

Hierarchical genetic algorithm versus static optimization— investigation of elbow flexion and extension movements

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Abstract

The applicability of static optimization (and, respectively, frequently used objective functions) for prediction of individual muscle forces for dynamic conditions has often been discussed. Some of the problems are whether time-independent objective functions are suitable, and how to incorporate muscle physiology in models. The present paper deals with a twofold task: (1) implementation of hierarchical genetic algorithm (HGA) based on the properties of the motor units (MUs) twitches, and using multi-objective, time-dependent optimization functions; and (2) comparison of the results of the HGA application with those obtained through static optimization with a criterion “minimum of a weighted sum of the muscle forces raised to the power of n ”. HGA and its software implementation are presented. The moments of neural stimulation of all MUs are design variables coding the problem in the terms of HGA. The main idea is in using genetic operations to find these moments, so that the sum of MUs twitches satisfies the imposed goals (required joint moments, minimal sum of muscle forces, etc.). Elbow flexion and extension movements with different velocities are considered as proper illustration. It is supposed that they are performed by two extensor muscles and three flexor muscles. The results show that HGA is a suitable means for precise investigation of motor control. Many experimentally observed phenomena (such as antagonistic co-contraction, three-phasic behavior of the muscles during fast movements) can find their explanation by the properties of the MUs twitches. Static optimization is also able to predict three-phasic behavior and could be used as practicable and computationally inexpensive method for total estimation of the muscle forces. © 2002 Elsevier Science Ltd. All rights reserved.

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1. Introduction

Different approaches are applied for the investigation of motor control strategies used by human nervous system during various motor activities. The main idea of the frequently used static optimization is to calculate the individual muscle forces according to their contributions in the formation of previously known (computed or measured) joint moments. Different objective criteria are proposed and tested (for review see Raikova, 1999; Tsirakos et al., 1997). Functions that minimize the sum of the muscle stresses raised to the power of two or three are most frequently used (Brook et al., 1995; Crowninshield and Brand, 1981; Prilutsky et al., 1998). Probably, more complex objective criteria have to be applied for motor tasks for which the endurance time or muscle

fatigue are not so important (Niemenen et al., 1995; Raikova, 2000). Such new propositions (Raikova, 1998) are scarcely due to the difficulties with the physiological interpretation of the optimization functions. Using static optimization and time-independent functions, the fast (dynamic) and the very slow (quasistatic) movements cannot be distinguished from each other, since the optimization is performed independently for every discrete time moment. Well-known dependences between the force developed by a muscle and its current length and the contraction velocity are not considered in the optimization process. In spite of this, static optimization is used for locomotion (Crowninshield and Brand, 1981; Prilutsky et al., 1997) and human cycling (Prilutsky and Gregor, 2000) and the authors report a good correlation between the predicted muscle forces and the corresponding processed EMG data.

As an alternative, “phenomenological” models have been used. They describe a muscle by constitutive equations as viscoelastic-contractile material with

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specific behavior during passive loading and neural stimulation. Such models consist of different passive and contractile components (Cheng et al., 2000; Hatzel, 1977; Rosen et al., 1999; Zajac, 1989). In order to use them, however, many specific muscle constants and real electrical stimulation of muscles should be known. For modeling purposes, usually processed EMG signals are used as neural inputs. A combined approach is used in Pedotti et al. (1978) and Happee and Van der Helm (1995). In objective functions, they incorporate the maximal forces of the muscles, being computed from force–length and force–velocity relationships, and add dynamic constraints based on a non-linear model of muscular dynamics. Investigations of the force-sharing problem that render an account for the properties of motor units (MU) twitches are scarce. Dul et al. (1984) proposed an objective criterion depending on the percentage of slow-twitch muscle fibers, but this led only to another way for distribution of the muscle forces.

Another approach widely used in biomechanics recently is the so-called “black box” method, which is most often implemented by means of artificial neural network (NN) (for review see Su and Wu, 2000). For an input, NNs use processed EMG signals, joint angles or joint torques, ground reactions, and they calculate the muscle forces as an output (Jonic et al., 1999; Koike and Kawato, 1995; Liu et al., 1999; Rosen et al., 1999; Savelberg and Herzog, 1997). The role of the “black box” layers is to approximate unknown, complex relationships between input and output parameters. These layers have no clear physiological meaning and that is why such an approach cannot help much in understanding the motor control strategies and the process of training and teaching. Genetic algorithms are more appropriate for the latter purposes (Schaal and Sternad, 1992). They deal only with the evolutionary nature of obtaining optimal solution and they do not impose restrictions on the model description. A genetic algorithm (GA) is an open structure where different objects can be defined by conventional means and the state of the object is being changed by natural genetic operations.

In order to combine the advantages of the various approaches, it seems expedient to refine the muscle model by including its MUs structure and the peculiarities of the mechanical response of MUs (twitches) to neural stimulation, i.e. not considering a muscle as a single force unit.

The aims of the paper are: (1) to present an implementation of hierarchical genetic algorithm (HGA) based on MUs twitch properties where the control variables are the time moments of neural stimulation of MUs and the software realization of the algorithm for motor control investigation; (2) to illustrate their potential possibilities investigating fast

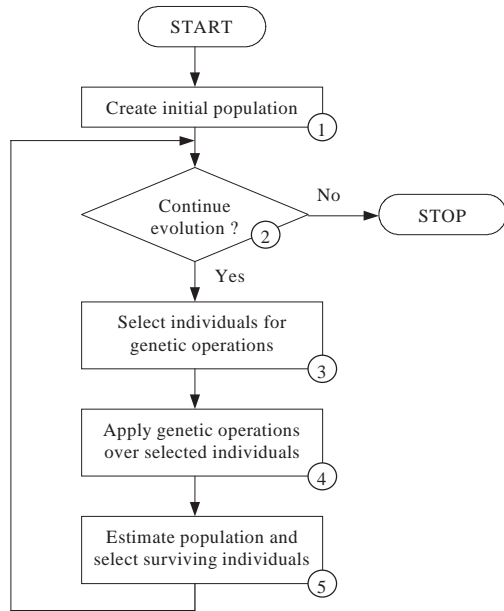
and slow elbow flexion and extension movements; and (3) to compare the results with those obtained by using static optimization with the objective function $\sum_{i=1}^N c_i F_i^n$ (Raikova, 1996).

2. Methods

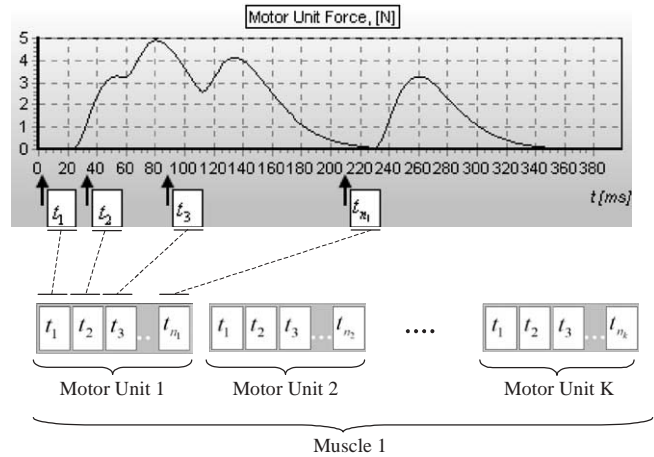
2.1. Hierarchical genetic algorithm (HGA)

GA has been inspired by the natural evolution where the fittest individuals survive (for basic concepts and theory see Man et al., 1999; Vose, 1999). GA presumes that each object can be described by a set of parameters named “individual” and its transition from state to state occurs by changing these parameters. In GA they are regarded as genes of a chromosome and can be structured as a string of values. The changes (next generations or populations) are performed by means of genetic operations (mutations and crossover). The obtained new sets of parameters (offspring individuals) together with the initial ones (parent individuals) are evaluated using some criteria combined into a fitness function. Only the best individuals (set of parameters) survive and the genetic operations are performed over them again. This process continues until a particular number of steps or a given error threshold is reached (see Fig. 1a). The algorithm reflects the process of evolution where the “better” chromosomes generate a larger number of offsprings and thus they have higher chances of survival. In the present model, genes encode the moments of neural stimulation of MUs (see Fig. 1b). Thus, a string of genes corresponds to a MU and the concatenation¹ of the strings of all MUs in a muscle represents the whole muscle. Then a single genome is obtained by concatenating the muscles’ strings. It corresponds to the overall neural activity of a muscle system. This activity is modified by applying genetic operations (Fig. 1c) over selected individuals of the current population. The new individuals obtained by these modifications are the new solutions of the task. The hierarchy level of the operations determines the object of influence of their applications—the genes of separate MUs, the genes of MUs of a given muscle or the whole muscle system genome. Given the moments of neural stimulation of each MU during the whole movement, its mechanical response can be calculated (Fig. 1b). If only one stimulus is being applied, then the form of the developed force (Fig. 2) is approximated by an analytical function (see Appendix A). The parameters of the twitch (T_{lead} , T_C , T_{hr} , T_{tw} , T_{ref} and F_{MU}^{max}) can be arbitrarily set, thus modeling different MU types (slow, fast, intermediate—see Tables 1 and 2). A parameter

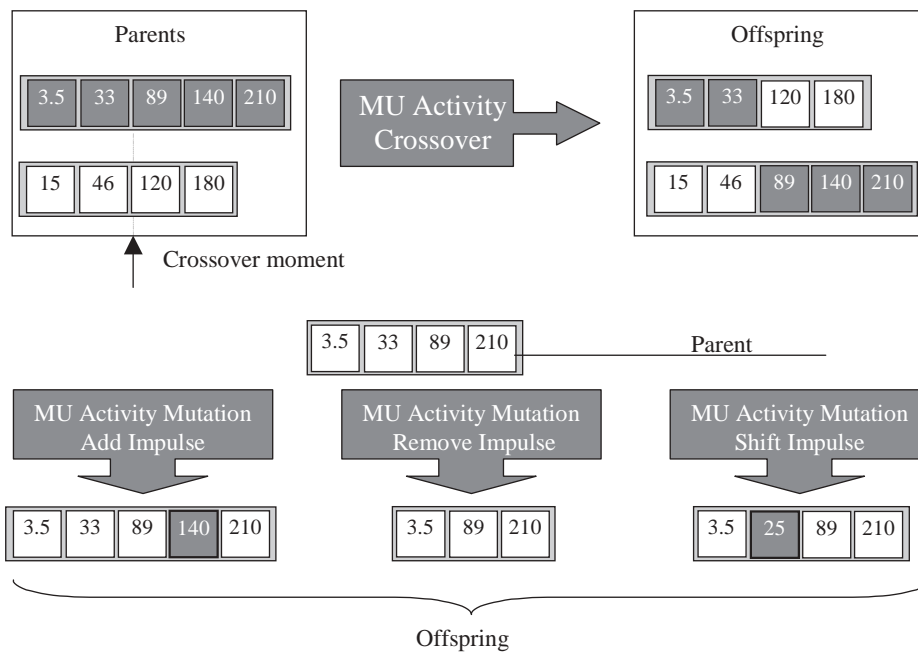
¹Concatenation: operation by means of which two or more strings are combined into one longer string.



A. HGA algorithm flowchart



B. Coding of the problem



C. Genetic operations

Fig. 1. Description of HGA. (a) General schematic representation: (1) Population with random gene values is created. (2) The termination condition for the algorithm is evaluated. It can be based on reaching a given number of steps or reaching a given error threshold. (3) The individuals who will participate in crossover and mutation operations are selected from the population. Usually, these individuals are chosen on the roulette wheel principle, which gives a higher priority to the fitter individuals. (4) By means of genetic operations, offspring individuals are obtained from the parent individuals. (5) The entire population, including new offspring individuals, is estimated for its fitness. On the basis of the estimation results, certain number of individuals are chosen to survive. (b) Coding of the current problem. t_i are the moments of neural stimulation of the MUs that are coded as genes of the individual. For a set of t_i the MU force is calculated as a function of time using MU twitch form (see Fig. 2). If the time interval between two successive impulses is $< T_{ref}$, then mechanical response of the MU remains the same, although if it is longer than T_{ref} , the twitches are superimposed. It is supposed for current computations that $T_{ref} = T_c$. Summing up the forces of all MUs of a muscle, the developed muscle force and its moment are calculated. (c) Genetic operations: examples of crossover and mutation operations (adding an impulse, removing an impulse, shifting an impulse) being applied over the time moments (given as numbers in the boxes) at which some of the MUs are stimulated. On the upper level of the hierarchy these operations may be applied over the activity of a muscle or the activity of the whole muscle system.

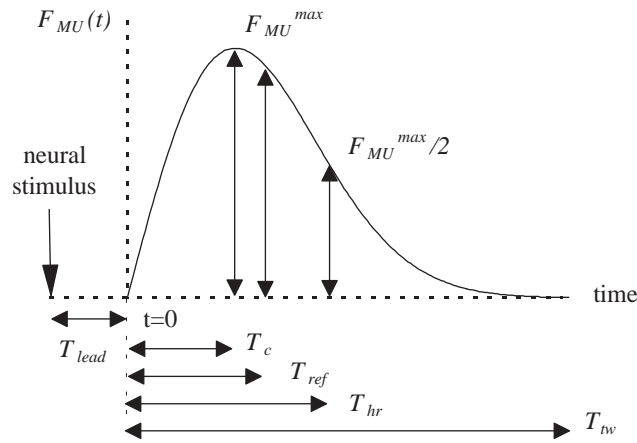


Fig. 2. MU twitch shape and parameters. F_{MU}^{\max} —maximal force of the MU caused by one neural stimulus; T_{lead} —“lead time”: the time between neural stimulation and beginning of the force development; T_c —“contraction time”: time from the start of the MU mechanical contraction to the time where MU force reaches its maximum; T_{ref} —“absolute refractory period”: during this time the MU is unable to respond to new neural stimulation (it is accepted for current computations that values of T_{ref} are equal to that of T_c), T_{hr} —“half-relaxation time”: time from the start of the MU mechanical response to the time when the MU force becomes twice lower than F_{MU}^{\max} ; T_{tw} —duration of the twitch (for the accepted terminology see Thomas et al., 1990; Wallinga-de Jonge et al., 1981).

Table 1
Number and type of MUs of the modeled muscles used for current simulations

Muscle	Total number	I type	II type	III type	IV type
BIC	78	20	19	19	20
BRA	80	20	20	20	20
BRD	19	5	5	4	5
TRI	69	18	17	17	17
ANC	18	5	4	4	5

These four MU types can be termed as follows: I—fast-twitch fatigue resistant (FR); II—fast-twitch fatiguable (FF); III—intermediate (IM); and IV—slow twitch (S) (see Loeb, 1987).

Table 2
Parameters of the considered four types of MUs

MU type	Parameters				
	T_{lead} (ms)	T_c (ms)	T_{hr} (ms)	T_{tw} (ms)	F_{MU}^{\max} (N)
I type	20	30	60	120	3.288
II type	30	40	100	240	1.910
III type	60	70	175	420	0.764
IV type	70	80	200	480	0.382

T_{lead} —lead time; T_c —contraction time; T_{hr} —half-relaxation time; T_{tw} —duration of the twitch; and F_{MU}^{\max} —maximal force (see Fig. 2).

that accounts for MU fatigue during prolonged motor activities is also provided. It is defined as a non-linear decrease of F_{MU}^{\max} , depending on the stimulation rate (MU activity) during the preceding time period. If a new neural stimulus reaches the MU after the absolute

refractory period T_{ref} , the mechanical responses are superimposed (Ruegg, 1989; Wallinga-de Jonge et al., 1981)—see Fig. 1b. If a new stimulus appears before the T_{ref} , the MU force does not change. Summing up the forces of all the MUs of a muscle, the forces developed by the modeled muscles are being calculated during the whole movement. Their moments and the total joint moments are also being calculated. Then the values of the imposed criteria and the fitness function (it is a weighted combination of these criteria) are evaluated. According to this evaluation, the best solutions are taken, which are the subjects of the genetic operations. For the purposes of the present paper, the following criteria were implemented and used: $\min(\Delta J)$ —the minimal error for the whole movement between the desired external joint moment M_{ext} (see Eq. (1) below) and the muscles’ moment calculated by the mechanical responses of the MUs to the current neural stimulation; $\min(\text{Sum})$ —the minimal sum of all muscle forces calculated by the mechanical responses of the MUs to the current neural stimulation for the whole movement; $\min(\text{Stress})^n$ —the minimal sum of the calculated muscle stresses (forces divided to the physiological cross-sectional areas (PCSA) of the respective muscles) raised to the power of n ; and $\min(\text{MUAct})$ —the minimal activation of all MUs, i.e. minimum of the total number of neural stimuli. Hence, the fitness function is $k_1 \min(\Delta J) + k_2 \min(\text{Sum}) + k_3 \min(\text{Stress})^n + k_4 \min(\text{MUAct})$, where k_i are constant “weights”.

2.2. Elbow model

Flexion and extension movements of the elbow with different velocities are considered for illustration. 1DOF model of the elbow joint (Fig. 3a) in the sagittal plane with five muscles, three flexors (BIC, BRA and BRD) and two extensors (TRI and ANC) (for abbreviations see the caption of Fig. 3), has been used. The moment equation has the form (Raikova, 1996):

$$\sum_{i=1}^5 d_i F_i = I_{zz} \ddot{\varphi} + Gl \sin(\varphi) = M_{ext}, \quad (1)$$

where F_i is the i th muscle force ($i = 1$: BIC; $i = 2$: BRA; $i = 3$: BRD; $i = 4$: TRI; $i = 5$: ANC), d_i is the moment arm of the i th force, I_{zz} is the inertial moment of the hand and forearm, $\ddot{\varphi}$ is the angular acceleration and G is the gravity force of the hand and forearm, l is the distance from O to the application point of G , and M_{ext} denotes the total external moment in the joint. It is accepted that d_i ($i = 1, 2, \dots, 5$) depend on elbow angle φ . They are calculated using regression equations (for BIC, BRA and TRI the equations are taken from Pigeon et al. (1996), for ANC and BRD—from Lemay and Crago (1996)). $d_i > 0$ for BIC, BRA and BRD, $d_i < 0$ for

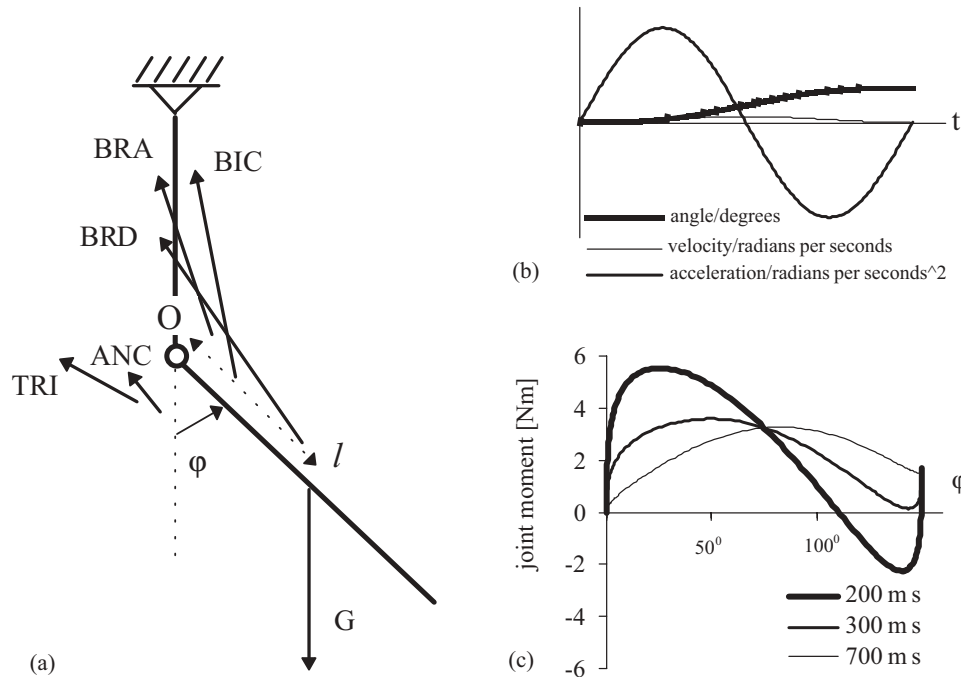


Fig. 3. Elbow model and movement parameters: (a) Main flexors and extensors included in the model: BIC (F_1)—m. biceps brachii, BRA (F_2)—m. brachialis, BRD (F_3)—m. brachioradialis, TRI (F_4)—m. triceps brachii, ANC (F_5)—m. anconeus. O is the rotation center of the elbow joint, φ is flexion/extension angle, G is the gravity force of the forearm and hand, l is the distance from O to the application point of G . The following parameters are used for present computations: $G = 13.72$ (N), $m = 1.4$ kg, $l = 0.215$ m, $I_{zz} = 0.01087$ kg m² PCSA: BIC—5.37 cm²; BRA—5.55 cm², BRD—1.33 cm², TRI—4.73 cm², ANC—1.24 cm². (b) General shape of angle displacement, velocity and acceleration obtained for a flexion motion using the Eq. (2). (c) External joint moments for different durations of an elbow flexion from 0° to 150° calculated using Eq. (1).

TRI and ANC (the counterclockwise direction is the positive one).

For the purposes of the modeling investigation the following law for angle displacement is assumed:

$$\varphi(t) = \varphi_{\text{int}} \pm \left[-A \frac{T^2}{4\pi^2} \sin\left(\frac{2\pi t}{T}\right) + Bt \right],$$

$$A = \frac{2\pi\varphi_{\text{ran}}}{T^2}, \quad B = A \frac{T}{2\pi}, \quad (2)$$

where t is time, T is the duration of the motion, φ_{int} is the initial angle, φ_{ran} is the amplitude of the angle change, (+) stands for flexion and (–) stands for extension. It is suitable to use such an approximation because this equation provides a good accordance with experimental data reported in the literature for angle displacement, velocity and acceleration for different slow and fast elbow motions (see Fig. 3b and the data reported in Gonzalez et al., 1996, 1999; Gottlieb, 1998; Yamazaki et al., 1994).

2.3. Static optimization

Static optimization is performed in order to compare the results obtained through HGA. The objective criterion used in the present paper is $f = \sum_{i=1}^5 c_i F_i^n$, where c_i is a weight factor of the i th muscle force. The analytical solution of the optimization problem (Raikova, 1996) gives the following expressions for the muscle

forces:

$$F_i = \frac{M_{\text{ext}}}{S} \left(\frac{d_i}{c_i}\right)^{1/n-1} \quad (i = 1, 2, \dots, 5), \quad \text{where } S = \sum_{j=1}^5 d_j \left(\frac{d_j}{c_j}\right)^{1/n-1} \quad (3)$$

and the signs of c_i are different for flexors and extensors (hence, they can be positive as well as negative numbers—see Raikova, 1999).

3. Results

Elbow flexions and extensions with different velocities can be modeled by altering T in Eq. (2). All flexions shown in the figures in this paper are with an initial angle 0° and final one 150°. The extensions are performed from 150° to 0°. The arm is fixed in a vertical position (see Fig. 3a).

3.1. Static optimization

It is shown in the first three plots in Fig. 4 how the predicted muscle forces change if the duration of the movement increases. The corresponding external joint moments (M_{ext}) for these three cases are shown in Fig. 3c. Three-phasic behavior of the muscles (flexors–extensors–flexors) can be predicted for very fast movement (Fig. 4a). For $T = 200$ ms, the first flexors’ burst

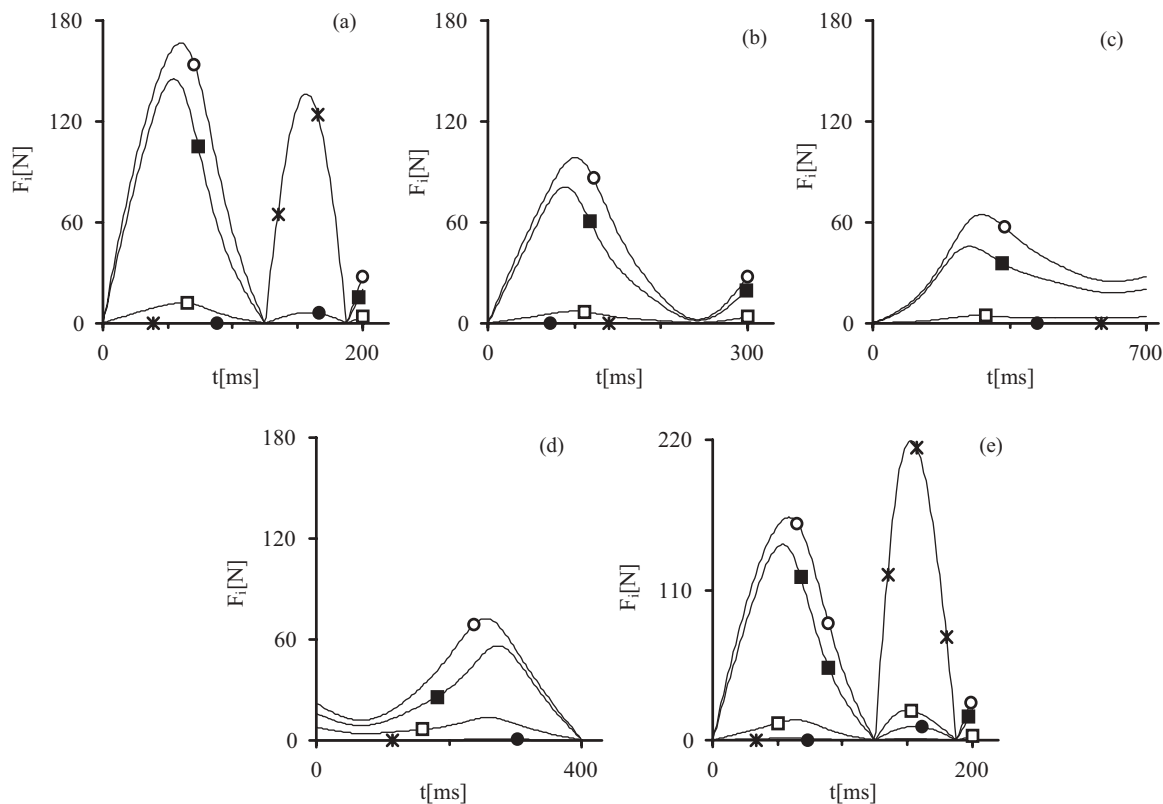


Fig. 4. Predicted muscle forces using static optimization. Fig. 4a–c correspond to different durations of an elbow flexion ($T = 200$ ms, $T = 300$ ms and $T = 700$ ms). Fig. 4d presents the results for an extension from 150° to 0° for 400 ms. The used objective function is $f = \sum_{i=1}^5 c_i F_i^n$, where $n = 2$, $c_i = (1/PCSA_i)^2$ for $i = 1, 2$ and 3 and $c_i = -1500$ for $i = 4$ and 5 if the joint moment M_{ext} is positive (see Eq. (1)), $c_i = 1500$ for $i = 1, 2$ and 3 and $c_i = -(1/PCSA_i)^2$ for $i = 4$ and 5 if the joint moment M_{ext} is negative. Fig. 4e is similar to Fig. 4a, but other weight coefficients are used in order to show the possibilities for the prediction of antagonistic muscle co-contraction, namely $n = 2$, $c_i = (1/PCSA_i)^2$ for $i = 1, 2$ and 3 and $c_i = -(PCSA_i)^2$ for $i = 4$ and 5 if the joint moment M_{ext} is positive, $c_i = (PCSA_i)^2$ for $i = 1, 2$ and 3 and $c_i = -(1/PCSA_i)^2$ for $i = 4$ and 5 if the joint moment M_{ext} is negative. The following notations are used: (○) BIC; (■) BRA; (□) BRD; (*) TRI; (●) ANC.

corresponds to the first positive part of the joint moment (see Fig. 3c), extensors' activity is predicted when this moment becomes negative, and the second flexors' burst appears during deceleration phase, just before finishing the movement. For the intermediate case ($T = 300$ ms, Fig. 4b), only flexors have non-zero predicted forces, because M_{ext} is always positive, the same refers to $T > 300$ ms (Fig. 4c). From the point of view of the predicted muscle forces, a flexion motion from 0° to 150° for more than 700 ms may be considered a quasistatic one, since the influence of the inertial moment is negligible. Of course, the latter value depends strongly on the used model parameters, i.e. on the interrelation between gravity force moment and inertial moment. Fig. 4d is an example for the extension movement. It has to be noted that the predicted muscle forces for an extension are mirror images with respect to the vertical axis to those obtained for a flexion with the same duration. The ratio between the predicted muscle forces in one synergistic group remains the same, independent of T , since the weight coefficients in the objective function and n are constants and the influence

of the muscle arms' change with changing elbow angle is negligible with respect to other parameters (see Eq. (3)). A possibility for the prediction of antagonistic co-contraction using a different set of weight coefficients in the objective function is shown in Fig. 4e (see $t \in [120, 180]$ ms, where TRI, ANC and BRD have simultaneously non-zero predicted forces). This co-contraction increases the total sum of all the muscle forces (see for comparison Fig. 4a). It is artificially predicted using specific weight coefficients and the reason for its appearance could not be currently related to some physiological fact.

3.2. Hierarchical genetic algorithm and its software implementation

On the basis of the approaches described in Method section, a software package² was implemented. More

²It is a stand-alone Microsoft Windows application. A pilot version is available on the web address <http://motco.dir.bg>. The user interface provides full control over the structure and properties of the motor

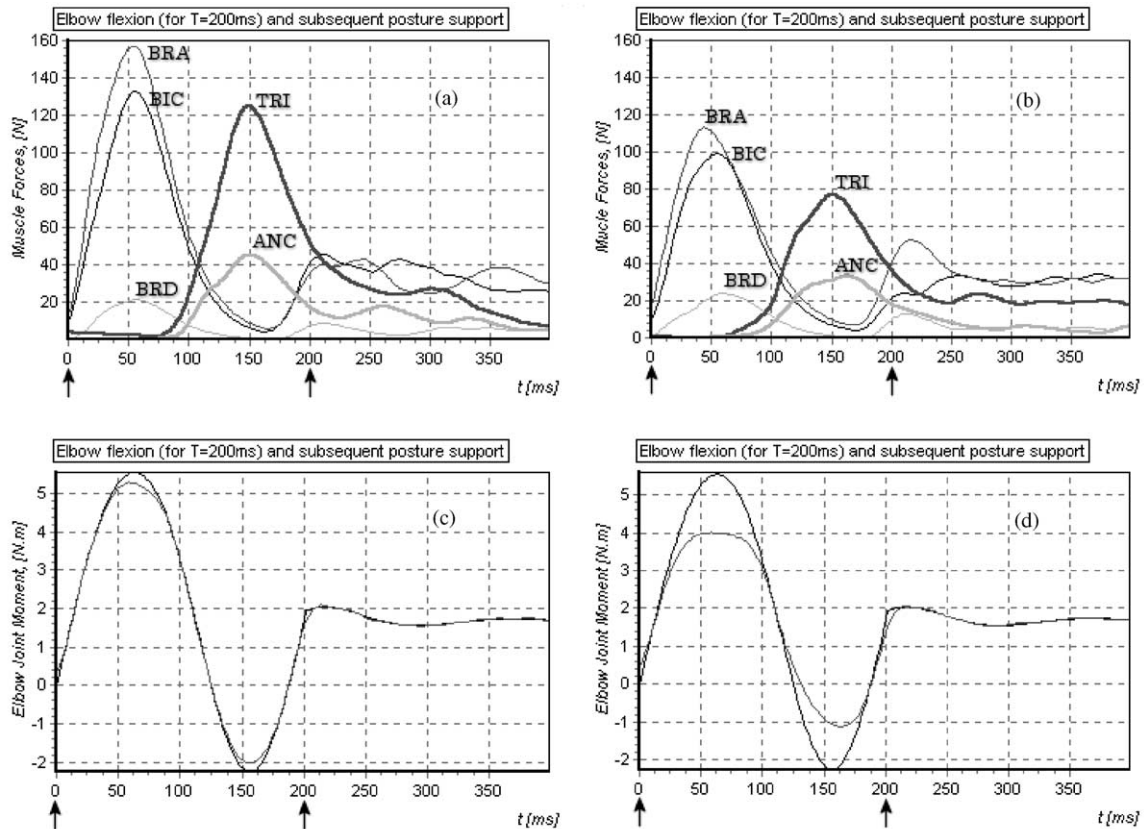


Fig. 5. Influence of MU-type composition of the muscles on the predicted results using HGA for investigation of 200 ms elbow flexion and subsequent 200 ms posture support (the arrows show the start and the end of the movement). The used fitness function is $10000 \cdot \min(\Delta J) + \min(\text{Sum}) + \min(\text{MUAct})$. Fig. 5a. Predicted muscle forces when all the muscles have about 50% MUs of the Ist type, 25% of the IInd type and 25% of the IVth type (hence the respective numbers in Table 1 are changed). Fig. 5b. Predicted muscle forces when all the muscles consist of about 25% of all types of MUs (see Table 1). Symbols: — BIC (black thin line); — BRA (dark gray thin line); — BRD (light gray thin line); — TRI (dark gray bold line); — ANC (light gray thin line). Fig. 5c and d. The respective calculated (gray curves) and desired (black curves) joint moments.

details can be found in Aladjov and Raikova (2001). Different planar elbow movements were investigated. Some of them are currently presented for illustration. The aim is to show the capabilities of HGA algorithm as well as to compare the results with those obtained by static optimization.

For fast motions, three-phasic muscle behavior is naturally predicted (Fig. 5a). It is also shown in this figure that if the muscles do not have fast enough MUs (Fig. 5b), it is not possible to satisfy the required joint moment (see for comparison Fig. 5d versus Fig. 5c) and to perform the movement with required acceleration. When the number of fast MUs was increased, which changed the MUs-type composition, it became possible.

(footnote continued)

system. Models can be constructed by consecutively adding bones, joints and muscles along with their properties. For example, lever arms, angles, PCSA, the number and kind of MUs, etc., can be defined for each muscle. New objective functions may be added to the default ones. The user may see at run time different views of the obtained results (force of a particular MU, predicted muscle forces, “simulated EMG”, error during satisfaction of different goals, etc.)

Because of the short time for movement completion, preferably fast MUs were activated (Fig. 6a). No MU is tetanically stimulated, but doublets (Bawa and Calancie, 1983; Gurfinkel et al., 1992) were encountered. It is also shown in this figure as to how individual twitches (Fig. 6a) form the force of the whole muscle (Fig. 6b and c) and the influence of the lead-time (Fig. 6b versus Fig. 6d). To form the shape of the required joint moment (see Fig. 5c), and hence the shapes of the muscle forces (Fig. 5a), sufficiently fast MUs have to be activated about 50 ms before the start of movement (Fig. 6c). The latter value depends of course on the chosen T_{lead} of MUs. The muscle force patterns are similar to those obtained by static optimization (Fig. 4a versus Fig. 5a) notwithstanding that the muscle PCSAs are not accounted in the used fitness function and that the criterion $\min(\text{Sum})$ is a linear one (see the caption of Fig. 5). The reason is that the number of MUs of each muscle was chosen to be proportional to the respective PCSA (see Table 1). Fig. 7, where an extension with duration 400 ms is investigated (see for comparison the results from static optimization shown in Fig. 4d),

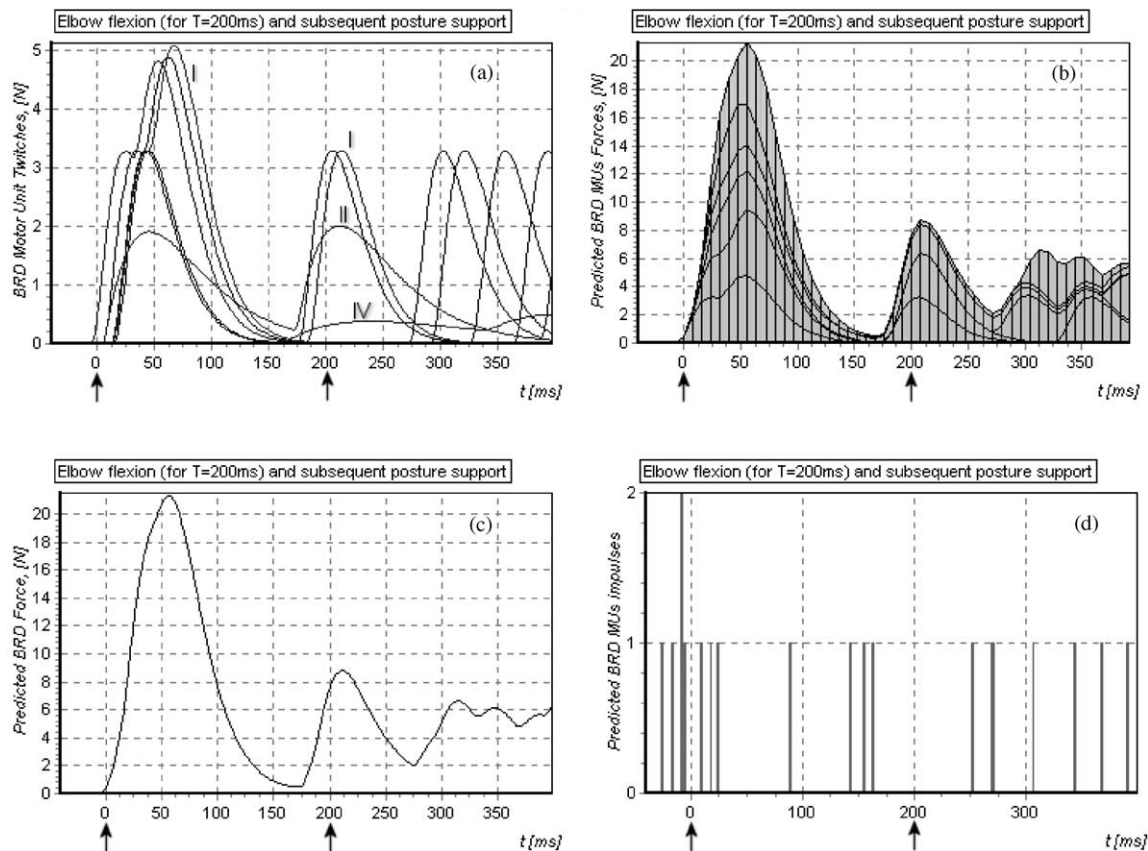


Fig. 6. Formation of the force of the whole muscle brachioradialis from twitches of its MUs. (a) The individual twitches—only FR (I), FF (II) and S (IV) MUs are chosen by HGA to be active. (b) The formation of the force from these twitches. (c) The total force of m. BRD. (d) The number of neural stimuli for the whole muscle calculated for every time period $\Delta t = 1$ ms (the so-called “simulated EMG” by the authors). This time period can be arbitrarily set. Note that the time scale for Fig. 6d originates before the start of the movement aiming to show the influence of the lead time. The arrows show the start and the end of the movement.

confirms this finding. The predicted muscle forces were similar when using $\min(\text{Stress})^2$ (Fig. 7a) and $\min(\text{Sum})$ (Fig. 7b) as one of the optimization criterion in the fitness function (note that the joint moment is satisfied well for both cases—Fig. 7c and d). This can be explained by the fact that all the muscles consist of the same MU types and proportion of these types, but their number differs from muscle to muscle (see Table 1). The probability for HGA to activate more MUs in a muscle with higher PCSA, respectively, with more MUs (for example BRA versus BRD), is greater, independently from that which criterion has been employed. The results from HGA application for different motions showed the presence of significant antagonistic co-contraction. In our opinion it is inherent to human movements because of the specific form of the MU twitch. It was greater when the requirement for smoothness of the motion was higher. This is illustrated in Fig. 8, where a longer flexion is investigated. The weight of the criterion $\min(\Delta J)$ was hundred times larger for Fig. 8a than that for Fig. 8b, while the remaining criteria have the same weights. As it can be

seen while comparing these two plots, the predicted muscle forces are higher and coarser and the degree of co-activation is bigger when the aim is to achieve greater accuracy in holding the joint moment. Independently, the apparent differences between Fig. 8c and d cannot be seen, the total error between the desired and computed joint moment for the whole period of 1200 ms is 0.0284 and 0.0321 N m, respectively. More coarse profile of the muscle force could be partially explained as a visual effect from a longer duration of the movement, but the main reason is the form of the twitch (see discussion).

4. Discussion

The paper presents an implementation of HGA based on MUs twitch properties. The capabilities of its software implementation are illustrated investigating elbow motions. The results are compared with those obtained by using static optimization. Elbow flexions and extensions in the sagittal plane with different

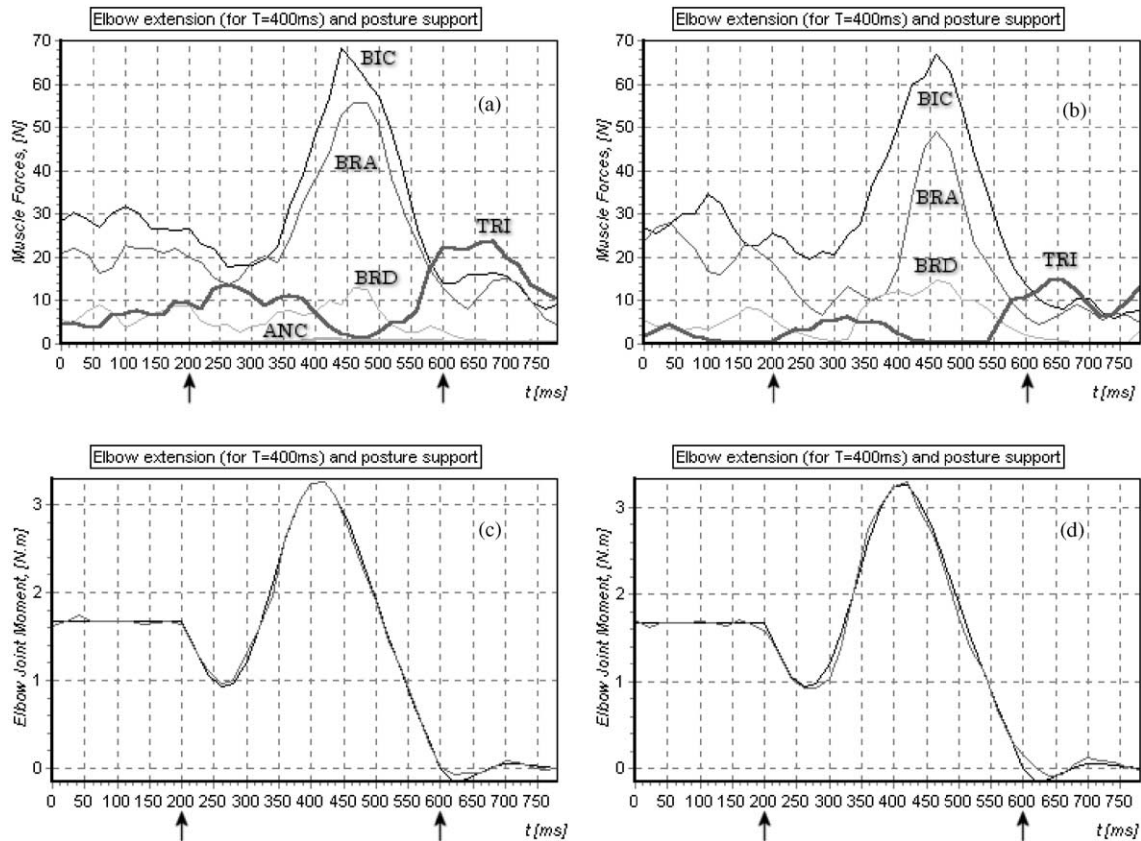


Fig. 7. Influence of different criteria in the fitness function on the predicted results using HGA for investigation of 400 ms elbow extension with preceding and subsequent 200 ms posture support. (a) Predicted muscle forces using the fitness function $100 \cdot \min(\Delta J) + \min(\text{Stress})^2 + \min(\text{MUAct})$. (b) Predicted muscle forces using the fitness function $100 \cdot \min(\Delta J) + \min(\text{Sum}) + \min(\text{MUAct})$. All the muscles consist of 25% of each type of MUs. Symbols: — BIC (black thin line); — BRA (dark gray thin line); — BRD (light gray thin line); — TRI (dark gray bold line); — ANC (light gray thin line). (c) and (d) Calculated (gray curves) and desired (black curves) joint moments for the respective fitness functions. The arrows show start and end of the movement.

velocities were chosen for illustration because one can clearly see the influence of dynamic properties of MUs and separate the influence of gravity and inertial forces by varying the movement duration. Furthermore, many authors have investigated these motions using different approaches (Gonzalez et al., 1996, 1999; Gottlieb et al., 1995a, b; Latash, 1994; Virji-Babul and Cooke, 1995; Yamazaki et al., 1994). An exact differentiation of MUs is not firmly experimentally established (Burke, 1999). Some authors (Gordon et al., 1997; Kernell, 1986) even raise the question as to whether the slow, fast, fast-fatigue-resistant and fast-fatiguable MUs are distinct types or they are descriptive categories from a continuous distribution of MU properties. In the literature, there are also evidences that the type of MUs and their presence in muscle depend on age, sex, training, etc. (Johnson et al., 1973; Thompson, 1994). So, in the present study, with no claims for comprehensiveness, it was decided to have four different types of MUs (see Tables 1 and 2). Certainly, there is no problem in applying the model and the software with a continuous distribution of MU properties. The number of MUs of

each muscle during the presented computations was comparatively less than the actual number. For example, literature reports that m. BIC has 774 MUs (Ruegg, 1989), but we use only 78, i.e. an MU in our model represents a group of actual MUs of the same type (see Table 1). This simplification does not significantly affect the general conclusions made in the paper, since the maximal force of each MU of a muscle is calculated in such a way that the sum of tetanus forces of all MUs is equal to the maximal force of the whole corresponding muscle (see Table 2). More so, in the literature, there are different opinions concerning the smallest muscle part (MU or a pool of MUs) that could be voluntarily controlled (Kosarov et al., 1978; De Luca and Erim, 1994). The computational cost increases rapidly with the increase of the number of controlled MUs, while precision does not improve significantly. A compromise between reality, accuracy and computational time should be made.

Contrary to static optimization, it was difficult to trace constant joint moments or movements that consist of linear segments by summing up MUs twitches (see

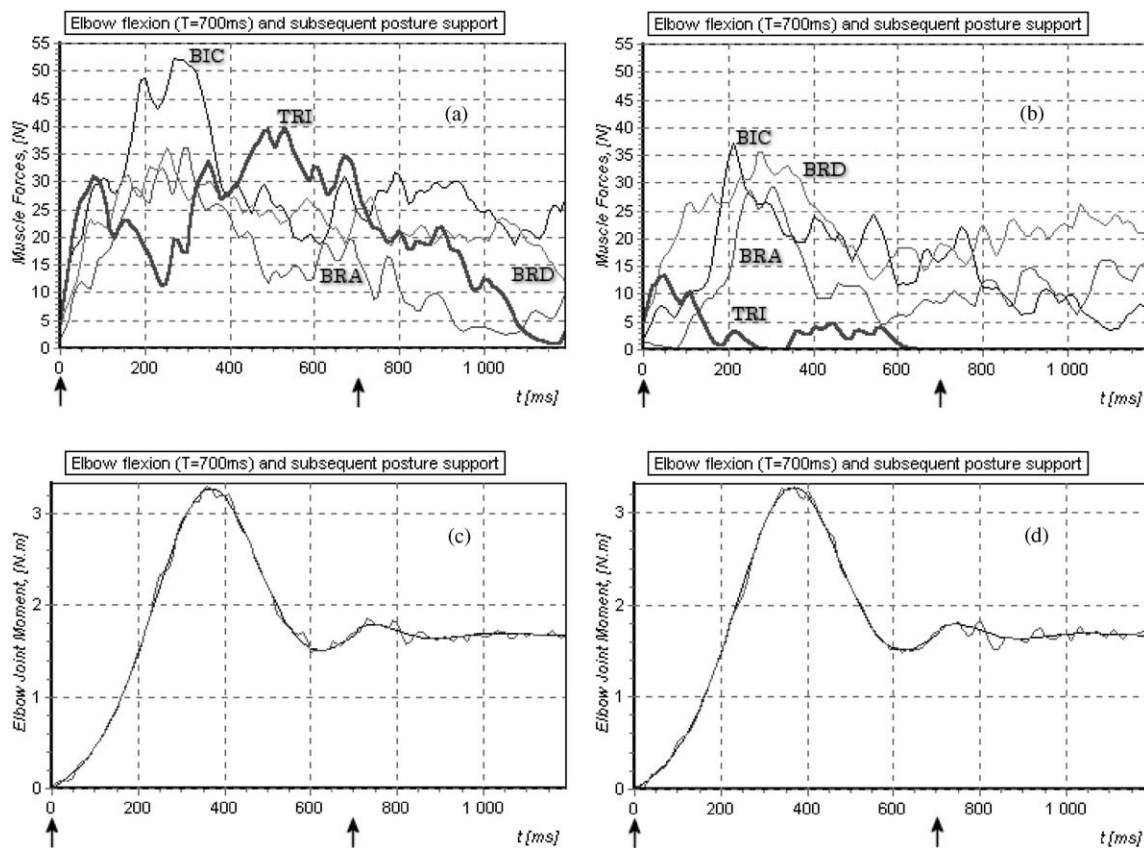


Fig. 8. Influence of different weights of the criteria in the fitness function on the predicted results using HGA for investigation of 700 ms elbow flexion and subsequent 500 ms posture support. (a) The fitness function is $10000 \min(\Delta J) + \min(\text{Sum}) + \min(\text{MUAct})$. (b) The fitness function is $100 \min(\Delta J) + \min(\text{Sum}) + \min(\text{MUAct})$. All the muscles consist of 25% of each type of MU, Symbols: — BIC (black thin line); — BRA (dark gray thin line); — BRD (light gray thin line); — TRI (dark gray bold line); — ANC (light gray thin line). (c) and (d) The calculated (gray curves) and the desired (black curves) joint moments for the respective fitness functions. The arrows show the start and the end of the movement.

Fig. 7, $t \in [0, 200]$ ms and Fig. 8, $t \in [800, 1200]$ ms). Our model curves of joint angle and moment are rather smooth that might not be the real case. Other reasons could be insufficient number of steps (computational time); little number of MUs used in the present calculations; step, uneven distribution of the maximal forces of individual MUs; and high smoothness of the analytical curve of the joint moment. It is most likely, however, that even if the above-mentioned problems are overcome, smoothness would not become sufficiently high, because of the discrete character of the MUs twitches. It is naturally difficult to approximate a linear function (joint moment) with a limited number of high non-linear ones (i.e. twitches, Fig. 2)—see Fig. 6a and b. The muscle co-contraction could also be connected with the latter. To some extent it is also useful to achieve a smoother movement since the moments of the forces of the MUs of the antagonistic muscles are with opposite signs. Some profiles of target joint moment cannot be fitted by mere summing up of the MUs twitches displaced in time, but by a simultaneous subtraction of antagonistic MUs twitches from that sum.

In general, the patterns of the predicted muscle forces were similar using HGA and static optimization with $n = 2$ and weight coefficients based on the muscle stress (Fig. 5a versus Fig. 4a; Fig. 7a versus Fig. 4d.). The main differences were in the predicted essential antagonistic co-contraction with HGA and apparent overlapping of the predicted forces of the muscles from the two antagonistic groups around the moments when the sign of the joint moment changes (see $t \in [80, 140]$ ms and $t \in [80, 200]$ ms in Fig. 5a. Such a prediction is closer to the experimental EMG data (Gonzalez et al., 1999; Gottlieb et al., 1992, 1995a; Latash, 1994) than the results from static optimization where all the predicted muscle forces are necessarily zero if the joint moment is zero according to Eq. (3)). The antagonistic co-contraction shown in Fig. 4e is artificially predicted, using specific weight coefficients in the objective function, whereas such an overlapping of the forces of antagonistic muscles, as the one in Fig. 5a, cannot be predicted. The results from the HGA could be related to the MU twitch profile and the "trace effect" named thus by the authors of the current paper. The force of an MU cannot decrease to zero at once, but with some

particular speed determined by T_{hr} and T_{tw} (see Fig. 2). So, when the joint moment quickly decreases (increases), what is obviously necessary is the antagonistic activity to compensate the moment caused by previously activated MUs that still develop some force. For example, see Fig. 5a, $t \in [80, 150]$ ms, where the joint moment quickly decreases (Fig. 5c), changing its sign from positive to negative. The essential residual forces of the previously activated MUs of m . BIC, BRA and BRA cause an essential positive joint moment. Hence, the antagonistic muscles ANC and TRI must be activated fairly before the joint moment becomes zero, so that this “trace effect” is compensated.

The greater is the weight factor of criterion $\min(\Delta J)$ in the fitness function compared to the weight factors of other criteria, the greater are the muscle forces and antagonistic co-activation (Fig. 8). This observation resembles the findings of Yamazaki et al. (1994) who reports about the dependence of EMG activity of major elbow flexors and extensors on the instructions given to the subjects. When the instruction for a rapid goal-directed movement is “strongly fix the upper arm at the target” the co-activation increases, but when the subject is free to relax arm this co-activation almost disappears.

Additional intervals (subsequently, and preceding the posture support) have been considered apart from the movement duration for all the figures showing the results from the HGA. Small sinusoidal oscillations to the angle displacement (hence of posture support) are added immediately after or (and) before the movement itself and are subsequently considered in the optimization process. These intervals have been added in order to be closer to natural movements, where fluctuations around the target point are commonly observed (Gottlieb, 1994), and because of the above-discussed problems with the tracing constant joint moment. Another reason is the lead-time (Fig. 6d versus Fig. 6b) as well as the necessity inherent to HGA to render an account for the previous state of MUs. Here, the estimation of the fitness function is performed for a time period including the whole movement and this is the evaluation of the current solution.

At this stage, our model does not account for well-known force–length and force–velocity relationships for a muscle. It is possible to account the first one assuming that the shape of the twitch depends on the current muscle length (Brown and Loeb, 1999). As to the force–velocity relationship, it can be supposed that it is somehow hidden in the properties of the MUs that constitute the muscle. The maximal contraction velocity of a muscle is connected with the slope of the twitch profile (hence with the value of T_c which is definitely limited from a physiological point of view—see Fig. 2) of the fastest MUs of this muscle and their number. This is why when the number of fast MUs is insufficient, it is impossible to perform very fast movements (see Fig. 5).

Using HGA, the interrelation between forces predicted in the muscles from a synergistic group is similar in all the studied motions, even in the case when different criteria have been used (see Fig. 7). For example, the predicted forces of BIC and BRA have always been greater than that of BRD, regardless of the fact that the latter has a bigger lever arm for all the possible values of φ . This is due to the lesser number of MUs of m . BRD (because of its less PCSA) in comparison with BIC and BRA (Table 1). The probability for HGA to activate more MUs from a muscle arises with the increase in the number of MUs that constitute that muscle. This probability also depends on the type of MUs. The interrelation between predicted muscle forces could be changed if the MUs composition of the muscles is different, i.e. some of the muscles are fast and others are slow, but such numerical experiments are not presented in the current paper. On the basis of our experience with the developed software, a general conclusion could be drawn: the probability of activating a particular MU depends strongly on the properties of its twitch (i.e. not only on its maximal force which is related to its size, but also on all other characteristics: contraction time, fatiguability, etc.). Certainly, there exist other factors that influence the muscle activity such as moment arms, injuries, etc. Since the different muscles are mixtures of MUs with different properties, it can be expected that they will play different roles in different movements. If some muscle consists mainly of fast MUs, then it can be expected to participate in satisfying the faster changes of the movement, if it consists of small MUs (with small maximal force) it will participate in precise movements or fine adjustments.

For static optimization c_i are allowed to have both positive and negative values. This is a mathematical convenience since all the muscles can be included in the computational algorithm and choosing different c_i , different interrelations between the predicted muscle forces can be modeled. Design variables in HGA are the time moments of neural stimulation of MUs. Their number is considerably higher than the fifth muscle forces used as design variables in static optimization. This leads to a large-scale optimization problem and a much longer computational time.

5. Conclusion

The main conclusion from the present paper is that static optimization can be used for dynamic conditions when investigating the basic features of the bone–joint–muscle complex (see also Hughes, 2000; Anderson and Pandey, 2001), but models based on the properties of MUs and their twitches allow to gain an insight into the human motor control. It is a very complex task to

control all the MUs for sufficiently realistic limb model. The proposed HGA presents a suitable means for its solution. Unlike NNs, the algorithm described in the paper is not a “black box” method and new knowledge about functioning of motor systems can be extracted. Possibilities for performing multi-objective, time-dependent optimization make the HGA a suitable means even for the investigation of dynamic tasks. It also allows further investigations of the dependence between the predicted muscle force and EMG signals, since one of the outputs of the program realization is time moments for neural stimulation of all MUs (Fig. 6d). The process of training and teaching a motor task can be researched as well, following the consecutive solutions of HGA or tracing how a solution of a task is modified when considering a newly defined task, but with similar aims. The proposed approach may further integrate the knowledge from different scientific areas and consolidate the efforts of different specialists for a better understanding of human motions and their control.

Appendix A

The analytical function describing the twitch shown in Fig. 2 has the following general form (see also Kosterin and Burdyga, 1990; Piotrkiewicz, 1982; Romanov, 1992):

$$F_{\text{MU}}(t) = pt^m e^{-kt}.$$

From the boundary conditions

$$F_{\text{MU}}(0) = 0, \quad F_{\text{MU}}(T_c) = F_{\text{MU}}^{\text{max}},$$

$$F_{\text{MU}}(T_{\text{hr}}) = \frac{F_{\text{MU}}^{\text{max}}}{2}, \quad F'_{\text{MU}}(0) = 0, \quad F''_{\text{MU}}(0) = 0,$$

the unknown parameters p , m and k are obtained

$$k = \frac{\ln 2}{-T_c \ln(T_{\text{hr}}/T_c) + T_{\text{hr}} - T_c}, \quad m = kT_c,$$

$$p = F_{\text{MU}}^{\text{max}} e^{-kT_c(\ln T_c - 1)}.$$

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