The Application of Neural Fuzzy Approaches to Modeling of Musculoskeletal Responses in Manual Lifting Tasks ⋆

Yanfeng Hou[1], Jacek M. Zurada[2], Waldemar Karwowski[3], and William S. Marras[4]

[1] Department of Electrical and Computer Engineering, University of Louisville
y0hou002@louisville.edu
[2] Department of Electrical and Computer Engineering, University of Louisville
jacek.zurada@louisville.edu
[3] Center for Industrial Ergonomics, Department of Industrial Engineering, University of Louisville karwowski@louisville.edu
[4] Biodynamics Laboratory, Institute for Ergonomics, The Ohio State University
marras.1@osu.edu

Summary. Electromyographic signals and spinal forces in trunk muscles during lifting motion can be used to describe the dynamics of muscular activities. Yet spinal forces can not be measured directly, and EMG signals are often difficult to measure in industry due to environmental hostilities. EMG waves, however, can be treated and analyzed as responses of a system that takes kinematics measurements and other auxiliary factors as inputs. By establishing the kinematics-EMG-force relationship using neural and fuzzy approaches, we propose models for EMG and spinal force estimation. Key variables affecting EMG and forces in lifting tasks are identified using fuzzy average with fuzzy cluster distribution method. An EMG signal estimation model with a novel structure of feedforward neural network is then built. And the spinal forces are estimated by a recurrent fuzzy neural network model. The proposed neural and fuzzy approaches can prune the input variables and estimate EMG and forces effectively.

Key words: EMG, Spinal forces, Neural networks, Fuzzy logic

1 Introduction

Manual materials handling tasks performed in industry have been related to the onset of low back disorders [1]. Since electromyography (EMG) response is a direct reflection of muscular activity [2], it is important to study the EMG signals generated during lifting motion of the human body. EMG signals provide useful information about the levels of physical exertion. Studying the forces applied to the spine is also

⋆ This study was conducted under a research grant on the "Development of a Neuro-Fuzzy System to Predict Spinal Loading as a Function of Multiple Dimensions of Risk", sponsored by the National Institute for Occupational Safety and Health (DHHS).

Y. Hou et al.: *The Application of Neural Fuzzy Approaches to Modeling of Musculoskeletal Responses in Manual Lifting Tasks*, StudFuzz **201**, 323–337 (2006)
www.springerlink.com

fundamental to the understanding of low back injury [3]. The forces on the spine during manual lifting are very useful to estimate whether a given lifting task would be safe. The clear understanding of the EMG and spinal forces in manual lifting plays an important role for guiding the reduction of musculoskeletal loading in heavy work situations [4].

However, the spinal forces can not be measured directly. Thus the low back biomechanical models are often used to estimate the loads on the lumbar spine using variety of human and environment related variables. Most biomechanical models rely on the EMG data because the internal behavior of muscles is usually described with EMG signals. However, the measuring of EMG is often difficult to perform in industrial environments. Since EMG signals are related to the kinematic characteristics, evaluating EMG from kinematics measurements and other auxiliary factors becomes a better choice [5].

In view of the above, the kinematics-EMG-force relationship could be found in the load evaluation system. The spinal forces are connected with kinematic variables through EMG signals. So models can be developed to express the relationships and estimate EMG and forces on lumbar spine [5, 6, 7]. These models do not need the measuring of EMG signals and the use of biomechanics model.

The information obtained for the evaluation of body stresses in manual lifting activities is normally uncertain, imprecise, and noisy. The muscle activities are influenced by multiple factors, without much knowledge of their underlying dynamics. Since the exact relationships between the multiple variables are not clear in many situations, neural networks and fuzzy logic are appropriate methods in this situation.

The neural and fuzzy approaches have been successfully applied to many complex and uncertain systems. They have played an important role in solving many engineering problems. Neural networks can model the nonlinear relationship between the input and output by extracting information from examples, while fuzzy systems provide an approximate human reasoning capability in a fuzzy inference system. Fuzzy systems are good at dealing with imprecise information and it is clear how they determine their output. However, it is usually hard to determine the membership functions in the fuzzy inference system. This problem can be solved by combining neural network with the fuzzy logic. The neural network can make up membership functions and extract fuzzy rules from numeric data. This hybrid method combines the advantages of the neural network and fuzzy logic approaches.

Different neural and fuzzy models can be developed to estimate the EMG signals and spinal forces due to manual lifting tasks. The input-output relationship of the EMG and force prediction systems, however, is not well understood. It is important to find out which variables have significant influence on the forces during the lifting motion, so that they can be selected as input variables. The kinematic variables such as velocities, accelerations, and angles affect the spinal forces. Furthermore, the differences between subjects also affect the EMG responses. Different people produce different patterns of EMG even though the kinematics data may be similar in doing the same task. Subject variables include body weight, height, arm length, etc. From a lot of input candidates, if we can remove those have little or no influence on the output and put emphasis on the important variables, a more parsimonious and more effective model could be built. So it is important to identify those important input variables before building the models for EMG and force evaluation.

The modelling of the kinematics-EMG-force dynamics can be divided into three parts. In the first part the key input variables of the models are identified using a fuzzy method called Fuzzy Average with Fuzzy Cluster Distribution (FAFCD). In the second part a neural network model is built to translate kinematics data into EMG signals under different task conditions. In the third part a hybrid neuro-fuzzy model is developed to predict the forces on the lumbar spine.

2 Identification of Input Variables using FAFCD

Since we do not know how significantly each input variable affects the output of the EMG and forces, all the associated kinematic variables and subject variables are recorded. The twelve kinematic variables are dynamic variables which change their values during the motion. While the fifteen subject variables are static variables which are the anthropometric characteristics of the subjects and they are the same during a motion for a particular subject. If we take all the kinematic variables and subject variables as input of the model, the dimension of the input space will be very high. It is important to identify the influence of the variables and select only the key variables as inputs of the model.

2.1 The Fuzzy Curve Method and Its Improvements

In [8] and [9], Lin et al. proposed their "fuzzy curves" method. There are m sampling data points obtained for a nonlinear system with one output variable and n associated input variables. For each input variable x_i, the m data points are plotted in the $x_i - y$ space. A fuzzy rule is defined according to each sampling data point (x_i^j, y^j) $(i = 1, 2, ..., n, j = 1, 2, ..., m)$ in the following form:

$$R_i^j : \text{IF } x_i \text{ is } \mu_{ij}(x_i) \text{ THEN } y \text{ is } y^j;$$

where $\mu_{ij}(x_i)$ is a Gaussian membership function of x_i^j. From m data points, m fuzzy rules can be obtained. The fuzzy membership functions for input variable x_i are Gaussian membership functions centered at x_i^j:

$$\mu_{ij}(x_i) = \exp(-(\frac{x_i - \overline{x}_i^j}{\sigma})^2) \tag{1}$$

where $\overline{x}_i^j$ and σ are the center and width of the membership function, respectively. The width of the Gaussian membership function is taken as about 20% of the length of the input interval of x_i. A "fuzzy curve" can be produced using defuzzification method:

$$C_i(x_i) = \frac{\sum_{j=1}^{m} y^j \mu_{ij}(x_i)}{\sum_{j=1}^{m} \mu_{ij}(x_i)} \tag{2}$$

The fuzzy curve stands for the $x_i - y$ relationship. It can tell us if the output is changing when x_i is changing. The importance of the input variables are ranked according to the ratio of the range of y covered by the curve to the whole range of y, which is defined as Influence Rate R. The Influence Rate for variable x_i can be written as

$$R_{x_i} = \frac{C_i(x_i^u) - C_i(x_i^l)}{a} \tag{3}$$

where $C_i(x_i^u)$ is the highest point on the curve and $C_i(x_i^l)$ is the lowest point on the curve. a is the whole range of y.

This method is easy to understand and to calculate. The result obtained is straightforward. However the method can not always work well. The distribution of the sampling data set will affect the result. In other words, the influence of the input variables obtained from this method may vary from sampling to sampling. The EMG and force prediction systems are complicated nonlinear systems. It is hard to control the distribution of the sampling data. Thus we can not apply the fuzzy curves method directly to the model.

In [10] the limitation of the fuzzy curve method is discussed and improved with Fuzzy Average with Fuzzy Cluster Distribution (FAFCD). To find out the $x_i - y$ relationship using fuzzy average method, each of the input variable (except x_i) should have roughly the same distribution along the axis of x_i, respectively. But for many practical applications, this requirement is normally hard to meet. The sampling data need to be preprocessed to become a representative data set before being used to determine the influence of input variables.

To transform the sampling data of force prediction system into the required form, we use the fuzzy clustering method in [10] to change the distribution of the data set. First the data points are divided into groups using fuzzy clustering method. The number of data points in each group (fuzzy cluster) will be different since the distribution of the original data is uneven. Then one data point (for instance, the fuzzy cluster center) is used to represent each group to obtain a new data set with the distribution of fuzzy clusters. Since different number of sampling data in small regions will be replaced by the same number of cluster center, we will obtain a new data set with better distribution.

Change the Distribution of the Data Set

Each of the sampling data point (vector) represents a point in the n-dimensional Euclidean space (n is the input dimension). The purpose of clustering is to partition the data set into clusters in such a way that data points in each cluster are highly similar to each other, while data points assigned to different clusters have low degrees of similarity.

To generate even cluster distribution, we partition the input space using fuzzy rules. We build a fuzzy rule base for the nonlinear system. Those data points that can excite a particular fuzzy rule with high firing strength are grouped to the same partition. The fuzzy rule base is in the form of

IF x_1 is A_{11} and x_2 is A_{21} and ... and x_n is A_{n1} THEN y is y^1
IF x_1 is A_{12} and x_2 is A_{22} and ... and x_n is A_{n2} THEN y is y^2
...
IF x_1 is A_{1m} and x_2 is A_{2m} and ... and x_n is A_{nm} THEN y is y^m

where $A_{ij}(i = 1, 2, ..., n; j = 1, 2, ..., m)$ and y^j are fuzzy sets of x_i and y, respectively.

If the width σ of Gaussian membership functions are the same for all the fuzzy sets, the fuzzy partition generated by the fuzzy rules is an even partition.

The method is implemented as follows: the first sampling data point is taken as center of a cluster and a corresponding fuzzy rule is built. The center of the Gaussian membership function is $\overline{x}_i^j = x_i^j$; the width σ' is $1/30$ of the normalized range of the input variable.

For every sampling data point, the firing strength of each existing rule is calculated:

$$G_j = \prod_{i=1}^{n}(\mu_{ij}(x_i)) = \prod_{i=1}^{n}\exp(-(\frac{x_i - \overline{x}_{ij}}{\sigma'})^2) \tag{4}$$

AND operation is used in (4).

If the firing strength $G_j \geq \beta$, then the sampling data point is similar to the data points in the partition. Thus it belongs to this partition. β is a predefined threshold as the least acceptable degree. It decides to what extent the similarity should be in order to be classified into the partition. If the firing strength is less than the threshold β, then a new fuzzy rule (a new partition) should be created.

After all the data are partitioned, Fuzzy c-means (FCM) algorithm is used to cluster data points in each small partition. FCM allows one piece of data to belong to two or more clusters [11]. It provides a method that group data points in multidimensional space into a specific number of clusters. The same number of clusters are set for each small partition so that the distribution can be more even. Or, if the partition is small enough, we can set only one cluster for each partition and find its center by FCM. We would like to use the centers of the clusters to represent the clusters. But for real world systems, the corresponding output of the system to the centers are not available, if the centers are not coincident to the existing data points. So we use the sampling data point closest to the center of a cluster to represent the cluster. The closest data point is decided by its Euclidean distance to the center.

There is a loss of information during this process, but we can control the number of partitions to make sure only redundant data points are removed while keeping enough data points to represent all the sampling data in the input space. This is done by adjusting σ'. If $\sigma' \to 0$, then each sampling data point is a partition; if $\sigma' \to \infty$, there is only one partition.

The procedure of FAFCD is listed as follows:

1. Normalize the original data set.
2. Cluster the original data.
3. Find cluster centers and use them to form a new data set.
4. Calculate the fuzzy curves of y in each input-output space on the new data set.

5. Identify key input variables according to their Influence Rate.

Using FAFCD method, the importance of input variables of the force prediction system can be identified.

2.2 The Key Variables Identified using FAFCD

All the input variables and output variables in the original data set are normalized to the range of $[0, 1]$. Then using the fuzzy clustering method described earlier, a new data set with a different distribution to the original data set was obtained. On this new data set, the fuzzy average of y_j in each $x_i - y_j$ space was calculated. The importance of the input variables are indicated by their Influence Rate R. Based on the Influence Rate, we can identify the key variables.

According to the average Influence Rate to all the muscles, the importance of the kinematic variables and subject variables are ranked as shown in Table 1 and Table 2 respectively. It is clear that kinematic variables have more influence to forces than subject variables. Thus these twelve kinematic variables should all be selected as inputs in modelling. As for subject variables, five variables (standing height, shoulder height, lower arm length, spine length, lower leg length) have bigger influence than the others. These variables should also be taken as inputs in modelling. While examining the Influence Rates of two variables "standing height" and "shoulder height", we found that the Influence Rates of these two variables are very similar, for all forces. In other words, these two variables are correlated. They are dependent variables to each other. Therefore one of them can be removed. So at last twelve kinematic variables and four subject variables were kept. The input dimension is decreased from 27 to 16.

Table 1. Rank kinematic variables by their Average Influence Rate

Rank	Variable Name	Average Influence Rate
1	Sagittal Trunk Moment	0.171
2	Lateral Trunk Moment	0.150
3	Axis Trunk Angle	0.144
4	Sagittal Trunk Velocity	0.134
5	Axis Trunk Moment	0.120
6	Sagittal Trunk Angle	0.118
7	Axis Trunk Acceleration	0.117
8	Sagittal Trunk Acceleration	0.105
9	Lateral Trunk Velocity	0.100
10	Axis Trunk Velocity	0.097
11	Lateral Trunk Angle	0.090
12	Lateral Trunk Acceleration	0.088

Table 2. Rank subject variables by their Average Influence Rate

Rank	Variable Name	Average Influence Rate
1	Standing Height	0.091
2	Shoulder Height	0.090
3	Lower Arm Length	0.080
4	Spine Length	0.078
5	Lower Leg Length	0.066
6	body weight	0.052
7	Trunk Breadth (xyphoid)	0.050
8	Trunk Circumference	0.041
9	Trunk Depth (xyphoid)	0.033
10	Trunk Breadth (pelvis)	0.032
11	Upper Arm Length	0.030
12	Elbow Height	0.027
13	Upper Leg Length	0.017
14	Trunk Depth (pelvis)	0.012
15	Age	0.002

Knowing the influence of each variable, we can use the identified variables as inputs, instead of using hypothetically selected variables. This can greatly reduce the complexity of the model and time of modelling. In building the fuzzy neural model, less input variables means less free parameters and shorter training time.

3 Prediction of EMG Signals of Trunk Muscles using a Neural Network Model

Since there is strong relationship between kinematics and EMG activity, we can build models to simulate such a relationship. Many studies concentrated on predicting torque or kinematics from EMG [12, 13, 14], whereas predicting EMG from kinematics variables has seldom been done. Here an EMG signal prediction model is built using neural network. Kinematics variables and subject variables are selected as inputs of this model. By adding regional connections between the input and the output, the novel architecture of the neural network can have both global features and regional features extracted from the input. The global connections put more emphasis on the whole picture and determine the global trend of the predicted curve, while the regional connections concentrate on each point and modify the prediction locally. Back-propagation algorithm is used in the modeling. A basic structure of neural network designed for this problem is discussed. Then to overcome its drawbacks, a new structure is proposed.

The objective is to predict EMG magnitude of ten trunk muscles during manual lifting tasks. All the kinematics variables and the first four subject variables are selected as inputs (see Section 2). In addition, timing of the motion should also be considered as one of the input variables [15]. Without timing, the system is modeling the static states, instead of the process of the dynamic lifting motion.

3.1 A Basic Model

For the problem described above, a basic feedforward neural network model with one hidden layer can be built. At first, this model has seventeen input variables including twelve kinematics variables, four subject variables, and one timing variable. The outputs are normalized EMG magnitudes of ten trunk muscles (Right Latissimus Dorsi, Left Latissimus Dorsi, Right Erector Spine, Left Erector Spine, Right Rectus abdominus, Left Rectus Abdominus, Right External Oblique, Left External Oblique, Right Internal Oblique, and Left Internal Oblique).

As stated before, timing is used as an input variable in order to represent the process of lifting motion. But if the available measurements of motions are not synchronized, that is to say, the measurements did not capture the motions with the same starting point and the same ending point, then introducing inaccurate timing into the model would make the prediction doubtful in view of the fact that most data have not been synchronized.

In this basic model, we are predicting the EMG signals point by point. Each input vector consists of twelve kinematics variables of one sampling point of one subject, as well as the corresponding four subject variables. The timing variable determines the sampling point of the current input. The kinematics variables are time series, while the subject variables of each subject are constants. All sampling points of all subjects in a same motion were used to train the network one by one. As we can see that, the number of the training examples (training vectors) could be very big. If we have fifty subjects doing a particular motion and we got 100 sampling points for each subject, then the number of training examples will be 5000. The network has been found to often suffer from overtraining. Decreasing the learning rate can be helpful, but this will make the learning process very slow, and the prediction quality is also not good.

3.2 The Improved Model

The unsatisfactory performance of the conventional network model stated above shows that predicting point by point may not be a good idea. After all, we are modeling the whole motion. It might be better for us to predict the entire span of motion at one time. Therefore, another network with all the sampling points of a subject as one whole input vector is built. The outputs are EMG magnitudes of ten muscles of all the 100 sampling points. Thus the input space is composed of 12 (kinematics variables) * 100 (samplings) + 4 (subject variables) elements. The output space is composed of 10 (EMGs) * 100 (samplings) elements.

In this model, each training example is the whole motion of a subject. And the outputs are the EMG signals of the whole motion. This makes the problem very clear and easy to deal with. The global connections form a fully connected feedforward neural network with two hidden layers. To increase the importance of subject variables, the subject variables are connected directly to the second hidden layer [16]. Additional "regional connections" are added to connect the input neurons and output neurons which belong to the same sampling data point. The subject variables are also connected to them.

The simulations show that if proper hidden layers and nodes are selected, the fully-connected neural network without regional connections is able to capture the kinematics-EMG characteristics. However, this model has two drawbacks. Firstly, although no explicit timing variable exists, this model also suffers from asynchronization of the motion. That is because the sampling data points are arranged in time sequence in the input space. Secondly, this big network is insensitive to subject variables. The importance of an individual input is decreased because too many inputs exist. To overcome these limitations, the regional connections are added to the model. Since they only connect the input neurons and output neurons which belong to the same sampling point, this model has a better "locality". When the values in a small area of the input space changed, it will only influence the output of the corresponding small area, without interfering values outside this small area.

3.3 Advantages

The first advantage of this model is that it takes the interactions between muscles into account. The muscle activities are complex in the motion. It is known that the interactions between muscles will influence the EMG signals. By learning the whole motion, the new model can take this into account. This is a global feature that can not be extracted from isolated sampling points. Although the timing is used as one of the inputs in the previous basic model, the input-output pairs are still independent points. When the data of one sampling point are fed into the network, the behavior of the muscles before and after this point is unavailable to the network. But when the data of the whole motion are fed into the network, such information is included. The second advantage is that the training time of this model is much shorter than the training time of the previous one. That is because we are predicting one sampling point at one time in the previous model. But in this model, we are predicting the whole motion of one subject.

The improved model has better locality. For the model without regional connections, although the MAE of the prediction is not bad, the prediction doesn't fit the curve very well in the small regions. By extracting the local features and modifying the output regionally, the model with regional connections can produce a better prediction.

The improved model does not suffer from incorrect timing. As mentioned before, the network without regional connections suffers from incorrect timing. If the data used to train the model captured the whole process of the motion, their EMG pattern normally will be first going up, then going down, ending with a low level of EMG value. This is typical since during the lifting, the muscle will first contract, and then begin to relax. If in a lifting motion, the rear part of the motion is missing (which means the recorded data start from the beginning of the motion, but end before the motion is finished), the incomplete motion will not follow such trend. However, in the basic model, the neural network will take it as complete. This makes the prediction not so satisfactory. After the regional connections are added, the timing is no longer a problem. Since these connections are connected "regionally", local features of each sampling point are extracted by them.

3.4 Results

The developed model gives good prediction quality in most situations. The MAEs of females are normally larger than that of males. For different muscles, we found that four muscles (Right Rectus Abdominus, Left Rectus Abdominus, Right External Oblique, and Left External Oblique) have smaller MAE than others. That is because for the manual lifting motion, the EMG signals of these four muscles are more or less static. Therefore they are easier to predict than others. We also found that the MAEs of the left muscles were larger than MAEs of the corresponding right muscles.

Simulations also indicate that the more complex the motion is, the more difficult to predict its EMG signals. In a trial that the weight of the object to be lifted is 15 lbs, the original height is floor, and the destination height is waist, then the overall MEA of the motion is 7.5%. But if the subject is also requested to turn his body for 60 degrees, the overall MEA increases to more than 10 percent. That is because the motion is not symmetric.

4 Prediction of Spinal Forces using a Recurrent Fuzzy Neural Network Model

Neural and fuzzy approaches have been used to improve or replace the biomechanics model. In [12], Lin et al. predicted the muscle activations from EMG signals using a four-layer feed-forward neural network model trained by back-propagation learning algorithm. Luh et al. built a neural network to model the relationship between the EMG activity and elbow joint torque [17]. Liu et al. useed a neural network to predict dynamic muscle forces from EMG signals [18]. In [19] and [20], neuro-fuzzy models were developed for EMG signal classification and prosthesis control. These findings focus on building the relationship between the EMG signals of muscles and the forces on the joint. They all require the EMG signals be measured in the laboratory, which is time consuming and often impractical in industry.

To predict the dynamic forces on lumbar spine without the measuring of EMG signals and the use of biomechanics model, a recurrent fuzzy neural network (RFNN) model is built. The feedback makes it possible to take past information into account. The output of the model is computed by the current data as well as the preceding data. Time delay is incorporated in the feedback connections. It serves to preserve the past information so that the RFNN is able to handle the dynamics. A learning algorithm is used to modify the RFNN's both premise parameters and consequent parameters in order to correctly identify the nonlinear relationship between the input and output.

In the spinal load estimation model, EMG signals are used as intermediate output and are fed back to the input layer. By doing that, more information (EMG) was provided to the model and the feedback of the intermediate output has a physical meaning (the direct relationship of EMG-force). This reflects the dynamics of the system in a clear and straightforward way. At the same time, the advantages of recurrent property is utilized. The rules generated from the model can be easily interpreted and can help us understand the muscle activities better. This solves the problem that the input and output of the system have no direct and explicit physical connection. At the same time, the advantages of recurrent neural network are utilized.

4.1 Model Construction

The EMG signals of ten trunk muscles are scaled and delayed before they are fed back to the input layer. The delay of EMG is used to represent the muscle activation dynamic properties. The interaction between muscles influences the EMG and the forces on the spine. By presenting the previous EMG to the input, we hope the modle can take such interaction into account. Direct physical relationships (kinematics data-EMG and EMG-force) reside in the model. The identified kinematic variables and subject variables are inputs of the model. Forces on the spine (lateral shear force, A-P shear force and spinal compression) are outputs of the model. They are not the forces measured from the experiments since they can not be measured directly. They are actually the forces obtained from the biomechanics model. After the direct prediction model is built, the biomechanics model will be no longer needed in future.

The function of each layer is described as follows.

Layer 1 is the input fuzzification layer, which represents linguistic sets in antecedent fuzzy membership functions. Each neuron describes a membership function and encodes the center and width of membership functions. The output of this layer is the degree of membership of each input:

$$y_j^1 = \mu_{ij}(x_i) \tag{5}$$

For external input, the following Gaussian membership function is used:

$$\mu_{ij}(x_i) = exp(-(\frac{x_i - \bar{x}_{ij}}{\sigma_{ij}})^2) \tag{6}$$

For the feedback input, the following sigmoid membership function is used:

$$\mu_{ij}(x_i) = \frac{1}{1 + exp(-x_i)} \tag{7}$$

Layer 2 computes the firing strength of each fuzzy rule. Nodes in this layer perform the product operation. Those links establish the antecedent relation which is an “AND” association for each fuzzy set combination (both the external input and the feedback). The output of this layer is the firing strength of each fuzzy rule:

$$y_j^2 = \Pi_{i=1}^n \mu_{ij}(x_i) \tag{8}$$

Layer 3 normalizes the firing strength of each fuzzy rule. The output of the third layer is the normalized firing strength of each fuzzy rule:

$$y_j^3 = \frac{\Pi_{i=1}^{n} \mu_{ij}(x_i)}{\sum_{j=1}^{m} \Pi_{i=1}^{n} \mu_{ij}(x_i)} \tag{9}$$

Layer 4 is the defuzzification layer. Center Average defuzzificaiton is used here. The output of this layer is the overall output using Center Average defuzzification:

$$y_j^4 = \sum_{j=1}^{m} y_j^3 W_{jk} \tag{10}$$

During the training process, both the consequent and the premise parameters are tuned simultaneously. The fuzzy rules are discovered from and refined by the given input/Output data. The forces predicted for time t depend on not only the inputs at time t, but also the predicted EMG at time $t-1$, which again depend on the previous inputs. This is a dynamic approach that can represent the dynamic properties of the forces better than a feedforward network.

4.2 Simulations and Results

The performance of the proposed recurrent fuzzy neural network is evaluated with two kinds of data. One is the sagittal symmetric lifting motions, while the other one includes nonsymmetrical lifting motions. To make the results comparable, similar task variables and subject variables are selected for these two motions. In both motions, the weight of the object is 30 lbs, lift height is 30 cm, lift style is stoop, and both-handed.

In a sagittal symmetric lifting motion, the subject does not turn his body. The motion is done sagittally. This kind of motion is simpler and easier to model, comparing to the nonsymmetrical motions. Simulations show that the recurrent fuzzy neural network can model the kinematics-EMG-force relationship and give an satisfactory prediction.

If we are predicting the asymmetrical motions, we could expect that the prediction errors will be bigger compared to the sagittal symmetric motions. That is because the motion is nonsymmetrical, thus more complex than the symmetric motions. The subjects were required to turn their bodies during the lifting task.

Statistical results are used to evaluate the system performance on different types of tasks. The overall Mean Absolute Errors (MAEs) of different tasks are shown in Table 3. The variations of lateral shear force, A-P shear force and the spinal compression are around 300 Newtons, 800 Newtons and 2500 Newtons, respectively. The MAEs are out of such ranges. From the results we can see that the MAEs of the predicted sagittal symmetric tasks are much smaller than those of the prediction for nonsymmetrical tasks. This is reasonable since the muscle activities are much more complicated in the nonsymmetrical tasks.

Table 3. Overall MAEs of different types of motions. The values are forces in Newtons (percentage errors are in brackets).

Force Names	Unsym. Motion	Sag. Sym. Motions
LSF	25.5 (8.22%)	20.5 (6.61%)
ASF	80.0 (9.52%)	68.5 (8.15%)
CMP	192.5 (7.86%)	167.0 (6.82%)

5 Conclusions

This chapter discussed the EMG and spinal force evaluation models using neural and fuzzy approaches. Input variables of the models were identified using a fuzzy approach, which greatly reduce the dimension of the input space of the models. A neural network model and a recurrent fuzzy neural network model were built for EMG evaluation and spinal force evaluation, respectively.

In the neural network model, the global connections provide the model's basic prediction reference, while the additional connections enable the model to extract the relationships among regional inputs. The additional connections can reduce the adverse influence of the problem of incorrect timing.

In the recurrent fuzzy neural network model, EMG was fed back to the input, acting as a bridge between the input and the output. The delayed EMG feedback allows for better representation of the muscle activation dynamics. At the same time, the advantages of recurrent neural network can be utilized. The model predicts forces directly from kinematics data, avoiding EMG measurements and the use of biomechanical model.

References

1. W. Karwowski, W.S. Marras (Editors), "The Occupational Ergonomics Handbook", 1999, CRC Press, Boca Raton.
2. P.A. Crosby, "Use of surface electromyogram as a measure of dynamic force in human limb muscles", *Med. and Biol. Eng. and Comput.*, vol. 16, 1978, pp. 519–524.
3. D.G. Lloyd, Besier, T.F., "An EMG-driven Musculoskeletal Model to Estimate Muscle Forces and Knee Joint Moments in Vivo", *Journal of Biomechanics*, 36 (2003), pp. 765–776.
4. W. Lee, W. Karwowski, W.S. Marras, D. Rodrick, "A neuro-fuzzy model for estimating electromyographical activity of trunk muscles due to manual lifting", *Ergonomics* 46 (1-3), JAN 15 2003, pp. 285–309
5. Y. Hou, J.M. Zurada, W. Karwowski, "Prediction of EMG Signals of Trunk Muscles in Manual Lifting Using a Neural Network Model", *Proc. of the Int. Joint Conf. on Neural Networks*, Jul. 25-29, 2004, pp. 1935–1940
6. Y. Hou, J.M. Zurada, W. Karwowski, W.S. Marras, "Prediction of Dynamic Forces on Lumbar Joint Using a Recurrent Neural Network Model", *Proc. of the 2004 Int. Conf. on Machine Learning and Applications (ICMLA'04)*, Dec. 16-18, 2004, pp. 360–365

7. Y. Hou, J.M. Zurada, W. Karwowski, "A Hybrid Neuro-fuzzy Approach for Spinal Force Evaluation in Manual Materials Handling Tasks", 2005 International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2005), submitted.
8. Y. Lin, G.A. III Cunningham, "A new approach to fuzzy-neural system modeling"; *IEEE Trans. on Fuzzy Systems*, vol. 3, no. 2, May 1995 pp. 190–198
9. Y. Lin; G.A. Cunningham, S.V. Coggeshall, R.D. Jones, "Nonlinear system input structure identification: two stage fuzzy curves and surfaces"; *IEEE Trans. on Systems, Man and Cybernetics*, vol. 28, no. 5, Sept. 1998 pp. 678 -684
10. Y. Hou, J.M. Zurada, W. Karwowski, W.S. Marras, "Identification of Input Variables using Fuzzy Average with Fuzzy Cluster Distribution"; *IEEE Trans. on Fuzzy Systems*, submitted.
11. S. Auephanwiriyakul, J.M. Keller, "Analysis and efficient implementation of a linguistic fuzzy c-means"; *IEEE Trans. on Fuzzy Systems*, vol. 10, no. 5, Oct. 2002 pp. 563–582
12. L. Wang, T.S. Buchanan, "Prediction of Joint Moments Using a Neural Network Model of Muscle Activations from EMG Signals," *IEEE Transactions on Systems and Rehabilitation Engineering*, 10(1), March 2002 pp. 30–37.
13. T.C. Arthur, F.K. Robert, "EMG-based Prediction of Shoulder and Elbow Kinematics in Able-bodied and Spinal Cord Injured Individuals", *IEEE Transactions on Rehabilitation Engineering*, 8(4), Dec.2000 pp. 471–480.
14. C.S. Pattichis, C.N. Schizas, "Genetics-based Machine Learning for the Assessment of Certain Neuromuscular Disorders", *IEEE Transactions on Neural Networks*, 7(2), March 1996 pp. 427–439.
15. B. Verma, C. Lane, "Vertical Jump Height Prediction Using EMG Characteristics and Neural Networks",*Journal of Cognitive System Research* 1920000 pp. 135–141.
16. S.T. Chen; D.C. Yu, and A.R. Moghaddamjo, "Weather Sensitive Short-Term Load Forecasting Using Nonfully Connected Artificial Neural Network", *IEEE Transactions on Power Systems* 7(3), pp. 1098–1105.
17. J.J. Luh, G.C. Chang, C.K. Cheng, J.S. Lai, T.S. Kuo,, "Isokinetic elbow joint torques estimation form surface EMG and joint kinematic data: Using an artificial neural network model", *J. Electromyogr. Kinesiol.*, vol. l, no. 9, 1999, pp. 173–183.
18. M.M. Liu, W. Herzog, H. H. Savelberg, "Dynamic muscle force predictions from EMG: An artificial neural network approach", *J. Electromyogr. Kinesiol.*, vol. 9, 1999, pp. 391–400.
19. S.E. Hussein, M.H., Granat, "Intention detection using a neuro-fuzzy EMG classifier", *Engineering in Medicine and Biology Magazine, IEEE*, vol. 21, no. 6, Nov.-Dec. pp. 123–129
20. K. Kiguchi, T. Tanaka, T. Fukuda, "Neuro-fuzzy control of a robotic exoskeleton with EMG signals", *IEEE Transactions on Fuzzy Systems*, vol. 12, no. 4, Aug. 2004 pp. 481–490
21. S. Wu and M. J. Er, "Dynamic fuzzy neural networks-a novel approach to function approximation," *IEEE Trans. on Systems, Man and Cybernetics* B, vol. 30, Apr. 2000, pp. 358–364.
22. S. Wu, M. J. Er, and Y. Gao, "A fast approach for automatic generation of fuzzy rules by generalized dynamic fuzzy neural networks," *IEEE Trans. on Fuzzy Systems*, vol. 9, Aug. 2001, pp. 578–594.
23. C.F. Juang and C.T. Lin, "An on-line self-constructing neural fuzzy inference network and its applications", *IEEE Trans. on Fuzzy Systems*, vol. 6, pp. 12–32, Feb. 1998.
24. C.H. Lee and C.C. Teng, "Identification and control of dynamic systems using recurrent fuzzy neural networks", *IEEE Trans. on Fuzzy Systems*, vol. 8, no. 4, Aug. 2000 pp. 349–366.

25. C.M. Lin and C.F. Hsu, "Supervisory recurrent fuzzy neural network control of wing rock for slender delta wings", *IEEE Trans. on Fuzzy Systems*, vol. 12, no. 5, Oct. 2004 pp. 733–742.
26. C.F. Juang, "A TSK-type recurrent fuzzy network for dynamic systems processing by neural network and genetic algorithms", *IEEE Trans. on Fuzzy Systems*, vol. 10, no. 2, Apr. 2002 pp. 155–170
27. F.J. Lin, R.J. Wai, "Hybrid control using recurrent fuzzy neural network for linear-induction motor servo drive", *IEEE Trans. on Fuzzy Systems*, vol. 9, no. 1, Jan. 2001 pp. 68–90.
28. F.J. Lin, R.J. Wai, C.M. Hong, "Hybrid supervisory control using recurrent fuzzy neural network for tracking periodic inputs", *IEEE Trans. on Neural Networks*, vol. 12, no. 1, Feb. 2001 pp. 102–115.
29. Y.C. Wang, D. Zipser, "A learning algorithm for continually running recurrent neural networks", *Neural Comput.*, vol. 1, no. 2, 1989 pp. 270–280.
30. R.J. Williams, C.J Chien, C.C. Teng, "Direct adaptive iterative learning control of non-linear systems using an output-recurrent fuzzy neural network", *IEEE Trans. on Systems, Man, and Sybernetics*, vol. 34, no. 3, Jun. 2004 pp. 1348–1359.
31. J. Zurada, W. Karwowski, and W. S. Marras, "Classification of Jobs With Risk of Low Back Disorders by Applying Data Mining Techniques", *Occupational Ergonomics*, 2005, vol. 5 no. 1, pp. 1–15.
32. W. Karwowski, "Cognitive Ergonomics: Requisite Compatibility, Fuzziness And Nonlinear Dynamics", Proceedings of *the 14 th Triennial Congress of International Ergonomics Association and the 35th Annual Meeting of the Human Factors Society*, San Diego, CA, 2000, pp. 1–580 * 1–583.
33. W. Karwowski, "The Human World of Fuzziness, Human Entropy, and the Need for General Fuzzy Systems Theory", *Journal of Japan Society for Fuzzy Theory and Systems*, 1992, vol. 4 no. 5, pp. 591–609
34. W. Karwowski, J. Grobelny, Y. Yang, and W.-G. Lee, "Applications of Fuzzy Systems in Human Factors", in: H. Zimmermman (Ed.), *Handbook of Fuzzy Sets and Possibility Theory*, Kluwer Academic Publishers, Boston, 1999, pp. 589–621.
35. W. Karwowski, and A. Mital, (Editors), "Applications of Fuzzy Set Theory in Human Factors", Elsevier Science Publishers, Amsterdam 1986.
36. G. W. Evans, W. Karwowski, and M. R. Wilhelm, (Editors), "Applications of Fuzzy Set Methodologies in Industrial Engineering", Elsevier Science Publishers, Amsterdam. 1989.