

Modeling investigation of learning a fast elbow flexion in the horizontal plane—prediction of muscle forces and motor units action

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Experimental investigation of practicing a dynamic, goal-directed movement reveals significant changes in kinematics. Modeling can provide insight into the alterations in muscle activity, associated with the kinematic adaptations, and reveal the potential motor unit (MU) firing patterns that underlie those changes. In this paper, a previously developed muscle model and software (Raikova and Aladjov, *Journal of Biomechanics*, 35, 2002) have been used to investigate changes in MU control, while practicing fast elbow flexion to a target in the horizontal plane. The first trial (before practice) and the last trial (after extensive practice) of two subjects have been simulated. The inputs for the simulation were the calculated external moments at the elbow joint. The external moments were countered by the action of three flexor muscles and two extensor ones. The muscles have been modeled as a mixture of MUs of different types. The software has chosen the MU firing times necessary to accomplish the movement. The muscle forces and MUs firing statistics were then calculated. Three hypotheses were tested and confirmed: (1) peak muscle forces and antagonist co-contraction increase during training; (2) there is an increase in the firing frequency and the synchronization between MUs; and (3) the recruitment of fast-twitch MUs dominates the action.

Keywords: Fast elbow flexion; Learning; Muscle force; Motor units; Antagonistic co-contraction

1. Introduction

The demands of the task are a primary consideration while learning to perform a discrete movement; it may require an increased speed, strength, or precision. The training methods used to make improvements in these criteria are important issues in the area of motor behavior for sport and rehabilitation. Training performed to increase the speed of limb movement can significantly alter the observed kinematics (Gabriel 2002). The measured angular accelerations can then serve to calculate the joint moments, and the individual muscle forces can be computed by applying different optimization techniques for solving the indeterminate problem (Raikova and Prilutsky 2001). Musculoskeletal modeling and surface electromyographic (SEMG) evidence suggest that antagonist co-activation plays a significant role during maximal effort tasks. Training to improve maximal effort performance can either increase or decrease the antagonist co-contraction, depending on the objectives (strength or

speed) and the instructions (for example more accuracy) given to the subject (Gottlieb *et al.* 1990, Bernardi *et al.* 1996, Patten and Kamen 2000, Croce and Miller 2003, Gribble *et al.* 2003).

The SEMG signals and/or predicted muscle forces can provide information about any alterations in motor coordination during the training process. However, this is insufficient for investigating the adaptations in the underlying motor units (MUs) firing patterns. This is important because MU firing patterns are the basic mechanism by which the nervous system controls the generation of skeletal muscle force. Unfortunately, the activity of individual MUs is concealed by the interference pattern recorded from the skin surface. Additionally, SEMG recordings do not reflect underlying differences in muscle fibre composition (Taylor *et al.* 1997). Indwelling recordings can be used to monitor MUs activity directly but only a small number can be studied due to the limited pick-up volume of needle or wire electrodes. The resulting data do not

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provide a complete view of what the entire muscle is doing.

Training has been shown to increase MU firing rates (Taylor *et al.* 1997, van Cutsem *et al.* 1998, Patten *et al.* 2001). In addition, the number of fast-twitch MUs can increase while a concomitant transition of slow-twitch MUs to intermediate ones (Karageorgos, Gus 1998) is present. MU synchronization is another phenomenon responsible for an increase in muscle force as a result of training (Milner-Brown *et al.* 1975, Connelly *et al.* 2000). Which of these processes is more important is unclear because SEMG signals and indwelling recordings of MU potentials cannot distinguish between the different MU types (Taylor *et al.* 1997, Chan *et al.* 2001). Moreover, ethical principles do not allow the precise *in vivo* registration of MU forces in humans as performed on animals (Celichowski 2000).

Modeling can be used to circumvent the difficulties associated with recording MUs and their individual force contributions, to provide insight into training-related adaptations in nervous control of skeletal muscle. For the sake of this paper, a previously validated muscle model and software (Raikova and Aladjov 2002, 2004, Raikova *et al.* 2005) have been used to investigate changes in MU control while learning to increase the maximal speed of elbow flexion to a target in the horizontal plane. Three hypotheses were tested: (1) peak muscle forces and antagonist co-contraction increases during training; (2) there is an increase in the firing frequency and synchronization between MUs; and (3) the recruitment of fast-twitch MUs dominates the action.

2. Methods

2.1 Model

The experimental procedure is described elsewhere (Gabriel 2002, Raikova *et al.* 2005). The subjects performed elbow flexion in the horizontal plane to a target, as fast as possible (figure 1a). They have practiced over a two-week period to increase the maximal speed of limb movement for the same degree of accuracy. Only the first (before practice) and the last (after extensive practice) trials of two subjects (the slowest and the fastest ones) have been used in the present investigation. From now on, the slowest subject will be designated as “Subject 1” and the fastest one as “Subject 2”.

Angular acceleration was calculated by differentiating the filtered joint angle data. The external joint moment was calculated as a product of acceleration and the inertial moment of the subject’s forearm and hand. The model had one degree of freedom for flexion/extension at the elbow joint in the horizontal plane. There were three flexor muscles in the model: the biceps brachii (BIC), the brachialis (BRA), and the brachioradialis (BRD). The two extensor muscles were the triceps brachii (TRI) and anconeus (ANC). Together, the flexor and extensor muscles balanced the external moment at this joint (figure 1b). The lever arms for

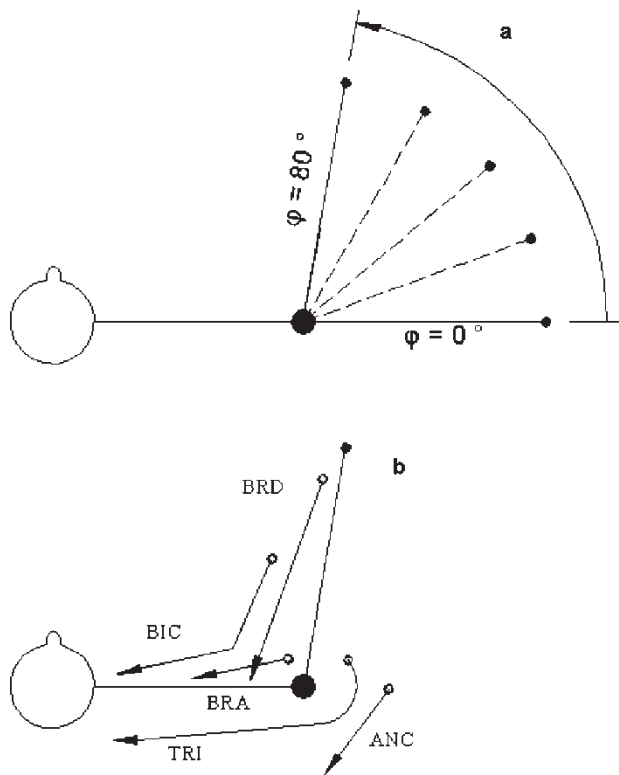


Figure 1. Schematic representation of the experiments and the model. (a) The motion—elbow flexion—is performed in the horizontal plane and starts at fully extended forearm ($\varphi = 0^\circ$) and stops at $\varphi \approx 80^\circ$. The external moment in the joint is calculated as $M = I_{zz}\ddot{\varphi}$, where $I_{zz} = 0.0581512 \text{ kg m}^2$ is the inertial moment of the subject’s forearm and hand and $\ddot{\varphi}$ is the angular acceleration. (b) The external joint moment is countered by the action of five muscles (two extensors—TRI and ANC and three flexors—BIC, BRA and BRD). So, $M = d_{\text{bic}}F_{\text{BIC}} + d_{\text{bra}}F_{\text{BRA}} + d_{\text{brd}}F_{\text{BRD}} + d_{\text{tri}}F_{\text{TRI}} + d_{\text{anc}}F_{\text{ANC}}$, where $d_{(*)}$ is the lever arm of the respective muscle force $F_{(*)}$ and these arms are positive numbers for flexors and negative numbers for extensors.

the muscle forces were assumed to depend on the elbow angle and were calculated using regression equations reported in the literature (Raikova and Aladjov 2004).

Each muscle has been modeled as a mixture of different MU types (Chan *et al.* 2001). The total number of MUs was 774 for BIC, 804 for BRA, 193 for BRD, 686 for TRI and 180 for ANC. The MUs within each muscle were based on the conventional division into three types (Burke 1981): fast-fatigable (FF), fast-fatigue-resistant (FR) and slow (S). Each muscle contained one third of each MU type. The main feature that characterized the force capability of the MU was the “twitch”. This is the mechanical response of the MU to a single input stimulus. The twitch form has been modeled using an analytical function, as proposed in Raikova and Aladjov (2002). Four twitch parameters served as inputs for the function: lead time, contraction time, half-relaxation time and maximal force (Raikova and Aladjov 2004). The twitches associated with the different MU types were modeled by changing these four parameters.

Assumption was made that the twitch parameters specific to each MU type were within the realistic limits for human skeletal muscles (Raikova and Aladjov 2004,

Raikova *et al.* 2005). The fastest MU had a contraction time of 30 ms and half-relaxation time of 60 ms. The slowest MU had contraction time of 70 ms and half-relaxation time of 175 ms. The values of the lead times were between 20 and 60 ms. The maximal amplitudes of the twitches were between 0.371 and 1.837 N and were different for different muscles depending on their maximal forces. The individual MUs' mechanical responses to the impulses were summed up to generate the total muscle force. The only stipulation was that the next impulse should fall after the contraction phase of the previous twitch.

2.2 Simulation

The inputs for the simulations were: angular displacement as a function of time; inertial moment I_{zz} of the subjects' forearm and hand, so the calculated external joint moment; the muscle lever arms; the number and properties (i.e. twitches) of the MUs for each muscle. The same set of MUs was used to simulate the four joint moment profiles with MotCo software (<http://www.clbme.bas.bg/projects/motco/>). Recall, the four joint moment profiles correspond to the trials before and after extensive practice for Subjects 1 and 2. The MotCo software is based on a hierarchical genetic algorithm that mimics the "trial-and-error" manner of learning. The algorithm chooses the MU impulse times of all modeled muscles so that the required motion gets performed. The whole muscle force is constituted as the sum of the forces of all MUs of one muscle, caused by these impulses. Then, the sum of all the muscle force moments (flexor and extensors) has to be equal to the given external joint moment.

The task was highly indeterminate, so three criteria were enforced. The first requirement was to minimize the deviation between the calculated and desired joint moment

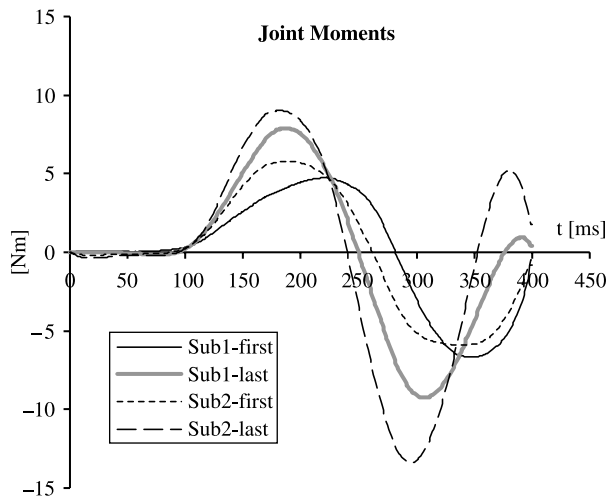


Figure 2. Calculated joint moments (the product of the inertia moment of the hand and forearm and the angular acceleration calculated by differentiation of the measured elbow angle) of the two subjects (Sub 1 and Sub 2) for their first trials (before practice) and last trials (after practice) of the motion.

(ΔJm). The other two criteria reflected the economy of the movement: one minimized the sum of impulses received from all MUs of all muscles (*Simp*) and the second one minimized the sum of all predicted muscle forces (*Sfor*) (Raikova and Aladjov 2003, Raikova and Aladjov 2004). The aim was therefore to minimize the following fitness function: $\text{FitFun} = k_1 \Delta Jm + k_2 \text{Simp} + k_3 \text{Sfor}$, where k_i are weight factors.

The external joint moments for the four conditions are presented in figure 2. Since the weight factors for the three criteria in the fitness function had a large impact on the predicted muscle forces (Raikova and Aladjov 2004), they were changed during the simulation. For the first trials of the two subjects, the weight factors were $k_1 = 40$; $k_2 = 1$; $k_3 = 1$. For the last trial of Subject 1, k_1 was increased to 60, and for Subject 2 it was increased to 100 (see Discussion) while k_2 and k_3 remained unchanged.

The large number of MUs (2637 in total), which had to be controlled by the algorithm, required a great deal of computation time for each simulation, especially when the required joint moment was close to the limit of the MUs' ability to develop the desired level of force. Each simulation finished when a good match between the required and calculated joint moment was obtained, i.e. when ΔJm reached a predetermined value. This value was different for the four joint moment conditions, and was chosen based on previous experience.

Upon completion of the simulation, one output of the software was the predicted muscle forces during the time-course of the entire motion. In order to estimate antagonistic muscle co-contraction, an index, *col*, was introduced. It was calculated according to the formulas:

$$\text{col} = \frac{\sum_{i=1}^2 F_i^{\text{ext}}}{\sum_{j=1}^3 F_j^{\text{fl}}} \quad \text{if } M > 0 \quad \text{and}$$

$$\text{col} = \frac{\sum_{j=1}^3 F_j^{\text{fl}}}{\sum_{i=1}^2 F_i^{\text{ext}}} \quad \text{if } M < 0,$$

where M is the external joint moment, F_i is the i th predicted muscle force and superscripts "fl" and "ext" denote flexors and extensors, respectively. Osu *et al.* (2002) introduced a similar co-contraction index based on SEMG signal.

3. Results

The predicted muscle forces for the two subjects (figure 3) increased considerably during their last trial, reflecting the increase in the peak positive and negative joint moments (figure 2). Subject 1 had maximal joint moments of 4.76 and 7.88 Nm for the first and last trials, respectively. The minimal values changed from -6.66 Nm for the first trial to -9.26 Nm for the last trial. Subject 2 had maximal joint moments of 5.81 and 9.01 Nm for the first and last trials,

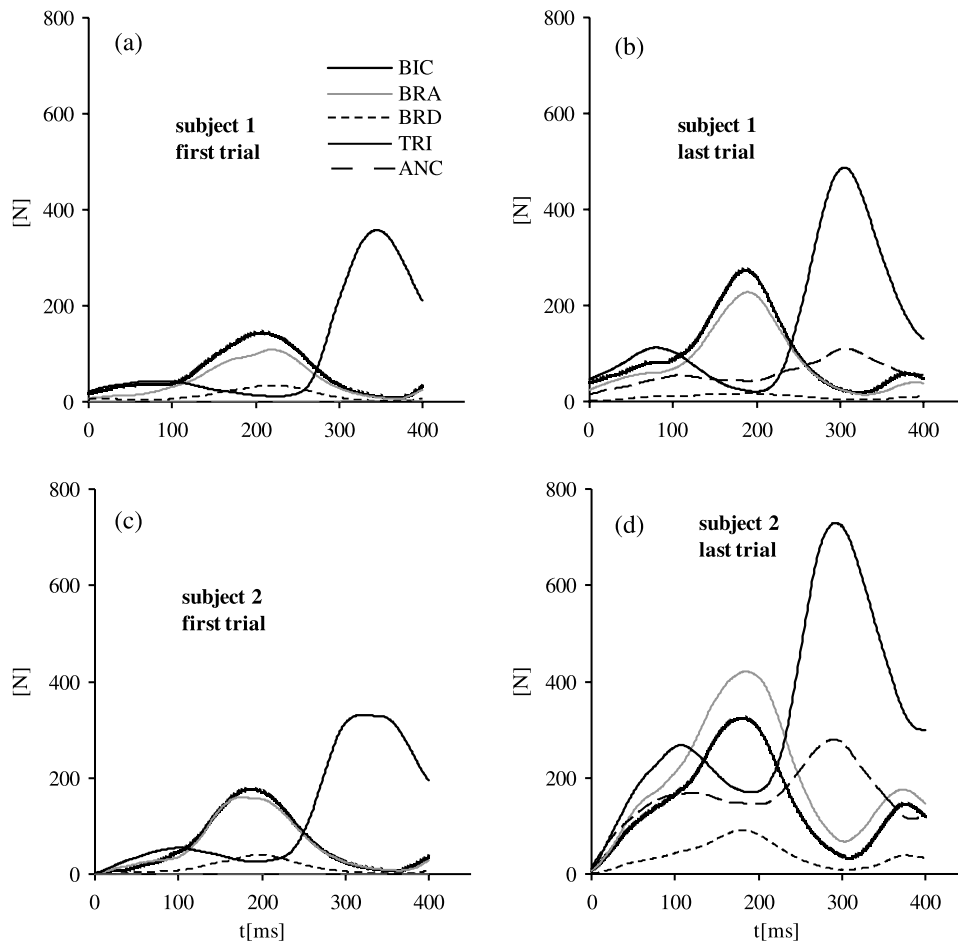


Figure 3. Muscle forces for the first and the last trials of the two subjects predicted by using MOTCO software.

respectively. The minimal values changed from -5.89 Nm for the first trial to -13.39 Nm for the last trial.

The predicted muscle forces for the first trials of both subjects were similar, but for the last trials, evident were different force distributions. The predicted force for the muscle BRA became greater than that for the BIC for the fastest subject (figure 3d). There was also a considerable

rise in the predicted force for the ANC for both subjects, but for the Subject 2 this force was much bigger. The ANC muscle force for both subjects was nearly zero during the first trial. Also important were the changes in the patterns of the joint moments. For the last trials (figure 2), a third positive phase was observed and it was more prolonged for the fastest subject (from 350 to 400 ms). The profile of the joint moments is a reason to have two-phases behavior of the muscles for the first trials (flexor–extensors) and three phases one for the last trials (flexor–extensors–flexors).

The calculated index of antagonistic co-contraction, coI , is shown in figure 4. In general, the co-contraction was essential before the beginning of the motion (from 0 to 100 ms) and around the time when the direction of the joint moment changed. For both subjects, coI was generally greater for their last trial than for their first trial. It should be noted that Subject 2 also showed considerable co-contraction during the last trial from 100 to 220 ms, where the respective joint moment had considerable positive values. Such high positive values suggest that only the flexor muscles had to be active. This unexpected result is to be discussed below.

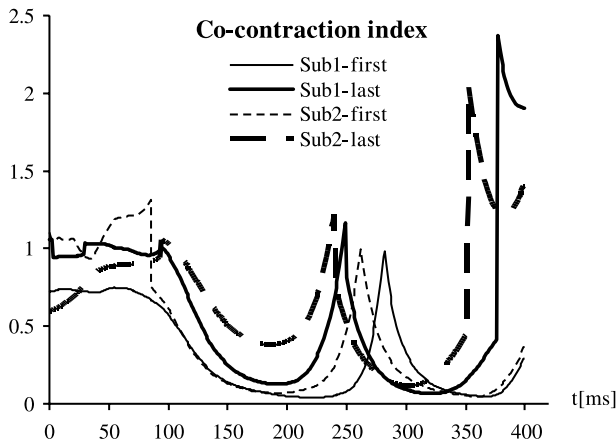


Figure 4. Calculated co-contraction index for the first and the last trial of the motion of the two subjects.

Another output of the software was the number of the impulses received by all the MUs within the muscle for a fixed time interval (here this interval was 3 ms) during the

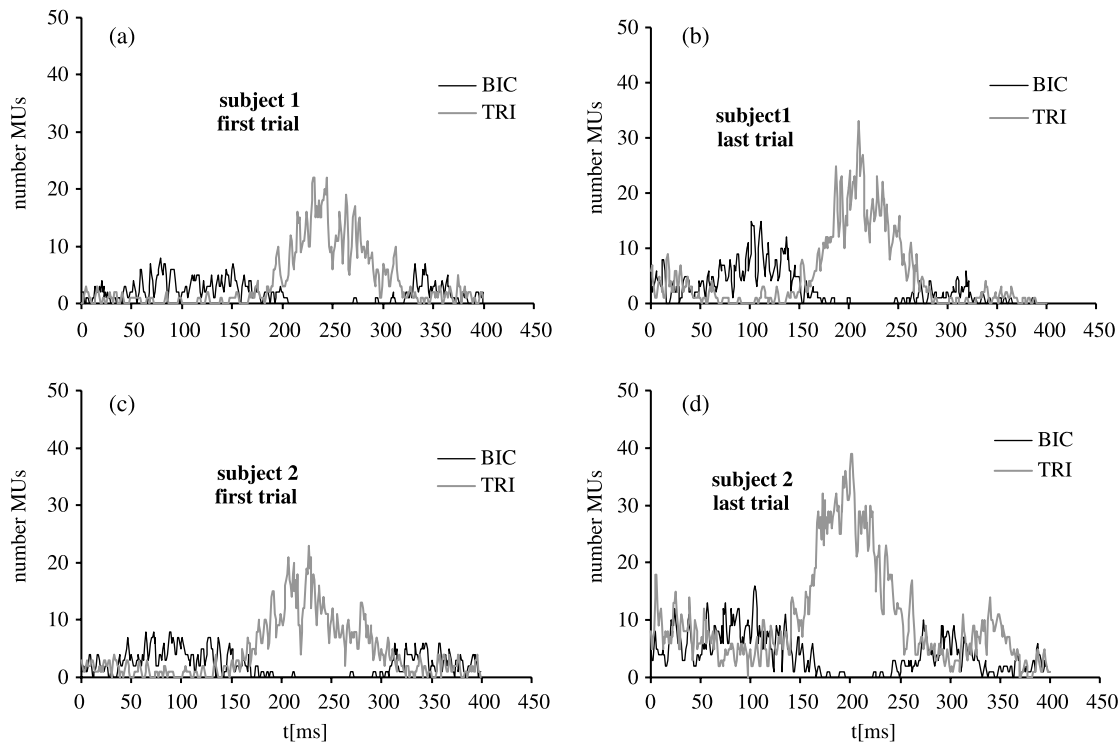


Figure 5. “Simulated EMG” activity (the number of impulses received by all MUs of a muscle within a time interval of 3 ms) of the main flexor (BIC) and the main extensor (TRI) for the two trials of the two subjects.

motion (figure 5), i.e. the so-called “simulated EMGs” (Raikova and Aladjov 2004). It was close in nature to the SEMG signal. Figure 5d shows that the co-contraction (i.e. simultaneous activation of TRI and BIC MUs) during the last trial for Subject 2 is quite large, especially during the intervals between 0 and 150 ms and 250 and 400 ms.

MU synchronization during the last trial for both subjects increased (figure 6a vs. b and c vs. d). After extensive practice, the MU impulses occurred closer together in time (figure 6b,d). Synchronization for Subject 2 was not so obvious (not shown in the figures) because nearly all of the extensor MUs had to be active to achieve the very high negative peak joint moment. However, the statistics of the interpulse intervals (IPI) shown in figure 7, indicated that synchronization has also increased for Subject 2 (figure 7c vs. d), especially for the TRI MUs. Nearly half of the intervals between the first and the second impulse and between the second and the third impulse for this muscle MUs were around 60 ms (figure 7d).

There was no significant difference between the two subjects with respect to the predicted muscle forces and simulated EMGs for the first trial (figures 3a,c and 5a,c). However, inspection of figure 7a,c indicates that the MUs of the two subjects did indeed behave differently. This is particularly true for the TRI of the Subject 2. The IPIs for the Subject 2 were shorter than those for the Subject 1 (figure 7c vs. a). The smallest IPI was 31 ms. This was due to the restriction imposed by the software: the force developed by a MU can not increase if a new stimulus

comes within its contraction time. Hence, doublets were not possible because the minimal IPI was limited by the contraction times of the modeled MUs.

The fast MUs of the BIC and BRA dominated muscle activity, especially for the last trials (figure 6a,b). The difference between the MU types is summarized in figure 8. The total number of active flexor MUs for Subject 1 decreased after training, but the participation of fast MU types increased (figure 8a; S1 t1 fl vs. S1 t40 fl). Subject 2 used nearly all the extensor MUs during the last trial that explains why the participation of the three MU types was equal. The total number of impulses for the fast MU types was always greater, and it increased after training (figure 8b). Except for the flexors of Subject 2, the number of MUs with only one impulse decreased after training (figure 8c). The number of MUs with two, three and four impulses increased after training (figure 8c,d,f). This indicates an increase in firing rate.

4. Discussion and conclusion

The hypothesis that the antagonistic muscle co-contraction increases after training was confirmed (figures 3 and 4). Co-contraction usually relates to joint stability (Solomonow *et al.* 1988). However reasonable this explanation, we cannot use it because a criterion for joint reaction forces was not included in the fitness function. An alternative explanation is based on the interaction between the form of the MU twitches and

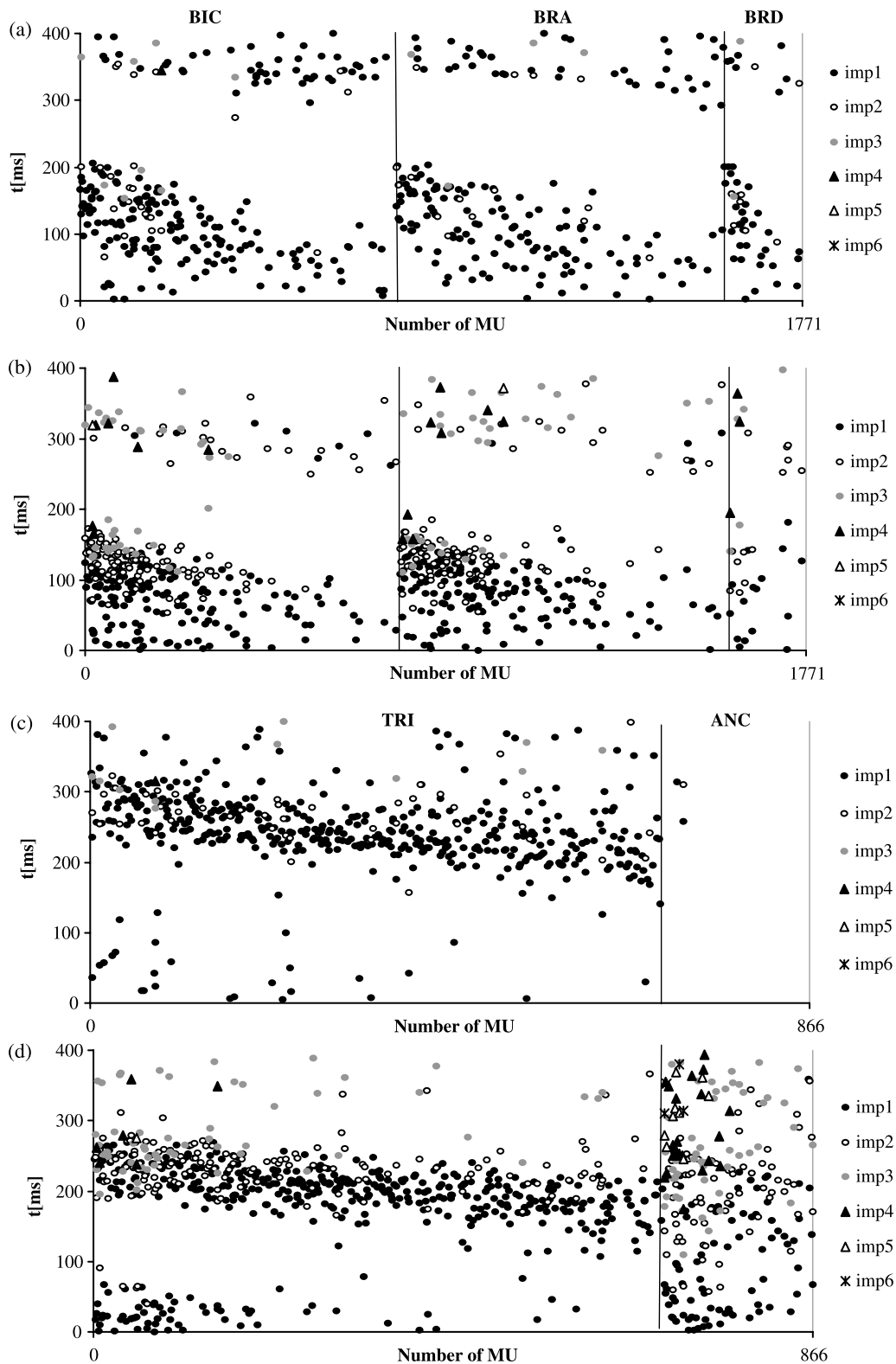


Figure 6. Time moments of impulses of each MU of all modeled muscles for simulation of the first and the last trial of the slowest subject (Subject 1). The MUs of each muscle are arranged from the fastest to the slowest one. Some MUs are activated only once, some twice, and some MUs receive even six impulses during movement. The respective successive impulses of each MU are plotted vertically, appearing at different times and are labelled differently. Figure 6a—flexors, first trial; figure 6b—flexors, last trial; figure 6c—extensors, first trial; figure 6d—extensors, last trial.

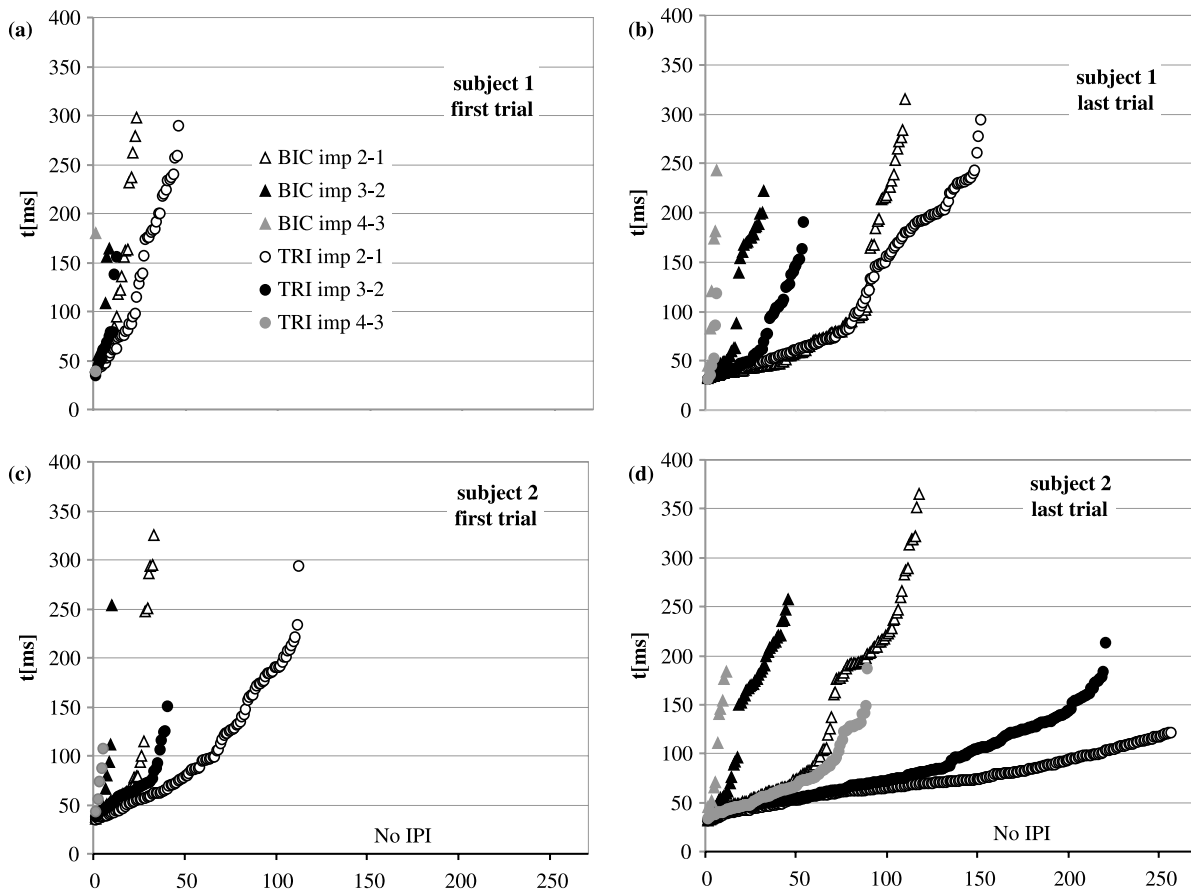


Figure 7. Statistics of the interpulse intervals (IPIs) between the first and the second impulse, between the second and the third impulse, and between the third and the fourth impulse for the muscles BIC and TRI during the first and the last trial of the two subjects. There are also MUs that receive five and six impulses during the motion, but these interpulse intervals are not shown in the figure. The horizontal axis is scaled according to the maximal number of interpulse intervals. IPIs are calculated on the base of the time moments of impulses (figure 6), predicted by the software, and are arranged in an ascending order, but not using the number of the MUs. Each point indicates one IPI.

dynamic motions with steep acceleration and deceleration phases. The relaxation times of the modeled twitches were between 110 and 270 ms, depending on the MU type. The joint moments of the simulated movement increased and decreased within a very short period, at a steep rate. However, the decrease in force of the active agonist MUs was slower, so more activity from the antagonistic MUs was necessary. These results are consistent with the findings of Ghez and Gordon (1987). These authors showed that antagonist muscle activity was necessary to actively terminate the rapid rate of increase in agonist muscle forces for dynamic muscle actions occurring within a short period of time.

The hypotheses about firing frequency and synchronization were also substantiated. The conclusions about the increase in firing frequency and synchronization were based on the impulse times of the modeled MUs. After training, the IPIs decreased (figure 7), and the individual impulses occurred within a very narrow region of time (figure 6d). The firing frequency increased because the number of MUs, which had received more than one impulse, increased considerably (figure 8), and the IPIs decreased from the first to last trial. The total number of

impulses also increased despite the decrease in number of active MUs in some muscles.

We also observed the dominant participation of fast MU types, most evident for the Subject 1 (figure 6b), but not always evident for Subject 2, especially for the extensor muscles. There are two possible explanations. The first reason may be due to the large negative joint moment achieved by Subject 2 during the last trial. The peak forces required from the extensor muscles were nearly at the limit that might be predicted by their physiological cross-sectional area and maximal stress. Thus, to achieve the large joint moments required by the task, nearly all MUs of both extensors had to be active. To achieve this, the weight coefficient k_1 was increased up to 100 while $k_2 = k_3 = 1$. This fact leads to the second possible explanation. The influence of the criteria connected with the minimal number of impulses and the minimal sum of all the muscle forces was practically negligible, leaving only the goal of matching the actual joint moment. As a result, the efficiency and economy of the motion was no longer important.

The genetic algorithm used to simulate the four joint moment profiles mimics the “trial-and-error” basis of

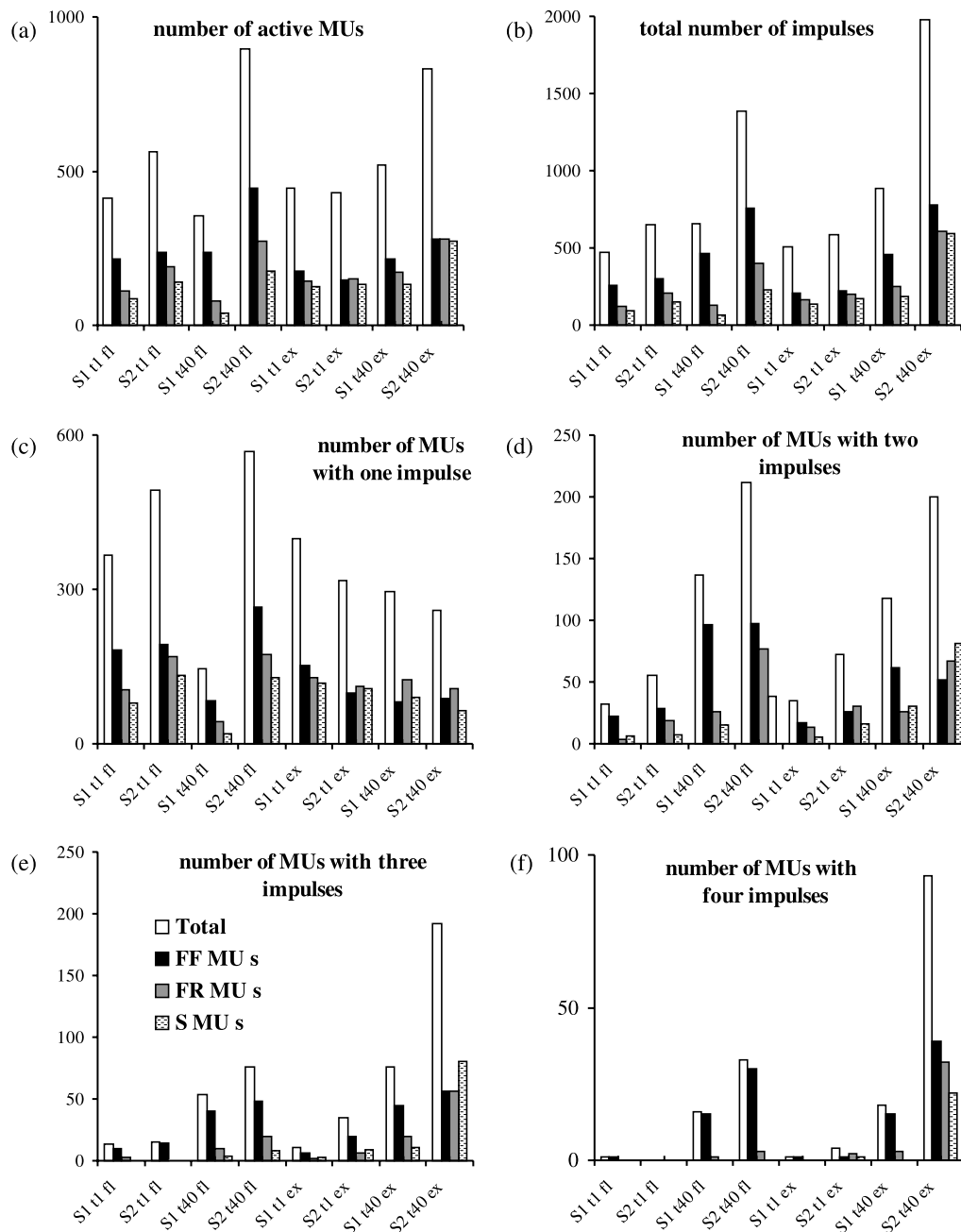


Figure 8. Statistics of the impulses during the motion (number of active MUs, total number of impulses, number of MUs receiving only one impulse, number of MUs receiving two impulses, number of MUs receiving three impulses, number of MUs receiving four impulses) separately for all flexors (hence BIC, BRA and BRD together) and for all extensors (hence TRI and ANC together). The data are given for all MUs (Total) and separately for different groups: FF MU s, FR MU s and S MU s. S1 t1 fl—Subject 1, first trial, all flexors; S2 t1 fl—Subject 2, first trial, all flexors; S1 t40 fl—Subject 1, last trial, all flexors; S2 t40 fl—Subject 2, last trial, all flexors; S1 t1 ex—Subject 1, first trial, all extensors; S2 t1 ex—Subject 2, first trial, all extensors; S1 t40 ex—Subject 1, last trial, all extensors; S2 t40 ex—Subject 2, last trial, all extensors.

learning in humans. The simulations, therefore, provide insight to potential, realistic mechanisms for increasing the maximal speed of limb movement. The first strategy used by the nervous system was to increase the MU firing frequency to increase force output of the muscles. There was also a preferential utilization of fast MU types. When this mechanism became insufficient, new MUs were included. The simulation results were dependent on the chosen fitness function, which reflected the aim of the

motion. For the first trial (before practice), the simulation was performed with requirements for the efficiency of the movement (minimal antagonistic co-contraction and minimal number of impulses). For the last trial, especially for Subject 2, the weight factors in the fitness function had to be changed so that the joint moment could be well described. This meant that the main goal of the algorithm became to achieve the required motion without further restrictions.

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