Experimental and modelling investigation of learning a fast elbow flexion in the horizontal plane

Rositsa T. Raikova[a,*], David A. Gabriel[b], Hristo Ts. Aladjov[a]

[a]Centre of Biomedical Engineering, Bulgarian Academy of Sciences, Academician G. Bonchev Street, Bl.105, 1113 Sofia, Bulgaria
[b]Department of Physical Education and Kinesiology, Brock University, St. Catharines, Ont., Canada L2S 3A1

Abstract

Changes in the kinematic and electromyographic characteristics that occur while learning to move as fast as possible have been studied experimentally. Experimental investigation of what happens to the individual motor units (MUs) is more difficult. Access to each MU is impossible, and the recruitment and force developing properties of all individual MUs cannot be known. Thus, what is currently known about MU firing is based on experiments that have recorded relatively few MUs compared to what exists in the entire muscle. A recently developed muscle model (Raikova and Aladjov, 2002, J. Biomechanics, 35, 1123–1135) composed of MUs with different properties can be used for such investigation. The process of learning fast elbow flexion in the horizontal plane was simulated and the results were compared with experimentally measured data. Comparing the simulation results of the very first trial of a particular subject with those of the last trail (at the end of the learning process), it can be concluded that the speed of limb motion and muscle forces increase initially as a result of the more synchronous MUs activation and the increase of firing rate of active MUs. Further improvement necessitated an appreciable reduction in the motor task requirements (i.e. less muscle force and less MUs' activity) set in the computational algorithm by optimization criteria. This forced the next process—inclusion of additional MUs.

© 2004 Elsevier Ltd. All rights reserved.

Keywords: Fast elbow flexion; Learning; Muscle force; Motor unit; Horizontal plane

1. Introduction

Motor learning can involve a novel task or familiar skills wherein the different performance aspects are refined during the teaching and learning process. In the first case, new muscle activation patterns must be established, while in the latter instance existing patterns are modified (Gottlieb et al., 1995b). To understand what happens during teaching and learning, movement parameters such as angles, velocities and accelerations are observed as well as surface electromyographic (SEMG) signals from different muscles. It has been observed that changes in these quantities depend on the

aim of the movement and on the instruction given to the subjects (Gottlieb et al., 1990; Yamazaki et al., 1994). However, there are a few generalizations that can be made thus far. Muscle co-contraction plays significant role in movement precision (Gribble et al., 2003), and an increase in limb speed is a result of an increase in neural drive as measured by an increase in the amplitude SEMG activity from both the agonist and antagonist muscles (Gabriel and Boucher, 2000; Gabriel, 2002).

Maximal effort training is a very important aspect of sport, rehabilitation, and for some ergonomic applications. This paper focuses on training-related changes in motor units' (MUs) activity. Using the SEMG signal it is very difficult to identify MUs, and the intramuscular recordings are from a limited volume of muscle tissue. What happens with MUs' activity during training is still

---

*Corresponding author. Tel.: +359 2 8700527; fax: +359 2 723787.
E-mail address: Rosi.Raikova@clbme.bas.bg (R.T. Raikova).

unclear. There is a limited amount of data obtained during isometric strength training that demonstrates an increase in MUs' firing rates (Van Cutsem et al., 1998; Patten and Kamen, 2000), but similar data on dynamic contractions do not exist, partly due to the methodological difficulties. The recently developed muscle model and MotCo software (Raikova and Aladjov, 2002) are capable of predicting individual MUs' firing rates and forces generated by the MUs, for all of the modelled muscles during a specified movement.

The software implementation is based on a hierarchical genetic algorithm (HGA) which iteratively, by a trail-and-error manner, refines the solution. It can be argued that this process can serve as a simple model of the natural learning process. During the execution of the HGA, a set of possible solutions (time moments for firing of all the MUs) is obtained. These solutions are then modified and combined between themselves (by means of genetic operations) and thus a new set of solutions is obtained. The best solutions are selected from both old and new solutions, according to criteria defined a priori, and the genetic operations are applied again.

The aim of the paper is to study the process of learning a fast elbow flexion in the horizontal plane by means of modelling and experimental validation, to provide insight into the learning process at the MUs level.

2. Methods

2.1. Experimental investigations

The experimental procedure has been described in detail in Gabriel (2002). Subjects performed fast elbow flexions in the horizontal plane. The instruction for the task was to move the limb "as fast as possible" to the required target. The motion started with the elbow in full extension ($0°$) and was supposed to end at $80°$ ($\pm 1.5°$) of elbow flexion. The measured and recorded parameters were angular displacement and SEMG signals of the biceps and triceps brachii muscles. One hundred trials were completed, each with 4 days of testing, for a total of four hundred trials. There was 15 s of rest between each trial and 5 min of rest after every 25 trials. Data were collected for the first five and last five trials of each test day. For example, on test day 1 data were collected for trials 1–5 and for trials 96–100, while on test day 4 trials 301–305 and 395–400 were recorded. Thus, there were a total of 40 records for each subject available for analysis. The displacement and SEMG signals were sampled at 2 kHz. Displacement was low-pass filtered (10 Hz, 3 dB) and numerically differentiated to obtain angular velocity and acceleration, while the SEMG data were linear envelope detected (60 Hz, 3 dB).

All signals were filtered with a zero-phase lag second-order Butterworth digital filter. Only the data of two subjects (subjects 1 and 2) were used for the present study.

2.2. Model

It was assumed that three flexors and two extensors participated in the elbow motion, namely biceps brachii (BIC), brachialis (BRA), brachioradialis (BRD) and triceps brachii (TRI) and anconeus (ANC). The numbers of MUs composing these muscles were BIC-774, BRA-804, BRD-193, TRI-686 and ANC-180. These numbers were proportional to the physiological cross-sectional areas of the respective muscles (Raikova and Aladjov, 2004). Ruegg (1989) observed that the BIC had 774 MUs, so the numbers used in the current work seem reasonable.

The parameters of the twitches[1] of these MUs were uniformly distributed in three main groups: fast-fatiguable, fast-fatigue-resistant, and slow MUs (Burke, 1999). The fastest MU had a contraction time of 30 ms and a half-relaxation time of 60 ms. The slowest MU had a contraction time of 70 ms and a half-relaxation time of 175 ms (Raikova and Aladjov, 2003; 2004). The values of the lead time were between 20 and 60 ms. The maximal amplitudes of the twitches were calculated using the maximal forces of the modelled muscles. The maximal amplitudes of the twitches were therefore between 0.371 and 1.837 N. The muscle moment arms were dependent upon joint angle and were calculated using linear regression equations (for details see Raikova and Aladjov, 2003). The external joint moment (M) was calculated by multiplying angular acceleration ($\ddot{\varphi}$) by the inertial moment (I_{zz}) of the subjects' forearm and hand (for subject 1 it was estimated that $I_{zz} = 0.0581512 \, \text{kg m}^2$), hence $M = I_{zz}\ddot{\varphi}$. This moment was an input parameter for the software. Other input parameters were the moment arms of the muscles and the number and type of MUs for each muscle.

The aim of the simulations was to find the appropriate firing rate for each MU within muscles so that the motion can be completed. Hence, the muscle forces were obtained as sums of the mechanical responses of the individual MUs. However, the predicted activation of MUs, and hence muscle forces, must satisfy the following equation for the experimentally obtained external joint moment:

$$M = d_{BIC}F_{BIC} + d_{BRA}F_{BRA} + d_{BRD}F_{BRD} + d_{TRI}F_{TRI} + d_{ANC}F_{ANC},$$

where d is the moment arm of the respective muscle force. For the flexors they were positive and for

---

[1] Twitch is the mechanical response of a MU to one single neural impulse.

extensors they were negative numbers, and F was the respective muscle force calculated as sum of the forces of all MUs that compose this muscle. In addition to minimizing the error between calculated and experimentally obtained joint moments, the software also sought to minimize both the sum of the muscle forces and the MUs' firing (i.e. the total number of impulses of all MUs). Together, these criteria comprised a "fitness function", which has been detailed in Raikova and Aladjov (2003).

2.3. Simulations

Two trials of subject 1 were simulated: the first trial (the slowest) and the last trial (the fastest, after learning). Thus, the two different joint moments were goals in the fitness function. The number and the type of MUs remained unchanged during all simulations. The weight of the criterion connected with the joint moment in the fitness function was 100 for the first trial, but was changed to 200 for the last trial (see the discussion). The weights of the other two criteria were 1. After a good agreement between the experimental and simulated joint moments, an additional simulation was performed to see how the HGA learned the movement. The time moments for firing of all MUs predicted by the MotCo software for the first trial were set as a solution of the last trial, but the required joint moment was changed to that for the last trial. Changes in the output parameters were then observed while HGA learned how to achieve the faster movement.

3. Results

The simulations of the first and the last trials for subject 1 showed that the required elbow joint moments (Fig. 1, A1 and B1) were achieved with a high degree of accuracy. The two curves for each joint moment completely overlap. During the learning process, subject 1 decreased the movement time required to reach the target area from 382 to 310 ms for the first and last trials, respectively (see arrows in Fig. 1, A1 and B1). To perform the movement more quickly, the predicted
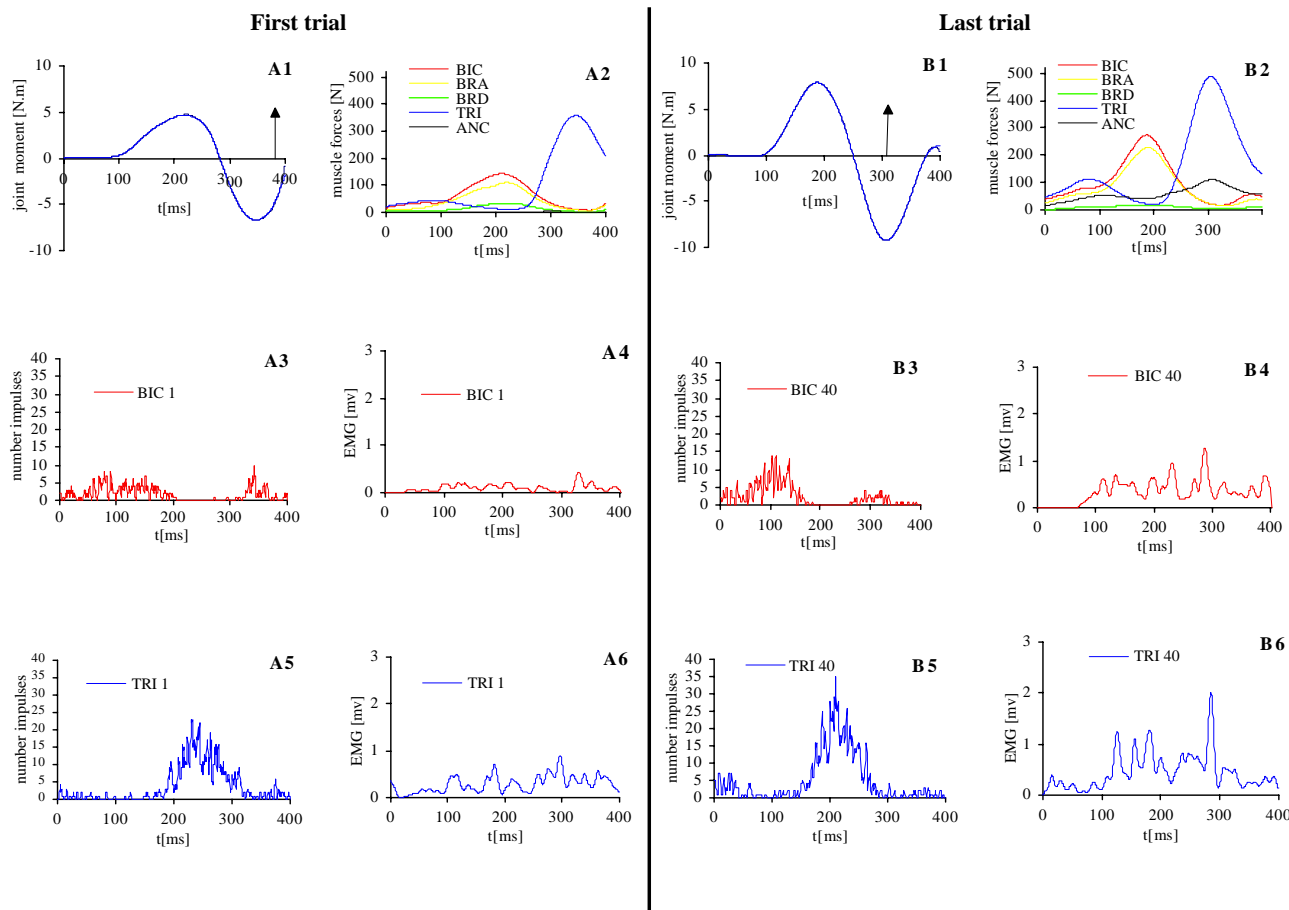

Fig. 1. Comparison between modelled and experimental results for the first and last trial of subject 1. A1 and B1—measured and calculated moments in the elbow joint (the vertical arrows show the time moments of reaching the target area); A2 and B2—predicted muscle forces; A3 and B3—simulated EMG activity of the biceps brachii; A4 and B4—experimental measured SEMG signals of biceps brachii; A5 and B5—simulated EMG activity of triceps brachii; A6 and B6—experimental measured SEMG signals of triceps brachii.

muscle forces changed (Fig. 1, A2 vs. B2). Except for the BRD, the maximal values of other muscle forces increased considerably. The force of the TRI increased from 357.74 N to 487.11 N. The force of BIC increased from 142.55 to 273.75 N, while that of BRA increased from 110.50 to 227.93 N. Activation of the ANC was minimal during the first trial (maximal value 2.8 N), while during the last trial its force increased considerably (maximal value 109.97 N).

There was a poor match between the simulated electromyographic (EMG) activity[2] and experimentally obtained SEMG signals of the biceps and triceps muscles (Fig. 1, A3 vs A4; A5 vs. A6; B3 vs. B4; and B5 vs. B6). The same was true for the predicted muscle forces (Fig. 1, A2 vs. A4 and A6; B2 vs. B4 and B6). The simulated EMG activity exhibited the classic triphasic pattern (BIC-TRI-BIC) observed for rapid movements (Gottlieb et al., 1992), but the real SEMG signals did not. Other participants such as subject 2 did, however, demonstrate the triphasic pattern (Gabriel, 2002).

The comparison of subjects 1 and 2 shown in Fig. 2 illustrates the problems with subject comparisons of experimental SEMG signals. The patterns of the joint moments during the slowest and the fastest trials of subject 2 did not differ markedly from those of subject 1. Although subject 2 was faster and stronger than subject 1, he altered angular acceleration during training in a similar manner. The maximal and minimal values of the joint moment during the fastest trial of subject 2, however, were significantly greater. Thus, only the last trial of subject 2 was simulated, as it required a great deal of computational time (thousands of steps) due to the large number of MUs. We observed that the weight coefficient for the function that minimized the deviation between the experimental and calculated joint moments had to be increased considerably. To increase the speed of limb movement further, there needs to be an additional decrease in the criteria minimizing muscle forces and MUs' activity. This process does not change, however, the three-phasic behaviour of the simulated EMG activity. It only results in the inclusion of new MUs.

The simulations showed that fast-twitch MUs dominated the task (Fig. 3). Note that the MU with number 1 was the fastest. The first third of the MUs of a muscle were fast-fatiguable, the second third were fast-fatigue-resistant, and the last third were slow-twitch. Comparing the first and the last trial of subject 1, it can be seen that the total number of impulses to the MUs of each muscle increases (except the BRD in which the force decreased during the last trial), the number of MUs that are activated more than one time increases, and the
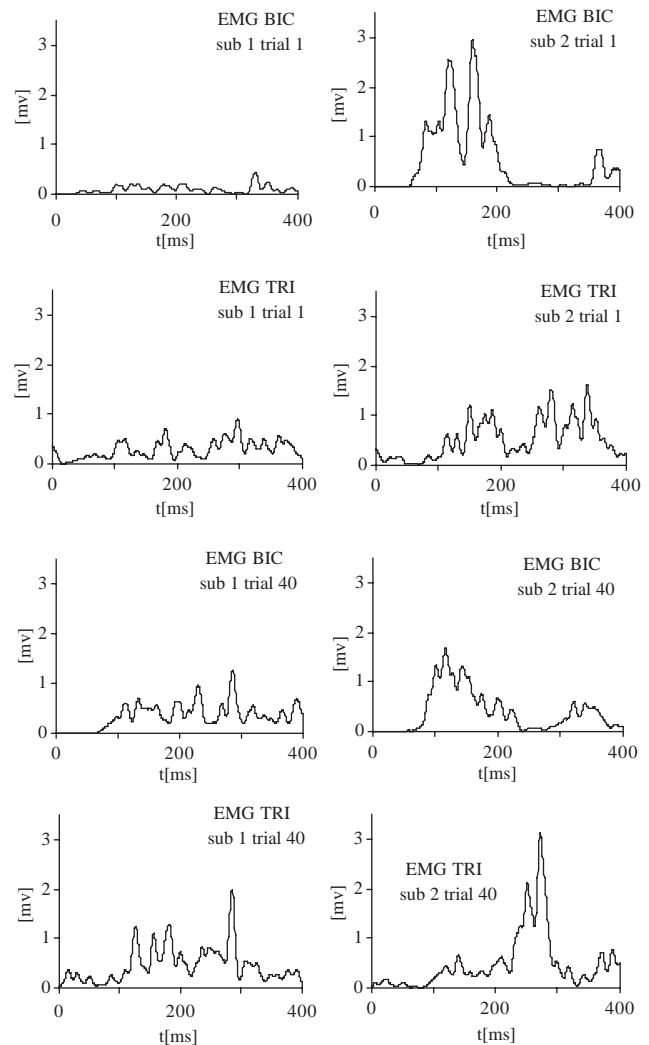

Fig. 2. Comparison of the measured SEMG signals from subject 1 (left panel) and subject 2 (right panel) for the first and last trials.

synchronization between MUs within a muscle increases.

The data in Table 1 for the MUs firing rates (impulses) for all five muscles support these visual observations. The main finding from this table is that the increase in the total muscle force during the last trial is due mainly to an increase in the firing rate of active MUs (the number of active MUs in all flexors even decreased). The number of MUs that received more than one impulse also increased considerably. This number for flexors increased from 48 to 209, while for extensors it increased from 46 to 207. The numbers in the last row of Table 1 show that the mean value of activation time of the MUs within each muscle (except for the BRD) decreased, indicating an increase of the mean firing rate as well as an earlier onset of MUs (see Fig. 3).

Fig. 4 illustrates the training process for the experimental movement for subject 1 (Fig. 4A) and for the HGA implemented in MotCo software (Fig. 4B). These

---

[2]The number of impulses received by all MUs of a muscle within a given time interval; this time interval is currently chosen as 3 ms.
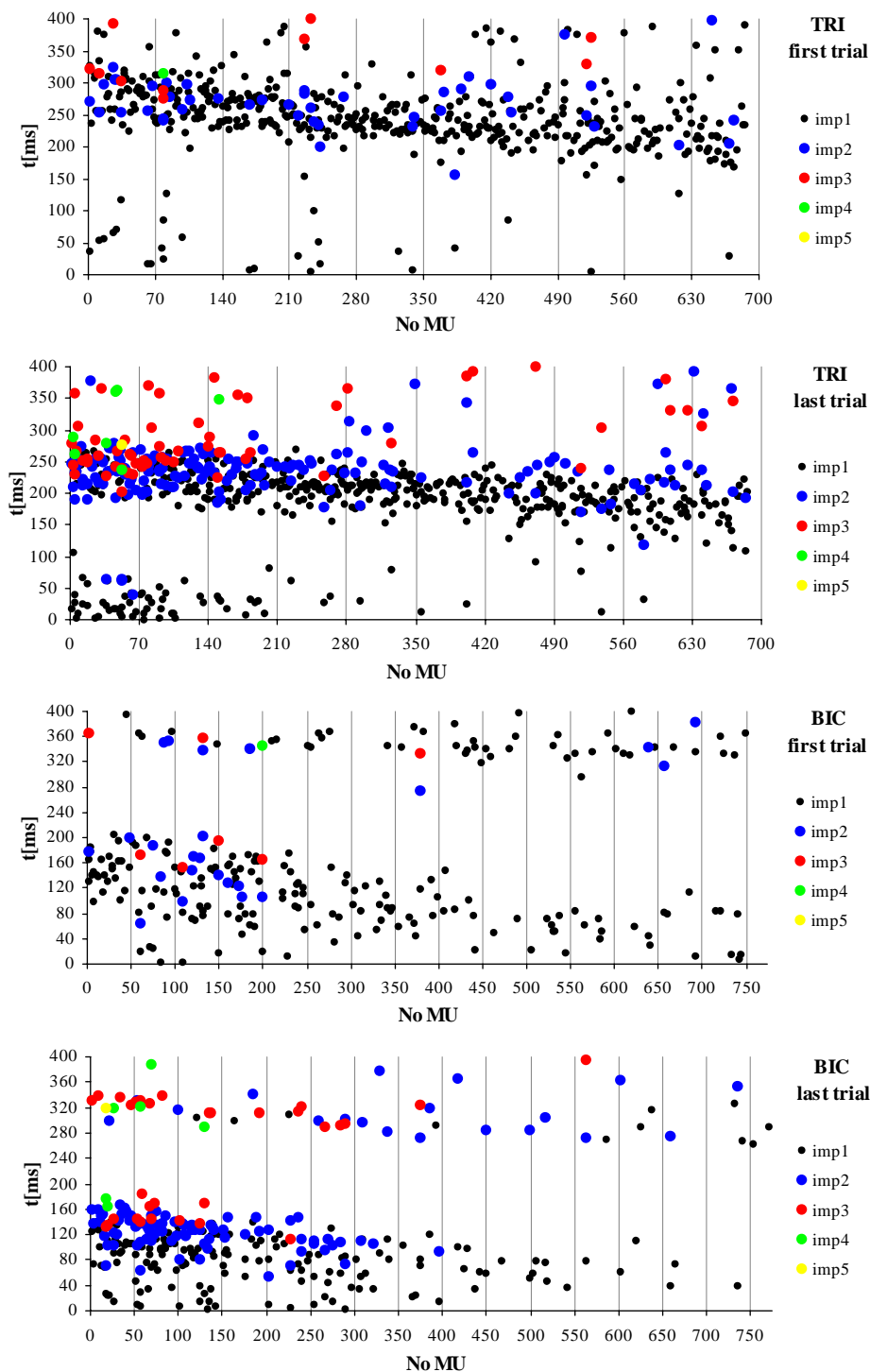
Fig. 3. Time occurrences of impulses (firings) of all MUs predicted by the MotCo software for the biceps and triceps brachii during the first and last trials.

figures present the changes in joint moment during different stages of training. The joint moments for subject 1 for the means of the first five and last five trials of each test day are shown in Fig. 4A. The calculated joint moments for different (but not equal) number of steps of the simulation are illustrated in Fig. 4B.

Both subjects 1 and 2 exhibited similar patterns of change in the joint moment profile during training. The simulations closely matched these training-related alterations (Fig. 4). To quantify these changes, the maximal and minimal values of the joint moments, and times at which the positive and negative phases occurred were investigated. These parameters are

Table 1
Statistics of the firing of the MUs of all modelled muscles of subject 1 for the first, i.e. (1), and the last, i.e. (40), trial simulated by the software. It has to be noted that during the last trial muscle ANC has one predicted MU with six and one with seven impulses

	BIC (1)	BIC (40)	BRA (1)	BRA (40)	BRD (1)	BRD (40)	TRI (1)	TRI (40)	ANC (1)	ANC (40)	Flexors (1)	Flexors (40)	Extensors (1)	Extensors (40)
Total number of impulses	235	332	188	287	52	37	503	649	3	236	475	656	506	885
Number of active MUs	204	180	168	159	42	16	445	439	3	105	414	355	448	544
Number of MUs with one impulse	181	69	151	74	34	3	399	291	3	46	366	146	402	337
Number of MUs with two impulses	16	78	14	51	6	8	35	94	0	21	36	137	35	115
Number of MUs with three impulses	6	26	3	26	2	2	10	47	0	16	11	54	10	63
Number of MUs with four impulses	1	6	0	7	0	3	1	6	0	13	1	16	1	19
Number of MUs with five impulses	0	1	0	1	0	0	0	1	0	7	0	2	0	8
Mean value of activation (ms)	167.27	127.22	174.13	134.37	161.66	160.63	245.98	199.12	202.03	193.96	—	—	—	—

illustrated in Fig. 5. Comparing them for subjects 1 and 2 and for the simulation, it can be concluded that phase I always decreased and phase III always increased during training. Interestingly, the early trials lacked a phase III. The parameters t_{min}, t_{max}, t_1 and t_2 also had a tendency to decrease, while phase II increased for subject 1 and the MotCo simulation, but for subject 2 it decreased. The peak values of the joint moment (M_{max} and absolute value of M_{min}) increased during training, but for the first subject M_{min} was quite variable.

4. Discussion

The purpose of this paper was to investigate how training-related changes in joint moments are generated at the level of the MUs. This is difficult to accomplish using experimental methods alone and requires modelling and simulation to provide further insight. The task we chose required maximal effort from each subject as he flexed his elbow as fast as possible to a target in the horizontal plane. The training process resulted in significant changes in joint moments for the experimental movement and these changes were matched by the simulations. The training-related changes in SEMG activity were poorly approximated by the simulated EMG activity. In the following paragraphs, we will discuss the theoretical and practical aspects of our results.

There is debate on whether SEMG signals are suitable for verification of predicted muscle forces. In the present paper the muscle was modelled as a mixture of MUs, and not as one simple musculo-tendon unit (one force-one control signal). Since the modelled MUs' firing times are predicted, the impulses can be summated to produce a simulated EMG activity. It is closer in nature to the electrical manifestation of muscle activity since it presents the number of impulses received by all MUs within a given time interval (Raikova and Aladjov, 2004).

Differences in electromechanical delay, movement of the muscle beneath the electrode, electrode type and cross-talk are just a few reasons for a lack of correspondence between simulated EMG activity and experimental SEMG signals for subject 1. The simulated EMG activity did, however, match the experimental SEMG signals for subject 2. Unfortunately, tuning the model is not a simple matter as the exact number and type of MUs within an individual's muscle cannot be known. The simulation results are therefore a general representation based on the joint moment.

The simulated EMG activity and experimental SEMG signals for subject 2 both demonstrated the classic triphasic activation pattern (Hannaford and Stark, 1985; Gottlieb, 1998; Gottlieb et al., 1995a). The trials of subject 1 were not characterized by a triphasic
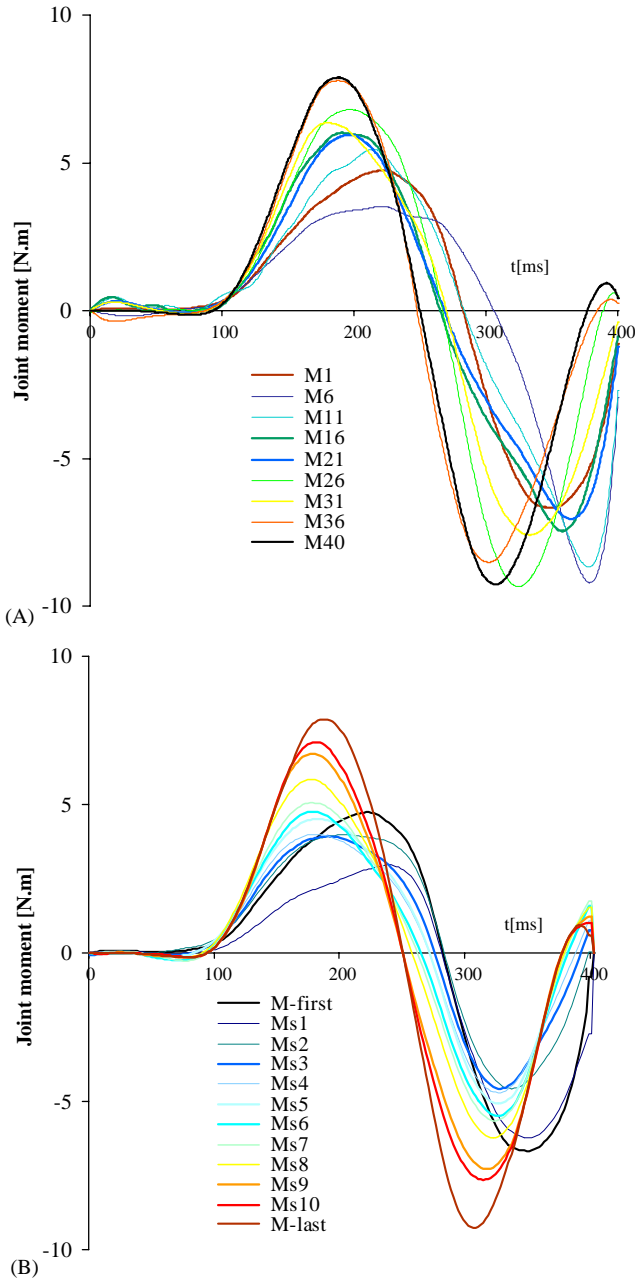
Fig. 5. Motion parameters for quantifying learning: M_{max}—global maximal joint moment; M_{min}—global minimal joint moment; T—duration of the motion; t_{max}—time for which M_{max} is reached; t_{min}—time for which M_{min} is reached; t_1—time where the joint moment crosses the zero line for the first time; t_2—time where the joint moment crosses the zero line for the second time.

Fig. 4. Changes in elbow joint moment during training. (A) Calculated joint moments from the measured data for angular displacements ($M1$, $M6$, ..., and $M40$—the joint moments of trials 1, 6, ... , 40). (B) Simulation with MotCo software (M-first—the simulated first trial, M-last—the simulated last trial, Ms1 to Ms10 are the calculated joint moments during different (but not equal) steps of the algorithm).

pattern. This can be easily explained based on movement time. Subject 1 was the slowest participant. His movement times were close to the critical movement time of 400 ms observed by Brown and Gilleard (1991) necessary for the appearance of the triphasic SEMG pattern during single-joint motions. Since the simulations predicted the triphasic muscle activity, and because the type of the MUs was not changed, we considered that the conclusions about the change in the MUs'
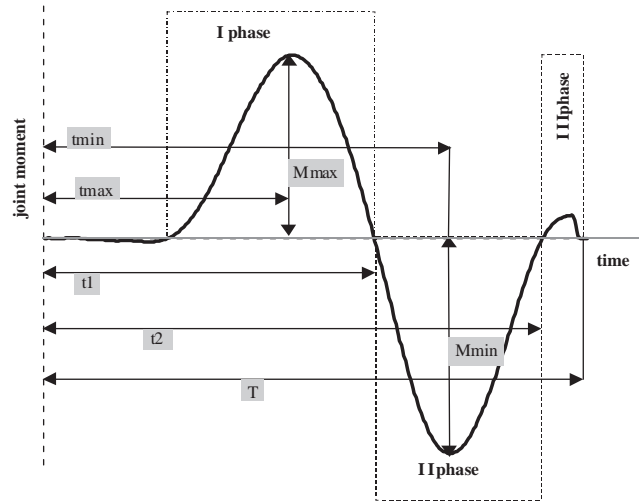
activity during training were representative. It should be noted that these conclusions are valid only for similar rapid motions and for the fitness function and parameters used in the model.

The main conclusion from the simulations is that the increase in the muscle forces related to training for rapid limb movement was mainly due to an increase in the firing rate of individual MUs and synchronization between MUs. When MUs fire more than once, the activity pattern is geared towards unfused tetanus, which is more economical as compared to the individual twitch. An increase of the number of active MUs is the next mechanism for an increase in acceleration of the limb. This strategy becomes important when faster MUs, more suitable for fast movements, exhaust their resources and slower MUs begin to participate too.

The influence of the weight factors in the fitness function used in MotCo software was discussed in detail in Raikova and Aladjov (2004). We acknowledged the fact that a good agreement between simulated and experimental joint moments could be obtained using a weight factor of 100 (even 50) at the respective goal for the first trial (the slowest motion) only. Independently that more than four million steps of the algorithm were performed, such good congruence between simulated and experimental joint moments was impossible to reach for the last trial (the fastest motion). To simulate it, the weight factor was increased up to 200. Preliminary simulations of the last trial of the second subject showed that this weight factor had to be increased further, which means an appreciable reduction of the criteria requiring less muscle force and less MUs' activity. The explanation of this is the following: these two criteria allowed for different levels of antagonistic

co-contraction and preferred these solutions for which the number of all impulses (firing rate) during the whole motion was lower. Therefore, increasing the weight of the criterion requiring more preciseness in matching the joint moment reduced the significance of the other two criteria. We observed experimentally that an increase in the speed of limb movement was associated with greater co-contraction (Gabriel and Boucher, 2000). Another reason is that for the HGA (and may be for humans), it was impossible to activate all MUs in a very narrow time period (see Fig. 3, TRI during the last trial for $t \in$ (200 ms, 300 ms)). The latter can also explain the considerable rise in ANC force. For the very fast, steep changes in the joint moment, fast MUs are more suitable because of their twitch form. Their number in the TRI is insufficient and the fast MUs of ANC have to be included too.

Finally, tracing the parameters defined in Fig. 5 for consecutive trials, a similarity between humans and the HGA in the way a motor task is learned can be observed. This suggests that the algorithm mimics the natural way of learning a motor task and that it was suitable for present investigation.

Acknowledgements

References

Brown, J.M.M., Gilleard, W., 1991. Transition from slow to ballistic movement: development of the triphasic electromyogram patterns. European Journal of Applied Physiology and Occupational Physiology 63, 381–386.

Burke, R.E., 1999. Revisiting the notion of "motor unit types". Progress in Brain Research 123, 167–175.

Gabriel, D.A., 2002. Changes in kinematic and EMG variability while practicing a maximal performance task. Journal of Electromyography and Kinesiology 12, 407–412.

Gabriel, D.A., Boucher, J.P., 2000. Practicing a maximal performance task: a cooperative strategy for muscle activity. Research Quarterly for Exercise and Sport 71, 217–228.

Gottlieb, G.L., 1998. Muscle activation patterns during two types of voluntary single-joint movement. Journal of Neurophysiology 80, 1860–1867.

Gottlieb, G.L., Corcos, D.M., Agarwal, G.C., Latash, M.L., 1990. Organizing principles for single joint movements. III. Speed-insensitive strategy as a default. Journal of Neurophysiology 63, 625–636.

Gottlieb, G.L., Latash, M.L., Corcos, D.M., Liubinskas, T.J., Agarwal, G.C., 1992. Organizing principles for single joint movements. V. Agonist-antagonist interactions. Journal of Neurophysiology 67, 1417–1427.

Gottlieb, G.L., Chen, C-H., Corcos, D.M., 1995a. Relations between joint torque, motion, and electromyographic patterns at the human elbow. Experimental Brain Research 103, 164–167.

Gottlieb, G.L., Chen, C-H., Corcos, D.M., 1995b. "Adequate control theory" for human single-joint elbow flexion on two tasks. Annals of Biomedical Engineering 23, 388–398.

Gribble, P.L., Mullin, L.I., Cothros, N., Mattar, A., 2003. Role of cocontraction in arm movement accuracy. Journal of Neurophysiology 89, 2396–2405.

Hannaford, B., Stark, L., 1985. Roles of elements of the triphasic control signal. Experimental Neurology 90, 619–634.

Patten, C., Kamen, G., 2000. Adaptations in motor unit discharge activity with force control training in young and older human adults. European Journal of Applied Physiology 83, 128–143.

Raikova, R.T., Aladjov, H.T.S., 2002. Hierarchical genetic algorithm versus static optimization—investigation of elbow flexion and extension movements. Journal of Biomechanics 35, 1123–1135.

Raikova, R., Aladjov, H., 2003. The influence of the way the muscle force is modeled on the predicted results obtained by solving indeterminate problems for a fast elbow flexion. Computer Methods in Biomechanics and Biomedical Engineering 3, 181–196.

Raikova, R.T., Aladjov, H.T.S., 2004. Simulation of the motor units control during a fast elbow flexion in the sagittal plane. Journal of Electromyography and Kinesiology 14, 227–238.

Ruegg, J., 1989. Muscle. In: Schmidt, R.F., Thews, G. (Eds.), Human Physiology. Spinger, New York, pp. 51–77.

Van Cutsem, M., Duchateau, J., Hainaut, K., 1998. Changes in single motor unit behaviour contribute to the increase in contraction speed after dynamic training in humans. Journal of Physiology 513, 295–305.

Yamazaki, Y., Ohkuwa, T., Itoh, H., Suzuki, M., 1994. Reciprocal activation and coactivation in antagonistic muscles during rapid goal-directed movements. Brain Research Bulletin 34, 587–593.