

An artificial neural network approach and sensitivity analysis in predicting skeletal muscle forces

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This paper presents the use of an artificial neural network (NN) approach for predicting the muscle forces around the elbow joint. The main goal was to create an artificial NN which could predict the musculotendon forces for any general muscle without significant errors. The input parameters for the network were morphological and anatomical musculotendon parameters, plus an activation level experimentally measured during a flexion/extension movement in the elbow. The muscle forces calculated by the 'Virtual Muscle System' provide the output. The cross-correlation coefficient expressing the ability of an artificial NN to predict the "true" force was in the range 0.97–0.98. A sensitivity analysis was used to eliminate the less sensitive inputs, and the final number of inputs for a sufficient prediction was nine. A variant of an artificial NN for a single specific muscle was also studied. The artificial NN for one specific muscle gives better results than a network for general muscles. This method is a good alternative to other approaches to calculation of muscle force.

Key words: elbow joint, muscle force prediction, neural network, sensitivity analysis

1. Introduction

For years, biomechanical engineers have been studying the complexity of the musculoskeletal system. One of the important issues is to find a simple way of determining muscle forces in order to understand joint function, bone loading and pathology. Methods for directly measuring muscle forces have not been available so far, and it has been difficult to calculate muscle forces because many muscles are cooperative. There are four general methods for estimating the muscle and tendon forces during human movements: (a) heuristic methods based on statics or inverse dynamics, which are based on simple assumptions for load sharing; (b) an inverse dynamical approach involving the processing of experimental motion data, modeling and static optimization to solve the muscle redundancy problem; (c) an EMG-to-force processing approach, and (d) a direct dynamical approach involving model-driven simulations of the

movement task. Tendon force has only rarely been recorded directly in humans because the procedures are invasive, in most cases require surgery, and may be injurious [2]–[4], [15].

Recently, there has been increased interest in employing artificial NN as a method for estimating muscle forces. Its big advantage in predicting muscle forces is that results can be obtained without knowledge of the exact analytical information between inputs and outputs. Neural networks have been used to estimate the relations between nonlinear properties of the musculoskeletal system. The NN system can form a fairly accurate mapping from joint angles, angular velocities and relevant myosignals to joint torques for arm movements in the horizontal plane [14]. The backpropagation type of artificial NN was also used for estimating the relation between elbow joint angle, EMGs and torque [18], [35], for predicting muscle recruitment, muscle response, the electromyographic and joint dynamics [23], [24], [32] and EMG prediction [27]. The dynamic tendon forces from EMG-

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signals in the gastrocnemius muscle of a cat were predicted by an artificial NN with a backpropagation algorithm [28] and the dynamic relationships between EMGs and knee torque production in humans were investigated [8]. Recently, an artificial NN has been applied to modeling and simulating a control of prosthesis. An NN model that incorporates available knowledge about finger functioning has been constructed and tested [18]. Thus in the task of grasping [33], NN can be applied to learn the correct grasping sequences from samples of the hand actually grasping objects of different shapes and sizes.

This study looks for a new computational way to estimate muscle forces. The first objective of the present study was to establish the possibility of a backpropagation NN object in the musculoskeletal system of the human elbow joint to create a function of the muscle activity, the musculotendon physiological properties and the joint kinematics. The object of a backpropagation NN was developed with a supervised learning algorithm (BPG). This NN was suggested in order to predict quickly, accurately and simply the muscle forces in the elbow actuators. The input and output relations were not known in advance. Here were used 7 muscles in the elbow joint, four flexors: *m.biceps brachii c.longum* and *c.breve*; *m.brachialis*; *m.brachioradialis*; and three extensors: *m.triceps brachii c.laterale*, *c.mediale* and *c.longum* across two movement speeds and two loading conditions (combination of a fast, a slow, a loaded, and an unloaded motion). The next objective was to evaluate 12 input muscle parameters which influence the resulting muscle forces. The input parameters were anatomical and physiological muscle properties.

Some authors considered only 4 inputs for their artificial neural network, the macroscopic properties of the muscles and muscle activity, and the output was the elbow moment [26]. The influence of muscle parameters on muscle models has been reported with various results. The variations in results depend on differences in the types of models and the types of motions simulated. Muscle models have been found to be sensitive to the tendon slack lengths of the series elastic elements and the optimal muscle fibre lengths [12], [21], [25]. The pennation angle had low sensitivity [21], [39]. For some parameters, the force-velocity properties and the muscle activation were found to have different sensitivities, depending on the motion simulated [20], [38]. Scovil [30] made an attempt to compare the sensitivity methods (the standardized sensitivity method and the partial derivative model) in order to evaluate the muscle parameters and evaluate muscle model sensitivity to perturbations in

12 Hill muscle model parameters in forward dynamic simulations of running and walking, varying each by $\pm 50\%$.

The last objective was to simplify the proposed NN object by using a sensitivity analysis to reduce the number of muscle input parameters.

2. Methods

The artificial NN approach is based on no knowledge of the relation between the input parameters (IP), the musculotendon morphological, physiological data and muscle fibre recruitment, on the one hand, and the output parameter (OP) of the muscle forces, on the other. An artificial NN was used to determine the muscle force from particular muscles. For this study the seven elbow joint actuators were chosen, four flexors: biceps brachii long head (BIClh), biceps brachii short head (BICsh), brachialis (BRA) and brachioradialis (BRD), and three extensors: triceps brachii long, medial, and lateral heads (TRIlh, TRImh, and TRIlm). Other elbow actuators were neglected for the purposes of this study. The elbow joint was selected because it provided a good visual demonstration, and for simplification it can be said that the elbow motion is uniplanar and uniarticular. The elbow flexion/extension movement investigated was without any motion in the shoulder, so all the elbow actuators were modeled as single joint actuators.

2.1. Training data (input and output parameters)

In order to train the proposed neural network object, it was necessary to know the input (IP) and output parameters (OP). Direct measurement of muscle force is, in most cases, an invasive approach, therefore the Virtual Muscle System [7] was used in order to achieve a relation with the output muscle force. Unlike the methods used in the Virtual Muscle System, in our study there are no known analytical relations between inputs and outputs.

The input parameters were the physiological characteristics of the participating muscles of the particular joint mechanism, together with further data about the movement and muscle activity.

The muscle parameters utilized in this investigation result from the Hill-type muscle model, including the active contractile and passive parallel elastic and viscous components [39]. The active contractile com-

ponent is based on the generally accepted notion that the active muscle force is the product of three factors: (1) a force-length relation, (2) a force-velocity relation, and (3) an activation level.

The input parameters express the passive Fl_p and active Fl_a muscle force-length factors which were taken in terms of published papers [6], [39]. The curves of the passive and active properties are fitted by parabolic and exponential functions derived from [36] and were scaled to provide a description for a specific muscle. The third input, the force-velocity factor Fv , was taken for concentric contraction from the Hill equation [10] and for eccentric contraction from the modified Hill equation [16].

There were five further constant musculotendon parameters: physiological cross-sectional area PCSA, optimum muscle fibre length L_0 , tendon slack length L_{TS} , maximum isometric muscle force F_0 , and optimum pennation angle α_0 . The physiological cross-sectional area PCSA was calculated as $PCSA = (V \cdot \cos(\alpha_0)) / L_B$ [19], [36]. Fascicle lengths L_B were taken instead of fibre lengths L_0 , because it is difficult to isolate individual fibres. However, a muscle fascicle, L_B , is composed of many muscle fibres, so the length of the muscle fibre is almost equal (the same) as the length of the muscle fascicle. The muscular parameters (optimum muscle fibre length, l_0 , fascicle length, L_B , pennation angle, α_0 and capacity of the muscle, V) were taken from [36] and converted to the different proportions of the specimen. The tendon slack lengths, L_{ST} , were theoretically calculated by the method published in [5].

Maximal isometric muscle force, F_0 , was calculated as $F_0 = PCSA \cdot \sigma$. The size of a specific muscle tension is a difficult quantity to measure in mammals and humans. The values have high variability, e.g., $\sigma = 25 \text{ Ncm}^{-2}$ [13], [31], Lieber cites for fast muscle $\sigma = 22 \text{ Ncm}^{-2}$ and for slow muscles $\sigma = 1\text{--}15 \text{ Ncm}^{-2}$ approximately [18], Hatze uses the value $\sigma = 40 \text{ Ncm}^{-2}$ [9], and the results based on these values will of course have high error variance [22]. The specific muscle tension for our research was applied $\sigma = 31.8 \text{ Ncm}^{-2}$ [29]. This value was taken because the same value is used as the default in the Virtual Muscle System [7] and this value is used for estimating the NN output parameter – muscle force.

The next two input parameters, musculotendon length L_{MT} , and velocity of muscle shortening v , have an effect on the maximum force that can be generated. Musculotendon length, L_{MT} , (the length of the entire muscle-tendon unit origin to insertion) was estimated from the anatomical positions of the muscle attachments and recorded kinematic data in various move-

ment conditions, and the velocity of muscle shortening, v , was calculated from this kinematic data. The arm movements were from full extension ($\varphi_E = 0^\circ$) to full flexion ($\varphi_F = 145^\circ$) [26] of the elbow joint for a fixed shoulder joint. The forearm was free to move in the sagittal plane of the elbow. The elbow flexion/extension movements were recorded using the 6-camera 60 Hz VICON Motion Analysis system, with two movement speeds (slow, 1.1 rad/sec and fast, 2.8 rad/sec), and two loading conditions (unloaded and with 4.2 kg dumb-bell) studied.

The electric activity of the observed muscles was recorded by surface electromyography (EMG). The EMG signal was processed by filtering frequencies that are lower than 20 Hz and higher than 500 Hz, offsetting, rectifying (rendering the signal to have excursions of one polarity), and integrating the signal over a specified interval of time [1]. The processed and normalized EMG signal was taken as the input of the muscle activity, $a(t)$, and the history of the muscle activity, $a_H(t + \Delta t)$. The history of the muscle activity ensures a direct expression of time of the neural network object. The input of the muscle activity during one flexion/extension cycle was distributed to the time steps (1–100 steps, one step Δt is 1/100 of the motion cycle) and then each input of the history of the muscle activity was moved by one step, two steps, and three steps in time, respectively. It should be noted that the muscle activity level was normalized by the muscular activity during the maximum voluntary isometric contraction of the muscle.

Table 1. The input parameters were the physiological characteristics of the participating muscles of the particular joint mechanism, together with motion data and data corresponding to muscle activity

1.	Passive force-muscle length factor	Fl_p [-]
2.	Active force-muscle length factor	Fl_a [-]
3.	Force-velocity factor	Fv [-]
4.	Physiological cross-sectional area	PCSA [m^2]
5.	Optimum muscle fibre length	L_0 [m]
6.	Tendon slack length	L_{TS} [m]
7.	Maximum isometric muscle force	F_0 [N]
8.	Optimum pennation angle	α_0 [rad]
9.	Musculotendon length	L_{MT} [m]
10.	Velocity of muscle shortening	v [$\text{m}\cdot\text{s}^{-1}$]
11.	Muscle activity	$a(t)$ [-]
12.	History of muscle activity-delay Δt	$a_H(t + \Delta t)$ [-]

The summary of all input parameters used is given in Table 1 (passive force-muscle length factor, Fl_p , active force-muscle length factor, Fl_a , force-velocity factor, Fv , cross-sectional area PCSA, optimum muscle fibre length L_0 , tendon slack length L_{TS} , maximum isometric muscle force F_0 , and optimum pennation

angle α_0 , musculotendon length, L_{MT} , velocity of muscle shortening, v , muscle activity, $a(t)$, and the history of muscle activity, $a_H(t + \Delta t)$.

For the problem of estimating the muscle force using an artificial neural network approach, two network object variants were proposed. For variant A, a network object for a general muscle was created, which means that the input data from all seven muscles can be used for training a single general network. For variant B1, a network object was created for each muscle separately, which means that the input data from one muscle provided inputs the one specific network object. Variant B1 does not contain the constant input parameters (the physiological cross-sectional area PCSA, optimum muscle fibre length L_0 , tendon slack length L_{TS} , maximum isometric muscle force F_0 , and optimum pennation angle α_0) because the setup has no influence on the network weights and biases during training. All muscles were tested for variant B1, even if the constant muscle parameters such as PCSA, pennation angle, etc., specific for each muscle have no influence on results.

2.2. The network architecture and training the network

The neural network architecture was a feedforward multilayer network – backpropagation (BPG), in this case consisting of three layers (an input layer and two hidden layers followed by an output layer). The feedforward multilayer network was fully connected, i.e., each neuron in a given layer was connected to every neuron in the next layer, while neurons in the same layer were not connected. A network object (Fig. 1) with 30 neurons in the 1st hidden layer and with 24 neurons in the 2nd hidden layer was proposed. Between the input layer and the 1st hidden layer and between the 1st and 2nd hidden layer a sigmoidal

transfer function was used. The multilayer network used sigmoidal transfer functions because they were differentiable functions. Between the 2nd hidden layer and the output layer a linear transfer function was used. A linear transfer function was used so that the neural outputs could take on any value. The sigmoidal and linear transfer functions were functions *tansig* and *purelin* of the neural network toolbox of MATLAB (The MathWorks Inc., Natick, MA, USA). In the course of backpropagation learning, the main goal was to find the solution with the smallest error and the fastest convergence with respect to the weights and biases of the network. By adjusting the weights of the network, the network object was trained to perform complicated problems, in this case, prediction of the muscle forces.

The neural network training was made more efficient if certain preprocessing steps were performed on the network representative set of input/target pairs. Post-training analyses were also carried out. The approach for scaling the network inputs and targets was to normalize the mean and standard deviation of the training set so that they had zero mean and unity standard deviation. Subsequently, the dimension of the input vectors was reduced by principle component analysis [11]. The input vectors were uncorrelated with each other, and the components with the largest variation came first. This eliminated those components that contributed the least to the variation in the data set.

To improve generalization, the framework of early stopping was performed. The data was divided into training, validation, and test subsets. When the validation error increased, the training was stopped. The learning error was minimized by modifying the network topology, by changing the number of neurons in the hidden layers, and by changing the learning rate. For both the validation and the test sets, one fourth of the data was taken, and for the training set one half of the data was taken. The BPG was also sensitive to the

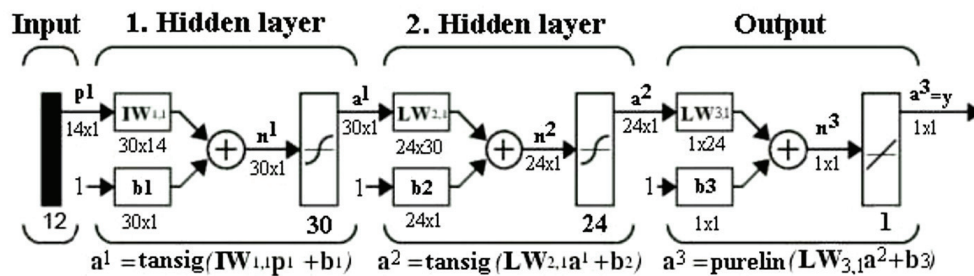


Fig. 1. Schematic representation of a three-layer feedforward neural network with a supervised learning algorithm (BPG). The input parameters were the physiological characteristics of the participating muscles of the particular joint mechanism, together with further data about the movement and muscle activity.

The output parameter for training the network object was the muscle force

number of neurons in their hidden layers. Too few neurons applied would lead to underfitting, and too many neurons would lead to overfitting. When the network learning rate was set too high, the correct solution was overskipped. When the network learning rate was set too low, the correct solution very often ended in a local minimum, or the algorithm converged very slowly. The numerical simulations were performed in MATLAB (The MathWorks Inc., Natick, MA, USA). The network objects in variants A and B were the same with a difference in the number of inputs. In the network object for general muscle (variant A) there were 12 inputs, musculotendon and activation parameters, with a combination of data sets in different motion conditions and different muscles. In the network object for specific muscle there were only 9 inputs (in addition to musculotendon constants) with a combination of data sets in different motion conditions only.

2.3. Sensitivity analysis

The measurement of some NN inputs is not trivial and the large number of inputs makes the task more complicated. Therefore, the network objects were used to evaluate sensitivity to the inputs. The aim was to find if it was possible to eliminate some of the inputs without increasing the network error. When the sensitivity to the input muscle parameters was being observed, the network object was the same at each event, and only one of the observed inputs was eliminated (the observed input had a value of zero).

In variant A, the NN object for general muscle, all observed muscles were investigated together. In variant B1, the NN object for specific muscles, we investigated two muscles: one flexor – *m.biceps brachii*, *c. longum* (BIClh) and one extensor – *m.triceps brachii*, *c. laterale* (TRlIt). The goal of the sensitivity analysis was to reduce the number of inputs needed for easy prediction of the muscle forces. Two ways were used to decrease the number of inputs – the performance of the sensitivity analysis and elimination of inputs with biomechanical relations. For example, it was possible to eliminate the maximum isometric muscle force, F_0 , because there is a direct biomechanical proportion between the physiological cross-sectional area, PCSA, and F_0 .

The correlation coefficient was used to compare the magnitude of an influence of input on the resulting muscle forces. Seven types of variant A were proposed. Each variant was examined with the different influence of the individual inputs.

4. Results

The method used in this study and in other models mentioned above were highly sensitive to the optimal muscle fiber lengths and had low sensitivity to the passive force-muscle length parameter [25], [38]. In the course of BPG learning, the goal was to find the solution with the smallest error and the fastest convergence. Several variants were performed according to the sensitivity analysis of the inputs. This could be done because some of the inputs were more sensitive than others to the results and to the network topology. The least sensitive inputs do not need to be applied to the NN object, and omitting them simplifies the procedure. The primary variant was for a general muscle with all of the 12 inputs (A1), see the first line in Tables 2 and 3. The cross-correlation coefficient to the force prediction for the 12 inputs variant is 0.97. Table 3 also shows the correlation coefficients that represent the sensitivity of the network to the particular inputs. The higher the value of the coefficient, the more insensitive the input is. The force-velocity factor input, Fv , has a very low sensitivity, hence in variant A2 this “insensitive” input is left out. In this way, we studied ways of simplifying the calculation and reducing the input. The cross-correlation coefficient for variant A2 without the force-velocity factor is 0.98, which is a 1% better value than in variant A1. Here one of the inputs also has a very low coefficient of sensitivity, the velocity of shortening v , which is also reduced in variant A3. By utilizing this method we reduced the number of inputs for variants A2–A4 and the network cross-correlation coefficients for the force predictions remained good.

Table 2. Correlation coefficients of the ability of an artificial neural network to predict muscle forces. The higher the number of correlation coefficient means the better results prediction

Variant	No. of inputs	Correlation coefficient – all parameters
A1	12	0.97
A2	11	0.9807
A3	10	0.9703
A4	9	0.9762
A5	7	0.9756
A6	5	0.701
A7	10	0.876
B1	7	0.983

In variant A5 some input parameters dependent upon the biomechanical relations between the inputs and dependent upon the small analytical influence were reduced. For example, the maximum isometric

Table 3. Correlation coefficients of the sensitivity to the inputs in specific variants.
The higher the number, the less sensitive the input parameter becomes

Variant	Correlation coefficients – Sensitivity to inputs											
	PCSA	L_0	L_{TS}	F_0	α_0	Fl_D	Fl_a	Fv	L_{MT}	v	a	a_H
A1	0.19	0.13	0.22	0.20	0.29	0.23	0.42	0.94	0.4	0.73	0.31	0.38
A2	0.44	0.11	0.50	0.44	0.51	0.71	0.02	×	0.20	0.86	0.64	0.51
A3	0.21	0.07	0.11	0.21	0.34	0.81	0.37	×	0.10	×	0.79	0.18
A4	0.31	0.10	0.17	0.31	0.26	×	0.19	×	0.15	×	0.85	0.24
A5	0.12	0.11	0.20	×	×	×	0.09	×	0.22	×	0.82	0.18
A6	0.16	0.03	0.09	×	×	×	0.39	×	0.07	×	×	×
A7	0.02	0.11	0.13	0.02	0.24	0.74	0.06	0.02	0.29	0.34	×	×
B1	×	×	×	×	×	0.96	0.60	0.13	0.42	0.60	0.88	0.25

muscle force, F_0 , is generally related with the physiological cross-sectional area, PCSA, through a specific tension constant. The pennation angle was eliminated on account of the small analytical influence in most cases. Variant A5 still produces relatively good results, with a correlation coefficient of 0.976, and the inputs were reduced to 7 parameters!

In variants A6 and A7 we studied the influence of muscle activation level and its history. In variant A6, in addition to activation, we eliminated all inputs as in variant A5, and in variant A7 we only eliminated the activation and the history of the activation inputs. The ability of a neural network object to predict muscle force without activation and activation history is very low; see the correlation coefficients for variants A6 and A7 in Table 2.

specific muscle (variant B1) gives the best results, see Table 3. For illustration of the observed results, some of the predicted forces for specific muscle by network variant B1 are described on Figs. 2–6. All these forces described are in loading condition fast motion and without 4.2 kg dumb-bell load. Original forces were calculated by the Virtual Muscle System [7].

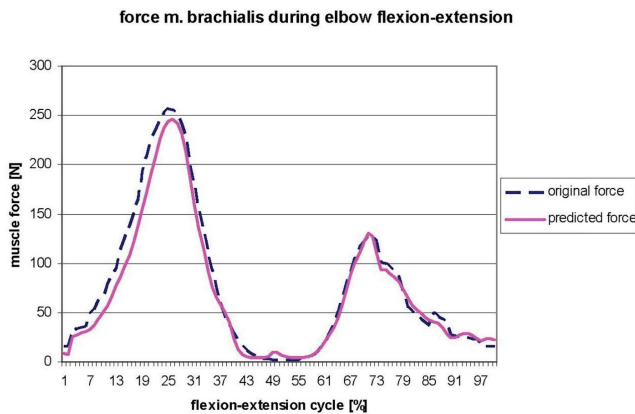


Fig. 2. The demonstration of the true and the predicted musculotendon force in specific variant fast motion and unloaded. For an illustration, application to the brachialis muscle is presented

In the last case we studied the prediction of muscle force by a neural network object for a specific muscle, variant B1. The constant muscle parameters were eliminated because for a specific muscle they are the same all the time, and they had no influence in adjusting the network weights and biases. The network object for the

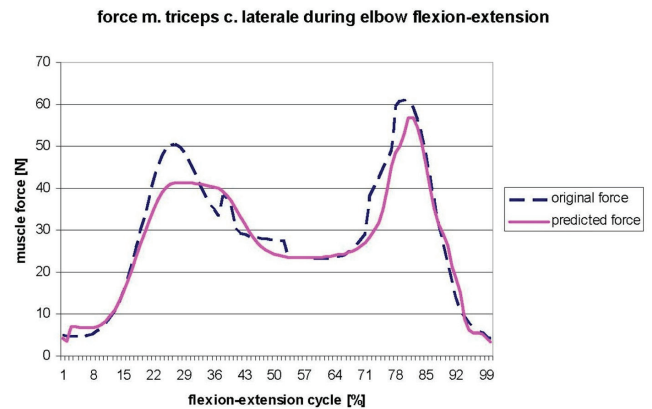


Fig. 3. The demonstration of the true and the predicted musculotendon force in specific variant fast motion and unloaded. For an illustration, application to the triceps c. laterale muscle is presented

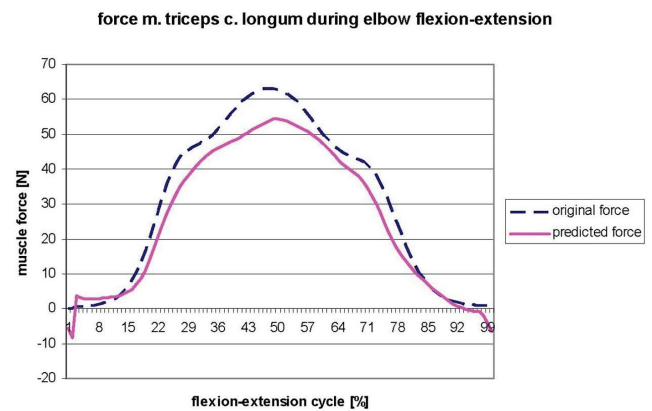


Fig. 4. The demonstration of the true and the predicted musculotendon force in specific variant fast motion and unloaded. For an illustration, application to the triceps c. longum muscle is presented

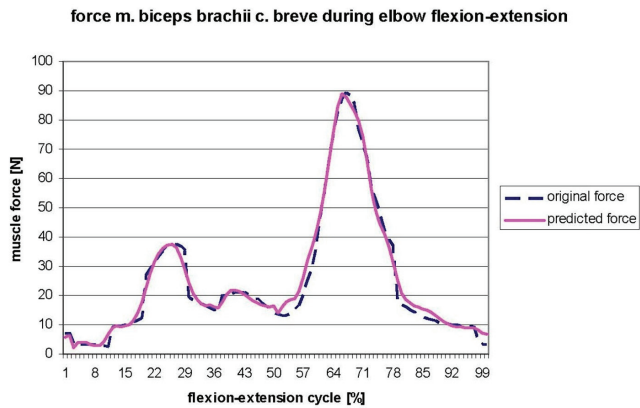


Fig. 5. The demonstration of the true and the predicted musculotendon force in specific variant fast motion and unloaded. For an illustration, application to the biceps brachii c. breve muscle is presented

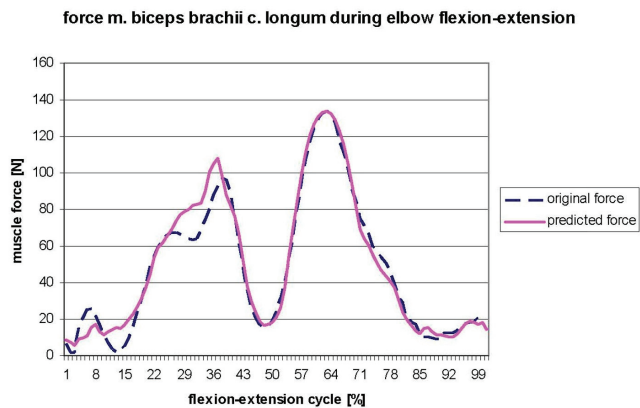


Fig. 6. The demonstration of the true and the predicted musculotendon force in specific variant fast motion and unloaded. For an illustration, application to the biceps brachii c. longum muscle is presented

5. Discussion and conclusions

This study aimed to find a way to predict muscle forces quickly, accurately, and simply with the use of an artificial neural network. An NN is a good instrument for achieving a solution without knowing the analytical relation between inputs and outputs and for solving complicated mathematical descriptions. However, there are some disadvantages: it is difficult to decide on the optimum network topology, the network is complicated, a long time is needed for training, and it is less suitable as a universal instrument for exact calculations. In the course of BPG learning, the main goal was to find the solution with the smallest error and the fastest convergence.

The predicted and original forces in Figs. 2–6 show that the designed NN model has in some cases

high invariability. Some of the fast changes in original force are not properly predicted, as is shown in Fig. 3 and in the first 30% of the movement cycle in Fig. 6. The model reacts slowly (with delay) to changes in original force values. Predicted forces are often underestimated, even if the curves of predicted and original forces are parallelly shaped (Figs. 2, 3 and 4). In some cases the curves intersect and the differences between the original and predicted forces are up to 10 N. Nevertheless, the predicted forces have good course and the errors are small as well for other possible methods (e.g., muscle force calculation by using different optimization criteria).

Achieving the smallest error depends on several limitations. The first limitation concerns the limited knowledge of the true output of the network in the training data. The training outputs were musculotendon forces calculated using the Virtual Muscle System [7]. Every computational method for muscle force calculations has limitations in analytical expressions, and the muscle models and computationally estimated musculotendon forces may not be correct. Correct results cannot be obtained if there is some incorrect data in training the network object. True outputs can be estimated only by direct measurements of the tendon forces [2]–[4], [17]. In this case the output data came from calculations, but we suppose the training process would be similar if correct output data were available. The second limitation is the amount of training data. In the human brain the new motor experiences set up the weights and biases of the neurons. Similarly, the results given from the artificial neural network depend strongly on the amount of training data, especially if the amount of training data is smaller than the real motion spectrum of the simulated system. In our case, there were sets of input/target pairs data only from 4 elbow flexion/extension movement conditions (the combination of a fast and a slow motion, and unloaded and with weight), each of them in four trials. The third limitation is the correct preprocessing and choice of a representative set of input/target pairs. Performing an early stopping algorithm and using data preprocessed by principal component analysis [11], good results were achieved.

In variant B1 the prediction of the muscle forces appeared better, but this prediction is always performed only for one specific muscle. In variant A the prediction of the muscle forces was performed for all observed muscles, and in several cases (A1–A5) the results were very satisfactory. Variant A is important for general applications, and in order to simplify the solution, a detailed sensitivity analysis was performed. The correlation coefficients expressed the sensitivity

of each important input to the results from each proposed NN object, see Table 3. After the evaluation of the sensitivity and biomechanical relations of some of the inputs, the maximum isometric muscle force, the pennation angle, the passive muscle force-length factor, the force-velocity of the muscle shortening factor, and the velocity of the muscle shortening input were eliminated (network variant A5) because without them the neural network prediction error does not increase rapidly. The results from the sensitivity analysis agree quite well with previous muscle model studies. The tendon slack length and optimal muscle length have been found to be sensitive to the muscle force prediction [12], [21], [25]. The pennation angle had low sensitivity [21], [39], as did the passive muscle force-length factor [25], [38].

The resulting number of inputs was finally decreased to 7 parameters with relatively good results, see Tables 2 and 3, variant A5. The most inconsistent input seems to be muscle activity, $a(t)$. When NN object variants A6 and A7 were trained without the muscle activation and its history, the mean absolute error performance function was twice greater than when training with the muscle activation level. The predicted force in variants A6 and A7 is also very different from the true force. It is evident that muscle activity, $a(t)$, includes information about the muscle state and work, and can describe various situations, e.g., the same velocity of muscle shortening, v , with different muscle loadings. This finding corresponds with the knowledge that if the muscle activity, $a(t)$, parameter equals zero, the muscle cannot produce the active force, F_{la} . In our case the NN object could not have only this extremely sensitive input because the activity of muscles also depends on the control task and can be quite different for the same joint angle and joint torque [34]. By way of contrast, Liu et al. [17], use of an artificial NN for prediction force from specific muscle only recorded EMG signals (recorded from the soleus muscle of a cat) and with very satisfactory results.

The black-box model was used for predicting musculotendon forces. In the case of acquiring the relevant quantity of training data and direct measured outputs (tendon forces) during the spectrum of movement activities, this approach provides a possible way to estimate musculotendon force. An analytical expression of tendon and activation dynamics and the biological expression between EMG signals and the muscle force output avoid this approach. In the future, studies with wide training sets can be predicted with a higher level of probability using this approach, and the data that is obtained may be adequate for some simulation studies.

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