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INFLUENCE OF THE INPUT MUSCLE PARAMETERS TO THE RESULTING MUSCLE FORCES

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Summary: *Determination of the muscle force that produce particular muscles is extremely difficult, because of the technical problems of definiting muscle parameters. However, orthopeadists, biomechanical engineers and physical therapists need to take muscle forces into consideration, because joint contact forces, as well as muscle forces, need to be estimated in order to understand the joint and bone loading. The magnitude of the muscle force varies with mechanical and physiological characteristics of relevant muscle and with muscle activity. In terms of these facts was proposed the neural network object to determine the muscle force from particular muscles and evaluate the sensitivity to input muscle parameters.*

1. Introduction

Years, biomechanical engineers have been trying to solve the complexity of the musculoskeletal system. By one of serious and important issues is find simple determination of muscle forces in order to understand joint function, bone loading and pathology. There are number of intrinsic and extrinsic design parameters in the musculoskeletal system, which have a different influence on the relevant muscle force, therefore, the objective of our work was evaluated these muscle parameters.

Recently, there has been increasing interest in employing artificial neural networks (NNs) as method for estimation of movement (Koike & Kawato, 2000). Current NNs can be trained to solve problems that are difficult for conventional computers or human beings. The big advantage of NNs is obtaining results without knowledge of the algorithm procedure or without full and exact information. The backpropagation types of NNs were used to estimate of relation between elbow joint angle, myosignals and static torque (Uschiyama et al., 1998) and also to predict of muscle forces from electromyography in animals (Savenberg & Herzog, 1997).

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There were evaluated Hill muscle model sensitivity to parameter perturbations in forward dynamic simulations of running and walking in the study Scovil & Ronsky (2005). Our approach is new, because presents an effective, readily and fast method to evaluate the sensitivity of input muscle parameters and it has not been performed by NNs yet. For muscle parameters were taken 14 muscle properties which were the physiological characteristics of the participating muscles of the particular joint mechanism, together with further data about the movement and electric activation of the muscles.

Numerous muscle parameters are difficult to obtain from noninvasive methods, therefore muscle parameters are most often taken from literature, where the data are compiled from both human and animal muscle experiments and have different initial conditions. This may cause the variation in results, therefore the influence of muscle parameters on the musculoskeletal simulations was evaluated.

2. The input muscle parameters (Input and output parameters)

The neural network (NN) was proposed to evaluate 14 input muscle parameters (Table 1), which influence the resulting muscle forces. To train the proposed NN object was necessary to know the output parameter (OP). As OP, the muscle force, applying the Virtual Muscle system (Cheng et al., 2000), was used in order to relate this to the real muscle force. In this case, the inputs were muscle morphometrical data, time depending on length of musculotendon and muscle activity. Benefit of our work was taken into account more muscle parameters and still evaluation of predicted muscle force sensitivity to muscle parameters.

Table 1 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 (fiber recruitment).

1.	Musculotendon length	L_{MT} [m]
2.	Velocity of muscle shortening	v [m.s^{-1}]
3.	Optimal pennation angle	α_0 [rad]
4.	Optimal muscle fiber length	l_0 [m]
5.	Physiological crossectional area	$PCSA$ [m^2]
6.	Tendon slack length	L_{ST} [m]
7.	Maximal isometric muscle force	F_0 [N]
8.	Active force-muscle length factor	Fl_a [-]
9.	Passive force-muscle length factor	Fl_p [-]
10.	Force-velocity factor	Fv [-]
11.	Muscle activity	$a(\Delta t)$ [-]
12.-14.	History of muscle activity	$a_H(\Delta t)$ [-]

As well as the musculotendon length, L_{MT}, having an effect on the maximum force it can generate, so does the velocity of muscle shortening, v. The musculotendon length, L_{MT}, (the length of the entire muscle-tendon unit origin to insertion) was estimated from anatomical positions of muscle attachments and recorded kinematic data, the velocity of muscle shortening, v, was calculated from recorded kinematic data (the slow movement and the fast movement unloaded, and loaded, respectively). For estimation force-velocity factor, Fv, and for maximal isometric muscle force, F_0, which a muscle can generate, is necessary to know the physiological crossectional area, *PCSA*, of the human skeletal muscle. Some of the muscular parameters were reported in Veger (1997) (the optimal muscle fiber length, l_0, the optimal pennation angle, α_0, and the capacity of the muscle, V) and converted to the different proportions of the specimen. Because *PCSA* crossing across all fibres of the muscle is estimated the optimal pennation angle, α_0, which determines organization fibres in a muscle. The tendon slack lengths, L_{ST}, were theoretically calculated by method published in (Garner & Pandy, 2003). Maximal isometric muscle force, F_0, was calculated as (1).

$$F_0 = PCSA \cdot \sigma \tag{1}$$

The size of specific muscle tension for our research was applied $\sigma = 31.8 N.cm^{-2}$ (Scott et al., 1996), is difficult quantity to measure in humanshe specific muscle tension. This value was taken, because the same value as default is used in Virtual Muscle system (Cheng et al., 2000).

Total force of muscle is given by sum of active and passive force. Therefore, the force-muscle length factor was taken into account in terms of (Gordon & Huxley, 1966), and the curves of passive, Fl_p, and active, Fl_a, properties, scaled to provide a destription for specific muscle are fit by parabolic and exponential functions. The force-velocity factor, Fv, was calculated from hill equation (Hill, 1970) for concentric contraction and modified hill equation (Krylow & Sandercock, 1997) for eccentric contraction.

An arm movements were from full extension $\varphi_E = 0°$ to full flexion $\varphi_F = 145°$ (Radford. & Carr, 2002) 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 60Hz VICON Motion Analysis system, two movement speeds (slow, 1.1rad/sec and fast, 2.8rad/sec) and two loading conditions (unloaded and with 4.2kg bar-bell) were studied. The electric activity of the observed muscles was recorded by surface electromyography (EMG). The processed EMG signal was done by filtering of frequences which are lower then 20Hz and higher then 500Hz, offsetting, rectifying (rendering the signal to have excursions of one polarity) and integrating the signal over a specified interval of time (De Luca, 1997). The processed and the normalized EMG signal was taken as the input of the muscle activity, $a(t)$ and the history of muscle activity, $a_{1H}(t+\Delta t)$, $a_{2H}(t+2\Delta t)$, $a_{3H}(t+3\Delta t)$. The history of muscle activity ensures direct expression of time, thereby dynamic of the object of neural network. The input of the muscle activity was distributed to the time steps (1-100 steps) and then each input of the history of the muscle activity was moved of one step, two steps and three steps in time, respectively. It should be noted that muscle activity level was calculated as the ratio between the current neural activity and the same activity during maximal voluntary isometric muscle contraction.

3. Neural network architecture

The neural network architecture was the feedforward multilayer network – backpropagation (BPG), in this case consisting of three layers (input layer and two hidden layers followed by an output layer). Feedforward multilayer network was fully connected - that was, each neuron in a given layer was connected to every neuron in the next layer, neurons in the same layer were not connected. The network object (Figure 1) with 30 neurons in the 1st hidden layer and with 24 neurons in the 2nd hidden layer was proposed. Between input layer and 1st hidden layer and between 1st and 2nd hidden layer there were used sigmoidal transfer function – tansig. Multilayer network used the sigmoidal transfer functions, because they were differentiable functions. Between 2nd hidden layer and ouput layer was used linear transfer function – purelin. Linear transfer function was used so the neural outputs took on any value. In the course of the backpropagation learning, the main goal was to find out the solution having the smallest error and the fastest convergence with respect to the network's weights and biases. By adjusting network`s weights, network object was trained to perform complicated problems, in our case, prediction muscle forces.

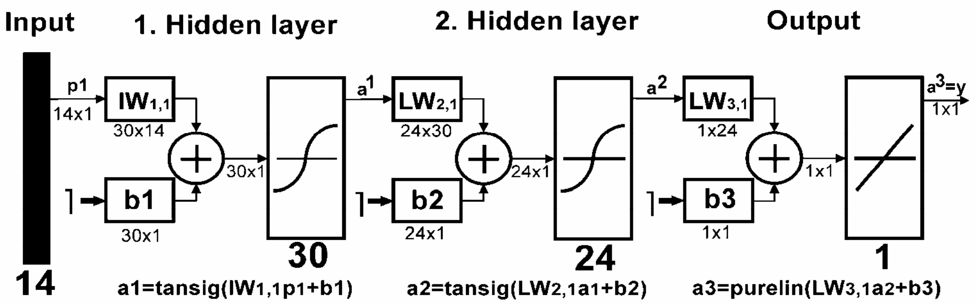

Figure 1 A schematic representation of three-layer feedforward neural network with supervised learning algorithm (BPG). The input muscle parameters were the physiological characteristics of the participating muscles of the particular joint mechanism, together with further data about the movement and muscle activity. The output parameter for training the network object was the muscle force.

The training sets were created for 7 musculotendon actuators 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* for 4 movement conditions (combination of fast and slow motion and unloaded and with weight). For each muscle were created 4 files with different movement conditions. Each file contained 392 patterns (98 data was for 1 movement). As a whole there were 28 files created. Finally, for the elbow problem was available 2744 data.

4. Results

The goal of the sensitivity analysis was decreased the number of the input muscle parameters (IMPs) for easily predicting the muscle forces. Some of IMPs are difficult to obtain or accuratelly compute, especially from the muscles, which are profundus. Therefore there was an effort to examine if some of IMPs were possible to eliminate without increasing the network error. Two ways were used to decrease of the number of IMPs – performance of the sensitivity analysis and finding of biomechanical relations between IMPs. For comparison of the size of influence IMPs on the resulting muscle forces was used the correlation coefficient.

After evaluated sensitivity some of IMPs could be eliminated the tendon slack length, *Lst*, and the passive force-muscle length factor, *Flp*, because without them the error of NN did not increase rapidly. Next IMPs were eliminated with regard to the biomechanical relations – the velocity of muscle shortening, *v*, the maximal isometric muscle force, F_0, and the optimal pennation angle, α_0.

The most inconsistent IMP was the muscle activity, *a*(*t*). When NN object was trained without the muscle activity, *a*(*t*), the mean absolute error performance function was twotimes greater than when training BPG with the muscle activity, *a*(*t*). It is also evident, that the muscle activity, *a*(*t*), includes information about the muscle state and work and can describe various situations as for example 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 equels zero value, the muscle can not produce active force, Fl_a. 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 (Tax et al., 1990).

5. Conclusions

This study presents an method to evaluate the sensitivity of the input muscle parameters (IMPs) to the resulting muscle forces and demonstrates that sensitivity is dependent on the system being proposed. It is obvious that exact measurement of some IMPs is an invasive or very difficult. Therefore decrease of IMPs, which are difficult to obtain increase accuracy. This analysis points out the importance of careful selection, accurate measurements of the most sensitive muscle parameters.

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7. References

De Luca, C.L. (1997) The use of surface electromyography in biomechanics. *Journal of Applied Biomechanics,* 13, pp. 135–163.

Garner, B.A. & Pandy, M.G. (2003) Estimation of musculotendon properties in the human upper limb. *Annals of Biomedical Engineering*, 31, pp. 207–220.

Gordon, A.M. & Huxley, A.F. (1966) The variation in isometric tension with sarcomere length in vertebrate muscle fibres, *Journal of Physiology*, 184, pp.170-192.

Hill, A.V. (1970) First and last experiments in muscle mechanics. *Cambridge University Press*. Cambridge.

Cheng, E.J., Brown, I.E. & Loeb, G.E. (2000) Virtual muscle: a computational approach to understanding the effects of muscle properties on motor control, *Journal of Neuroscience Methods*, 101, pp.117–130.

Koike, Y. & Kawato, M. (2000) Estimation of movement from surface EMG signals using a neural network model, *Biomechanics and neural control of posture and movement*, Springer, pp.440-457.

Krylow, A.M. & Sandercock, T.G. (1997) Dynamic force responses of Muscle involving eccentric contraction, *Journal of Biomechanics*, 30, pp.27–33.

Radford, M. & Carr, A. (2002) Total elbow replacement, *Current Orthopaedics*, 16, 5, pp.325-330.

Savenberg, H.H.C.M. & Herzog, W. (1997) Prediction of dynamic forces from electromyographic signals: An artificial neural network approach, *Journal of Neuroscience Methods*, 78, pp.65-74.

Scott, S.H., Brown, I.E. & Loeb, G.E (1996) Mechanics of feline soleus: I. Effect of fascicle length and velocity on force output, *J. Muscle Res. Cell. Motil*, 17, pp.207-19.

Scovil, C.Y. & Ronsky, J.L. (2005) Sensitivity of a Hill-based muscle model to perturbations in model parameters. *Journal of Biomechanics*, article in press, published by Elsevier.

Tax, A.A., Denier van der Gon, J.J. & Erkelens, C.J. (1990) Differences in coordination of elbow flexor muscles in force tasks and movement tasks, *Experimental brain research*, 81, pp.567-572.

Uchiyama, T., Bessho, T. & Akazawa, K. (1998) Static torque angle relation of human elbow joint estimated with artificial neural network technique, *Journal of Biomechanics* 31, pp.545-554.

Veger, H.E.J., Yu, B., An, K.N. & Rozendal, R.H. (1997) Parameters for modeling the arm. *Journal of Biomechanics*, 30, pp.647–652.