INTRODUCTION

The first objective of our research was to establish the possibility of a general artificial neural network (NN) object in the musculoskeletal system of the human elbow joint as a function of the muscle activity, musculotendon (MT) physiological properties and the joint kinematics. The object of backpropagation (BPG) NN with supervised learning algorithm was suggested, in order to fast, accurately and simply predict the muscle forces in the 7 elbow actuators during flexion/extension movement activities. The second objective was to evaluate 14 input muscle parameters which influence the resulting muscle forces. The last objective was to simplify the proposed NN object by the sensitivity analysis to the muscle input parameters. It was studied, because some of the inputs were more sensitive to the results and the network topology than others. The most insensitive inputs need not to be applied to the NN object and it would be made easier to use.

METHODS

The approach is based on the non-knowledge of relation between input parameters, the MT morphological and physiological data and the muscle fiber recruitment, and the output parameter the muscle force. To train the proposed neural network object was necessary to know the input and output parameters. The direct measurement of muscle force is in most cases extremely invasive approach, therefore the Virtual Muscle System (Cheng et al., 2000) was used in order to relate this to the real muscle force. The input muscle parameters utilized in this investigation result from the Hill-type muscle model including active and passive components (Zajac., 1989). The input parameters express the passive and active muscle force-length factors. Third input was the force-velocity factor. Next were five constant MT parameters, physiological crossectional area, optimal muscle fiber length, tendon slack length, maximal isometric muscle force and optimum pennation angle. The (MT) length and the velocity of muscle shortening were input parameters estimated from anatomical positions of the muscle attachments and recorded kinematic data in various movement conditions. Last inputs were the muscle electrical activities of the observed muscles recorded by surface electromyography (EMG). The processed EMG’s were filtered, rectified, smoothed and normalized. The processed EMG signal was taken as the input of the muscle activity and the three levels of history of muscle activity. The history of muscle activity ensures direct expression of time, thereby dynamic of the object of neural network.

The neural network architecture was the feedforward multilayer network (BPG), in this case consisting of three layers (input layer and two hidden layers followed by an output layer). The feedforward multilayer network was fully connected, that means the 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 with 30 neurons in the 1st hidden layer and 24 neurons in the 2nd hidden layer was proposed. Between input layer and 1st hidden layer and between 1st and 2nd hidden layer were used sigmoidal transfer functions. Between 2nd hidden layer and output layer was used linear transfer function. In the course of the (BPG) learning, the main goal was to find out the solution having the smallest error and the fastest convergence with respect to the network’s weight and biases. By adjusting network’s weights, network object was trained to predict muscle forces.

The measurement and calculation of some NN inputs is not trivial and the more inputs make a solving the more complicated. Therefore, the network object was used to evaluate the sensitivity to the inputs. Here was an effort to examine if some inputs were possible to eliminate without increasing the network error.

RESULTS AND DISCUSSION

Several variants were performed according to the sensitivity analysis to the inputs. Primary variant was for the general muscle with all of the 14 inputs. The cross-correlation coefficient to the force prediction for the 14 inputs variant is 0.97 (97% of prediction). The force-velocity factor input had coefficient of non-sensitivity very high, hence in the next variant this “insensitive” input was left out. This way the possible simplification of calculation and inputs reduction was studied. The cross-correlation coefficient for the variant without force-velocity factor was 0.98. Here also one of the inputs had very high coefficient of non-sensitivity, the velocity of shortening which was reduced in the next variant too. By this way were reduced several inputs and still the network cross-correlation coefficients for the force prediction were good. In one variant was studied influence of muscle activation level and its history. In the one of variants were aside from the activation input eliminated also history of activation inputs. The ability of proposed NN object to predict muscle force without activation and activation history was much lower, the correlation coefficient was 0.87. The achievement of the smallest error depends several limitations. The first limitation is the knowledge of the true output of the network training data. The training outputs were calculated musculotendon forces and no directly measured, for example by using optic fiber sensors (Komi, et al.,1987; Finni et al., 2000). In our case the output date were calculated but we suppose the training process would be similar but with directly estimated muscle forces. Second limitation is the number of training datasets. In our case the sets of input/target pairs data were only from four 4 elbow flexion/extension movement conditions, which is smaller than full real motion spectrum in elbow. Third limitation is a correct preprocessing and choice of representative set of input/target pairs. Performed and early stopping algorithm and with data preprocessed by principal component analysis were provided good results.

REFERENCES


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