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PREDICTION OF MUSCLE FORCES USING NEURAL NETWORK BACKPROPAGATION

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Summary: *The muscle forces in human beings are difficult to exactly determine, because many muscles act cooperatively. Consequently, the model of a backpropagation neural network with a learning algorithm (BPG) was suggested. The proposed model predicted the muscle forces about 7 elbow actuators without advance knowledge of the relation between inputs and outputs.*

1. Introduction

The objective of this study was to use neural network for prediction of muscle forces. Generally, BPG is more available than other types of network for problems of this type. BPG was programmed, using the Matlab Neural Network Toolbox. In standard BPG is a gradient descent algorithm, in which the network weights are moved along the negative of the gradient of the performance function. Properly trained BPG tend to give reasonable answers when presented with inputs that the network has never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs.
The architecture of BPG was the feedforward multilayer network, in this case consisting of three layers (two hidden layers of sigmoid neurons followed by an output layer of linear neurons). Therefore, based on the learning set of input parameters and the known outputs, the weights of neural inputs in network were set up, and after learning - training the network, the neural network could response to new inputs.

2. Materials and methods

The proposed model of the neural network simulated the cooperation of 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.

2.1 Collecting the training data

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In the neural network for estimating muscle forces, 14 input parameters were used, and it was assumed that these parameters influence the resulting muscle force. The input parameters 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. The parameters were obtained experimentally, from the technical literatures, and by calculation.

Elbow flexion/extension movements were recorded using the 6-camera 60Hz VICON Motion Analysis system across two movement speeds (slow, 1.1rad/sec and fast, 2.8rad/sec) and two loading conditions (unloaded and with 4.2kg bar-bell). Electric activation of the observed muscles was recorded by EMG (De Luca, 1997). The processed EMG signal and the normalized EMG signal were taken as muscle activation and history of muscle activation. The used input parameters were: musculotendon length, L_{MT}, velocity of muscle shortening, v, pennation angle, α_0, optimal muscle length, l_0, physiological crossectional area (Veger et al., 1997), *PCSA*, tendon slack length (Garner et al., 2003; Vilímek, 2004), L_{ST}, maximal isometric muscle force (Cheng, 2000), F_0, force-velocity factor (Fung, 1981; Krylow et al., 1997), Fv, active force-muscle length factor, Fl_a, passive force-muscle length factor, Fl_p, muscle activation, $a(t)$, and three degrees of history of muscle activation, $a_{1H}(t+\Delta t)$, $a_{2H}(t+2\Delta t)$, $a_{3H}(t+3\Delta t)$.

The output parameter also needs to be known for training. The training output parameter for a network object was the muscle force, and in order to relate this to the real muscle force, the Virtual Muscle system was used, see (Cheng et al., 2000).

2.2 The preprocessing data

Neural network training were 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. Consequently, the dimension of the input vectors was reduced by principle component analysis (PCA). The input vectors were uncorrelated with each other and the components with the largest variation came first, which eliminated those components that contributed the least to the variation in the data set.

2.3 The network object and training the network

The objective of BPG was to verify possibilities of neural network in the course of muscle prediction outputs from Virtual Muscle system (Cheng et al., 2000). A general muscle model, including properties and training inputs and outputs of investigated elbow muscles, was developed. The training inputs were taken from all of four movement types (combination of fast and slow motion and unloaded and with weight). There were 4×98 = 392 of training sets (4 cycles of movement types in 98 steps with 14 inputs) for one muscle.

To improve the generalization, the framework of early stopping was performed. The data was divided into training, validation and test subsets. For the validation, one fourth of the data was taken, for the test set one fourth of the data was taken and for the training set one half of the data was taken. When the validation error increased, the training was stopped.

In the course of learning the BPG, the main goal was to find the solution with the smallest error and the fastest convergence. Minimization of learning error was performed by modifying the network topology, by changing the number of neurons in the hidden layers and by changing the learning rate. The BPG was also sensitive to the number of neurons in their hidden layers. Too few neurons led to underfitting. Too many neurons led to overfitting. If the learning rate of the network was set up too high, the correct solution was overskipped. If the network learning rate was too low, the correct solution very often ends in the local minimum, or the algorithm converges very slowly. Finally, the network object with 30 neurons in the 1st hidden layer and with 24 neurons in the 2nd hidden layer was proposed. A schematic representation of proposed BPG appears in Fig. 1.

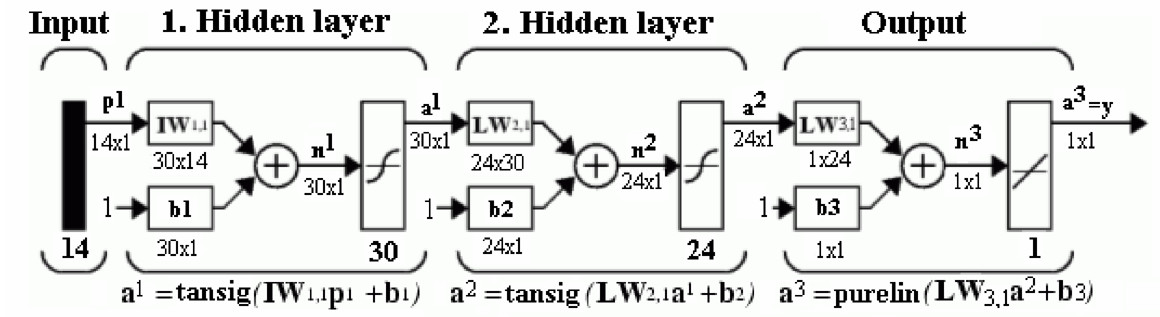

Fig. 1 The proposed feedforward multilayer neural network

3. Results

Generally, this network BPG could be used for predicting the muscle force for all muscles, not only for the elbow joint, but this of course depends on the training data and on preprocessing a representative set of input/target pairs. The validation set should be representative of all points in the trainig set.

It was useful to investigate the network response in more detail, performed a regression analysis between the network response and the corresponding targets (Fig. 2). In this study the muscle force prediction (Tab. 1) was better, *C*=0,97, than in our previous study (Vejpustková et al., 2004), where the data was not preprocessed by PCA and the correlation coefficient was weaker, *C*=0,89.

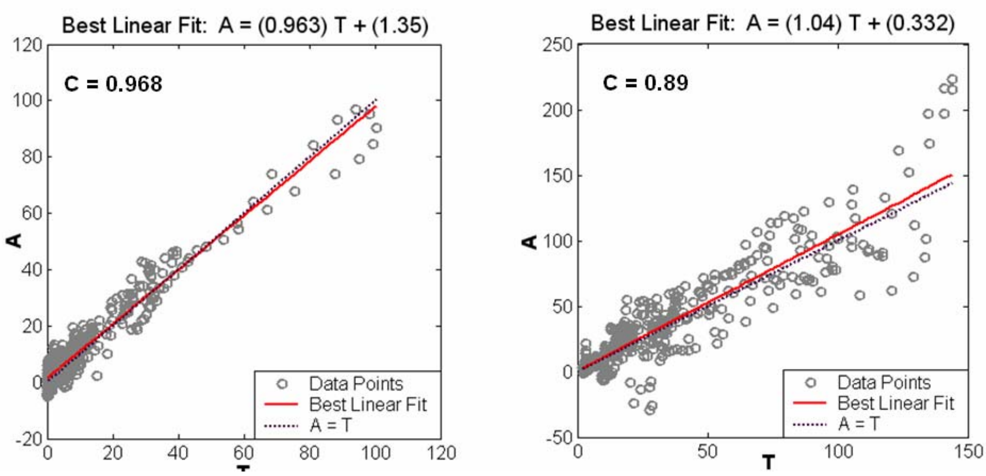

Fig. 2 A regression analysis between the network response and the corresponding targets. On the left side (processed d.), *C* is very close to 1, which indicates a good fit. On the right side (raw d.), *C* is weaker. The perfect fit (output equal to targets) is indicated by the dashed line.

Tab. 1 The correlation coefficient, *C*, and the mean absolute error, *MAE*, between the network with/without preprocessing data.

Error	**Processed data**	**Raw data**
MAE [-]	3,46	13,45
C [-]	0,97	0,89

4. Conclusions

The network object BPG was very difficult to learn and generalize. The error was minimized due to the preprocessing data by PCA, but BPG is not yet a good instrument for widespread application. The error is probably due to the small size of the training set, but could be of course result from errors in the calculation of the muscle forces by the Virtual Muscle system (Cheng et al., 2000). In terms of results from a regression analysis is important to performed certain preprocessing steps, because after the erorr decreased fourtimes.

5. Acknowledgements

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