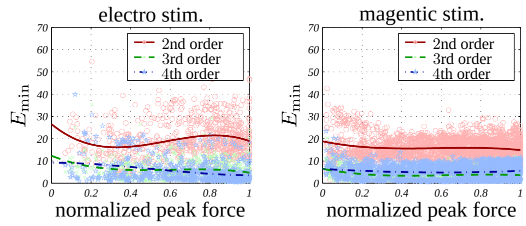

Fig. 4. Minimized quadratic errors $E_{\min}$ dependent on the normalized peak value $\hat{F}/\hat{F}_{\max}$

the 3^{rd} order model. The average time constants are $\overline{T}_{a,\mathrm{opt}} = 36,62\,\mathrm{ms}$ for fES and $\overline{T}_{a,\mathrm{opt}} = 38,35\,\mathrm{ms}$ for *RPMS*. Setting $n = 3$ in eq. (3) and transforming it into Laplace domain and considering the latency T_l the transfer function

$$G_a(s) = G_a'(s)e^{-sT_l} = \frac{T_{a,\mathrm{opt}}}{2e^{-2}}\frac{1}{(1+sT_{a,\mathrm{opt}})^3}e^{-sT_l} \tag{5}$$

is obtained, to describe the activation dynamics of single muscle twitch. In order to analyze the dispersion of the parameter T_a between the individual subjects, data with 12 additional subjects has been recorded. 2984 data sets of in total 20 subjects (aged from 20 to 35 yrs) have been evaluated. The average time constant $\overline{T}_a$ and its standard deviation $s_{T_{a,\mathrm{opt}}}$ have been calculated. The results are summarized in tab. 2.

Table 2. Average time constant $\overline{T}_a$ with standard deviation $s_{T_{a,\mathrm{opt}}}$

	electr. stim.	magnetic stim.
$\overline{T}_a$ in ms	22.58 - 53.22	26.71 - 49.81
$s_{T_{a,\mathrm{opt}}}$ in ms	1.04 - 5.21	0.99 - 5.88

From this table it can be seen, that T_a varies a lot between the individual subjects, but the standard deviations of the particular subjects are small. Also there is a strong dependency of T_a to the peak value of the generated force. These results have to be taken into consideration, when the parameters of the model and the controller are adapted to the individual patient. The average time constant is $T_{a,\mathrm{opt}} = 38.4\,\mathrm{ms}$.

As the third step the derived model for single muscle twitches is enhanced for repetitive stimulation. By increasing the stimulation frequency the individual force responses begin to merge which results in a partial or complete tetanus. This effect is called temporal summation. The pulse rate f_{rep} is for discrete realization expressed as the number of samples between two stimuli and is calculated as $k_{\mathrm{rep}} = f_s/f_{\mathrm{rep}}$ whereas f_s is the sample rate of the discrete implementation. Based on eq. (3) the temporal summation can be written as

$$y_{a,\mathrm{rep}}[k] = \sum_{i=0}^{\infty} y_a[k - ik_{\mathrm{rep}}] \quad . \tag{6}$$

Fig. 5 illustrates the principle of temporal summation. It can be seen that in steady state, the superposition has a periodic and a constant part. After applying some algebra it can be shown that the constant part $\hat{y}_{a,\mathrm{rep}}$ can be calculated as

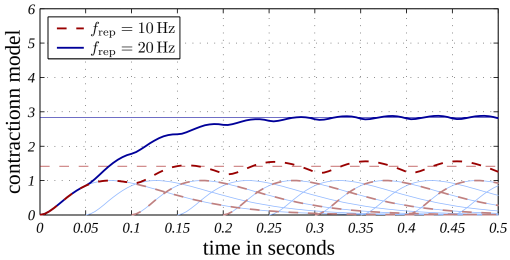

Fig. 5. Principle of temporal summation

$$\hat{y}_{a,\text{rep}} = \frac{1}{k_{\text{rep}}} \sum_{k=0}^{f_s/1\text{Hz}} y_a[k] \quad , \tag{7}$$

whereas it is assumed that a muscle twitch is decayed after 1 s or $k = f_s/1\text{Hz}$ samples. Fig. 6 shows the force response of isometric muscle contractions with different stimulation intensities. It can be seen, that

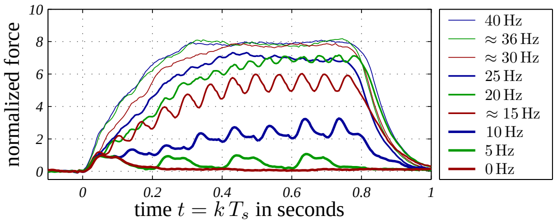

Fig. 6. Measured force response induced by *RPMS* dependent on the repetition rate f_{rep}

the constant values in steady state differ from those in fig. 5 despite normalization with respect to the maximum peak value $\hat{F}_{max}$ measured at the muscle twitch of a single stimulus. This is due to the so called nonlinear pulse rate dependent temporal summation. To simplify the model structure this nonlinearity will be taken into account by modelling the nonlinear recruitment behavior in the subsequent section. For further analysis this nonlinearity will be compensated by normalizing the recorded muscle forces with respect to their respective constant values $\hat{y}_{a,\text{rep}}$. Fig. 7 shows that the average muscle contraction can be modelled very well with a reference function that has the average time constant $\overline{T}_{a,\text{opt}} = 38.44\,\text{ms}$.

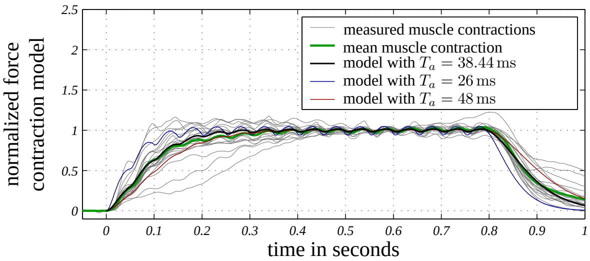

Fig. 7. Isometric muscle contraction induced by *RPMS* with $f_{\text{rep}} = 20\,\text{Hz}$

2.2 *Recruitment behavior*

As mentioned in the introduction of section 2 the recruitment behavior describes the spatial summation of motor units which is mainly dependent on the stimulation intensity u. Since the nonlinear temporal summation has also to be taken into account, the recruitment behavior will be described with the two-dimensional function $p(u, f_{\text{rep}})$. The recruitment behavior is recorded under isometric conditions using the setup depicted in fig. 2. The intensity u is increased in 20 % steps (from 0 % to 100 %) and the frequency is increased in 2.5 Hz steps (15 Hz – 35 Hz). The experiment has been made with seven healthy subjects so that in total 882 data sets have been evaluated. This data indicates, that a frequency of 20 Hz is the best tradeoff between force generation and coil heating. As can be seen in fig. 8, the relative recruitment p is obtained by normalizing the measured steady state forces F_{ss} with respect to the forces $F_{ss,\text{max}}$ measured at maximum stimulation intensity at a stimulation frequency of $f_{\text{rep}} = 20\,\text{Hz}$.

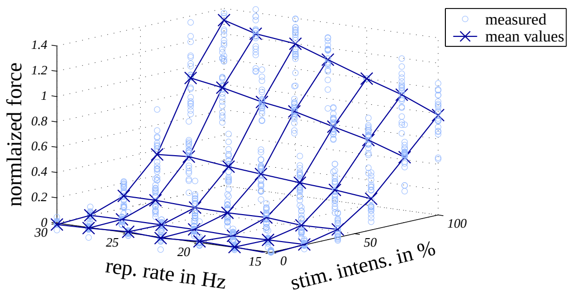

Fig. 8. Measured recruitment behaviour

Assuming that p_u and p_f are independent, the relative recruitment field can be calculated as

$$p(u, f_{\text{rep}}) = p_u(u) p_f(f_{\text{rep}}) \tag{8}$$

where p_u describes the recruitment dependent on the stimulation intensity and p_f describes the component dependent on the repetition rate.

In order to analytically describe the nonlinearity the formula (proposed in [Riener 1997])

$$\begin{aligned} p_u(u) = \beta_1 ((u - u_{thr}) \arctan(\alpha_{thr}(u - u_{thr})) - \\ -(u - u_{sat}) \arctan(\alpha_{sat}(u - u_sat)) + \beta_2) \end{aligned} \tag{9}$$

is used.

Similar to p_u the dependency of the recruitment behavior on the stimulation frequency has been determined with the same normalization. The formula

$$\begin{aligned} p_f(f_{\text{rep}}) = \delta_1 (f_{\text{rep}} - (f_{\text{rep}} - f_{sat}) \cdot \\ \cdot (^1/_\pi \arctan(\gamma_{sat}(f_{\text{rep}} - f_{sat})) + 0.5)) + \delta_2 \end{aligned} \tag{10}$$

approximates the average nonlinear recruitment $p_{\text{rec},f}$.

The manually adapted parameters of eq. (9) and eq.(10) are summarized in tab. 3 and the normalized recruitment field is shown in fig. 9.

In order to obtain the absolute stationary value of the generated muscle force, $p(u, f_{\text{rep}})$ has to be multiplied with the force $F_{ss,max}$ recorded at maximum intensity

Table 3. Parameters of eq. (9) und eq. (10) to approximate the average relative recruitment of *RPMS*

	u_{thr}	u_{sat} f_{sat}	α_{thr}	α_{sat} γ_{sat}	β_1 δ_1	β_2 δ_2
p_u	48%	98%	5	4	0.738	0.539
p_f	—	25 Hz	—	0.05	0.0597	-0.321

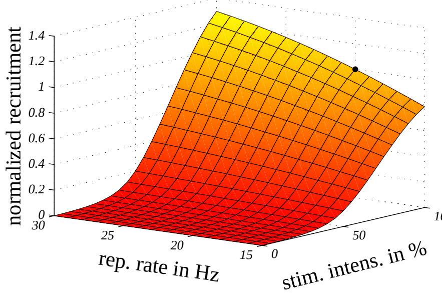

Fig. 9. Modeled recruitment behaviour

u and at a stimulation frequency of $f_{\text{rep}} = 20$ Hz (marked reference point in fig. 9):

$$F_{ss}(u, f_{\text{rep}}) = F_{ss,\max}\, p(u, f_{\text{rep}}) \qquad (11)$$

2.3 *Complete isometric contraction model*

In order to obtain a complete model of the muscle contraction with *RPMS* the components of section 2.1 and 2.2 are integrated in a common model. Since the recruitment represents the number of recruited motor units, and the activation dynamics model the time response of the twitch of the respective motor units it seems appropriate to choose the order of the models as depicted in fig. 10. This Hammerstein-structure is also assumed for fES related models.

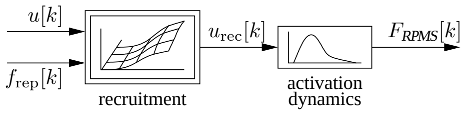

Fig. 10. Model of the induced muscle contraction in hammerstein-structure

When eq. (6) and eq. (11) are combined in order to calculate the generated force F_{RPMS} one has to consider, that the model of the activation dynamics as well as the recruitment model contain the stationary value of the linear temporal summation $\hat{y}_{a,\text{rep}}$. Since the activation dynamics are modelled as a LTI-system, the dependency of $\hat{y}_{a,\text{rep}}$ on the stimulation frequency f_{rep} can be described as

$$\hat{y}_{a,\text{rep}}(f_{\text{rep}}) = \hat{y}_{a,\text{rep,20Hz}}\, \frac{f_{\text{rep}}}{20\text{Hz}}\,, \qquad (12)$$

where $\hat{y}_{a,\text{rep,20Hz}}$ is the reference value at a stimulation frequency of 20 Hz. Thus the signal $u_{rec}(u, f_{\text{rep}})[k]$ can be calculated as

$$u_{rec}(u, f_{\text{rep}})[k] = \frac{F_{ss,\max}}{\hat{y}_{a,\text{rep,20Hz}}}\, \frac{p_{rec}(u[k], f_{\text{rep}}[k])}{f_{\text{rep}[k]}/20\text{Hz}}\,. \qquad (13)$$

3. SYSTEM IDENTIFICATION

The used approach for the nonlinear systemidentification is based on a normalized radial basis function network (NRBF, [Broomhead and Lowe 1988]) and a truncated convolution sum. To reduce the number of unknown parameters orthonormal basis functions (OBF) [Nelles 2001] are used. The theory and the capabilities of this approach in conjunction with *RPMS* are described in [Angerer *et al.* 2004].

To describe the system identification the OBF $\mathbf{R} \in \mathbb{R}^{m_r \times m}$ are defined by

$$r_{ji} = \frac{1}{\sqrt{m/2}} \sin\left(j\,\pi\,\left(1 - \exp\left(-{}^{i-0.5}/\zeta\right)\right)\right) \qquad (14)$$
$$\forall\; j = 1 \ldots m_r \qquad \text{and} \qquad \forall\; i = 1 \ldots m$$

with the length m of the truncated convolution sum, the number m_R of OBF and a form factor $\zeta \in \mathbb{R}$. These functions are orthonormalized by a Cholesky decomposition according to $\tilde{\mathbf{R}} = (\mathbf{C}^T)^{-1}\,\mathbf{R}$ with $\mathbf{C}^T\,\mathbf{C} = \mathbf{R}\,\mathbf{R}^T$ and $\tilde{\mathbf{R}} \in \mathbb{R}^{m_r \times m}$.

The NRBF is defined by its activation functions:

$$\mathcal{A}_l = \frac{\mathcal{E}_l}{\sum_{j=1}^{p} \mathcal{E}_j} \text{ with } \mathcal{E}_l = \exp\left(-\frac{(u - \chi_l)^2}{2\,\sigma^2}\right) \qquad (15)$$

where $\chi_l \in \mathbb{R}$ are the centers and $\sigma \in \mathbb{R}^+$ is a smoothing parameter.

If these definitions are included in a truncated convolution sum, the estimated system can be written as

$$\widehat{y}[k] = \left[\underline{A}_1^T[k]\,\tilde{\mathbf{R}}^T \ldots \underline{A}_q^T[k]\,\tilde{\mathbf{R}}^T\right] \cdot \widehat{\underline{\Theta}}[k] \qquad (16)$$

This approach requires no model or system feedback, respectively. The output signal of the model is only used to calculate the cost function

$$E = \frac{1}{2\,N} \sum_{k=1}^{N} (y[k] - \widehat{y}[k])^2 \qquad (17)$$

which is minimized by a recursive least squares [Nelles 2001, e.g.] algorithm in order to obtain the optimal parameter set $\widehat{\underline{\Theta}}$.

The identification approach is used to determine the unknown parameters $\widehat{\underline{\Theta}}$ to describe the isometric muscle contraction for a single subject. Therefore the setup depicted in fig. 2 is used with a second stimulation coil, placed above the innervation area of the triceps brachii. The biceps and the triceps are stimulated over 30 seconds with a randomized stimulation intensity and a repetition rate of 20 Hz. The identification approach is configured with 96 parameters and the model described above is used to determine the initial parameters $\widehat{\underline{\Theta}}[0]$. In fig. 11 and 12 the identification results are depicted as recruitment behavior and activation dynamics of the biceps and the triceps. As can be seen in these figures the determined contraction model matches the presented model whereas the possible range of the different charachteristics has to be taken into account.

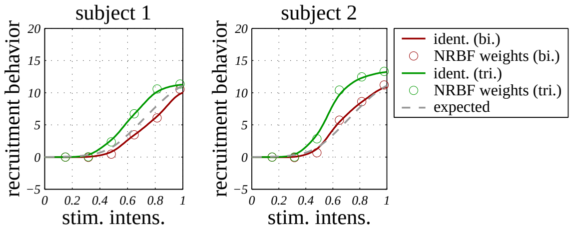

Fig. 11. Identification results: recruitment behavior

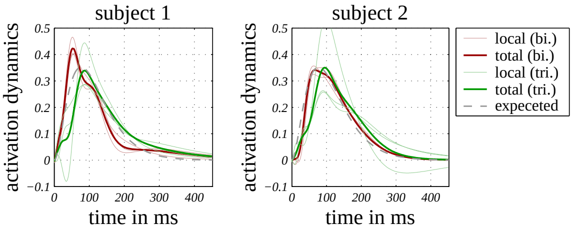

Fig. 12. Identification results: activation dynamics

4. CONCLUSIONS AND FUTURE WORK

The presented experiments and the identification process indicates that the developed model is very usefull as description for nonlinear control path in order to induce forearm (and finger) movements by *RPMS*. However, the different model parameters (recruitment behavior and activation dynamics) have to be adapted for a single subject. To avoid time-consuming experiments as described in section 2, the proposed identification process can be used to determine the model parameters for a single subject. The presented model and the system identification have to be expanded for non-isometric conditions in further studies.

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