Prediction of EMG Signals of Trunk Muscles in Manual Lifting Using a Neural Network Model

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***Abstract*—An EMG (electromyography) signal prediction model is built using artificial neural network. Kinematics variables and subject variables are selected as inputs of this model. A novel structure of feedforward neural network is proposed in this paper to obtain better accuracy of prediction. By adding regional connections between the input and the output, the new 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, we propose a new structure.**

I. Introduction

EMG signals provide important characteristics that describe muscle activities during motion of the human body. Yet to measure these signals is very costly and the amount of related data is very large. EMG waves, however, can be treated and analyzed as responses of a system that takes kinematics measurements and other auxiliary factors as inputs. The objective of this paper is to develop working model of systems involving manual lifting tasks that would translate kinematics data into EMG activity.

Since there is strong relationship between kinematics and EMG activity, we can build models to simulate the relationship and predict one by using the other one. Many studies concentrated on predicting torque or kinematics from EMG [1], [2], [3], whereas predicting EMG from kinematics variables has seldom been done. Here we are trying to build such a model that uses kinematics (and other variables) as input to predict the EMG signals. Since the exact relationship between the multiple input variables and EMG signal is not clear, finding the transfer function between them is difficult. The ANNs can extract the implicit nonlinear relationship between the signals by learning from training data. This makes it a proper method for building the kinematics - EMG model, thus we can avoid establishing a complex mathematical model to express the muscle activation dynamics.

Our task is to predict the EMG magnitude of ten trunk muscles during manual lifting tasks. It is important to know which variables affect the EMG signals during the motion, so that they can be selected as input variables for our model. Obviously the kinematics variables such as velocities, accelerations, and angles recorded during the motion will affect the output EMG. Furthermore, the differences between subjects also affect the EMG. Different people will produce different patterns of EMG signal even though the kinematics data may be similar in doing the same task. So both kinematics variables and subject variables (weight, height, arm length, etc.) are selected as inputs. In addition, timing of the motion should also be considered as one of the input variables [4]. Without timing, the system is modeling the static states, instead of the process of a motion. Some other variables may also have certain influence on the EMG, but for simplicity, They are not introduced into the model.

A. Kinematics Variables

Trunk Moment, Trunk Angle, Trunk Velocity and Trunk Acceleration are the parameters used to describe the kinematics of the motion. Each of them has three aspects: Sagittal, Lateral, and Axis. For instance, in the case of trunk moment, there are three variables: Sagittal Trunk Moment, Lateral Trunk Moment, and Axis Trunk Moment. So totally there are 12 kinematics variables used in the model.

B. Subject Variables

The differences between subjects have important influence on the EMG signals. For better prediction, some "subject variables" which describe the characteristics of the subjects are selected as part of the input. These variables include gender, age, weight, standing height, shoulder height, elbow height, upper leg length, lower leg length, upper arm length, lower arm length, spine length, trunk depth (pelvis), trunk breath (pelvis), trunk depth (xyphoid), trunk breath (xyphoid), and trunk circumference.

II. Methods

A. 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 28 input variables including 12 kinematics

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variables, 15 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 whole process of a 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 12 kinematics variables of one sampling point of one subject, as well as the corresponding 15 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 huge. If we have 50 subjects doing a particular motion and we got 100 sampling points for each subject, then the number of training examples will be 5000. Because of too many training examples, 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.

B. 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 10 muscles of all the 100 sampling points. Thus the input space is composed of 12 (kinematics variables) * 100 (samplings) + 15 (subject variables) elements. The output space is composed of 10 (EMGs) * 100 (samplings) elements.

1) Structure overview: 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 structure of the new model is shown in Fig. 1. The solid connections form a fully connected feedforward neural network with two hidden layers. The darkest "neurons" stand for the subject variables. To increase the importance of subject variables, they are connected directly to the second hidden layer [5]. The dotted connections are additional "regional connections". They only connect the input neurons and output neurons which belong to the same sampling point (variables of the first sampling point are enclosed in the dashed rectangle). The white "neurons" in the figure are hidden neurons of the additional connections. The subject variables are also connected to them.

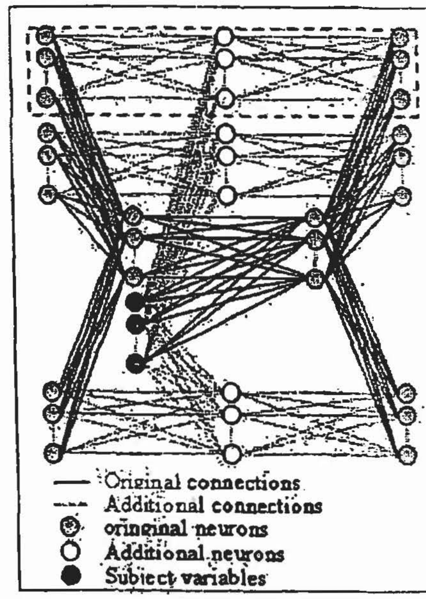

Fig. 1. The neural network structure with regional connections

2) Structure evolution: The global connections (solid connections) have two hidden layers, with 100 hidden units in each layer. Since increasing the number of hidden neurons did not get better learning result in the simulations, the second hidden layer is added. Because of a big input size, adding a layer can increase learning capability of our model.

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. Nevertheless, 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 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) 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.

4) Algorithm: The hyperbolic tangent activation function (tanh) is used in the hidden layers, while the unipolar sigmoid activation function f_u= 1/(1+exp(-0.1*net) is used in the output layer. This is because the range of the normalized EMG data is from 0 to 1, which fits the output range of the unipolar sigmoid activation function.

The output of the first hidden layer of the global connections can be expressed as:

$$\mathbf{Y}^{l1}_{global} = \tanh(\beta * \mathbf{V}^{l1}_{global} * \mathbf{X}_{global})$$

$\mathbf{V}^{l1}_{global}$ is the weight matrix of the first hidden layer of the global connections.

$\mathbf{X}_{global}$ is the input vector of the global connections (it contains all the sampling points).

β is the slope of the hyperbolic tangent activation function, and tanh function operates on each element of the product of $\mathbf{V}^{l1}_{global}$ and $\mathbf{X}_{global}$.

$\mathbf{Y}^{l1}_{global}$ is the output vector of the neurons of the first hidden layer.

Similarly, the output of the second hidden layer can be expressed as:

$$\mathbf{Y}^{l2}_{global} = \tanh(\beta * \mathbf{V}^{l2}_{global} * [\mathbf{Y}^{l1}_{global} \,;\, \mathbf{S}])$$

$\mathbf{V}^{l2}_{global}$ is the weight matrix of the second hidden layer of the global connections.

S denotes the vector of subject variables.

$[\mathbf{Y}^{l1}_{global} \,;\, \mathbf{S}]$) concatenates S to the input vector of the second layer because subject variables are connected to this layer directly.

$\mathbf{Y}^{l2}_{global}$ is the output vector of the neurons of the second hidden layer.

Then the scalar product of $\mathbf{Y}^{l2}_{global}$ and the weights is calculated:

$$\mathbf{O}'_{global} = \mathbf{W}_{global} * \mathbf{Y}^{l2}_{global}$$

$\mathbf{W}_{global}$is the weight matrix of the output layer of the global connections.

Similar to the above, the forward pass of regional connections computes:

$$\mathbf{Y}_{regional\_i} = \tanh(\beta * \mathbf{V}_{regional\_i} * \mathbf{X}_{regional\_i})$$

$$\mathbf{O}'_{regional\_i} = \mathbf{W}_{regional\_i} * \mathbf{Y}_{regional\_i}$$

The subscript $regional\_i$ means the regional connections of the ith sampling point. There are 100 sampling points, so i is from 1 to 100.

Then the neurons of the output layer combine the outputs of both the global connections and the regional connections:

$$\mathbf{O}'_{combined\_i} = \mathbf{O}'_{regional\_i} + \mathbf{O}'_{global(i\_to\_i+10)}$$

$$\mathbf{O}_{combined} = f_u(\mathbf{O}'_{combined})$$

$\mathbf{O}'_{global(i_to_i+10)}$denotes part of vector $\mathbf{O}'_{global}$ which has the elements only from i to $i + 10$ (output of the ith sampling point).

Backward pass of the error back propagation algorithm is omitted here.

III. SIMULATIONS

A. Model parameters

Some parameters of the model are listed below, in which "global" stands for the global connections in the model, and "regional" stands for the regional connections in the model. For example, "Global learning rate" means the learning rate of the global connections. "Regional learning rate" means the learning rate of the regional connections (The global connections and the regional connections often need different learning rates, in order to make sure they can be fully trained at the same time).

TABLE I
MODEL PARAMETERS

Global hidden units	100 + 100
Regional hidden units	35
Global learning rate	0.01
Regional learning rate	0.05
Momentum	0.8
Maximum Epoch Number	1000

B. Data preprocessing

Ill-conditioning of the data could greatly decrease the performance of a neural network model. Our data from experiments are raw data, which need preprocessing before they are used in the model.

Since the motions done by different subjects are not synchronized very well, incorrect timing will make the prediction more difficult. Thus having the motions synchronized as good as possible is one of the goals in data preprocessing.

Some subjects might move faster than the others in doing a motion. Subsequently, the sampling points of their motions may be fewer than those move slower. Since the input dimension of our model is constant, we have to redo the sampling by using a program, to keep all the data have the same number of sampling points.

The raw kinematics data have different ranges. Some of them have a range from -150 to +150, while some others may change only from 0.2 to 0.9. Such data must be normalized before use. In our model, all input variables are normalized to the range from -2.0 to 2.0. Subject variables are also normalized. Gender was coded into: male: 2, female: -2. Other subject variables were normalized to the range from -2.0 to 2.0.

Because the unipolar sigmoid activation function was used in the output layer, the target (EMG) need to be normalized to the range of 0.15 to 0.85, to avoid the saturation regions of the activation function.

C. Other considerations

Nguyen-Widrow initialization [6] method was used to initialize the weights. Simulations show that in our case this kind of initialization helps the model to avoid saturation of some neurons. It was found that the states of hidden neurons often became saturated (-1 or 1) quickly, after several training epochs. This happens even the inputs have been normalized and the initial weights are small. The saturation of the hidden neurons makes the output of the network become very reluctant to change. Nguyen-Widrow initialization has been found to solve this problem very well.

Cross-validation is used to prevent the network from overfitting the patterns. We divide the subjects into a training set, a test set and a validation set. Every so often, we check the network performance on the validation set. If we find that the error rise on the validation set reaches the maximum error rise allowed, we stop the learning.

IV. RESULTS

A. The model has better locality

Fig. 2 shows EMG signal of muscle "Left Erector Spine" in a motion. The solid curves are the predicted EMG signals. We can see that 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 (Fig. 3).

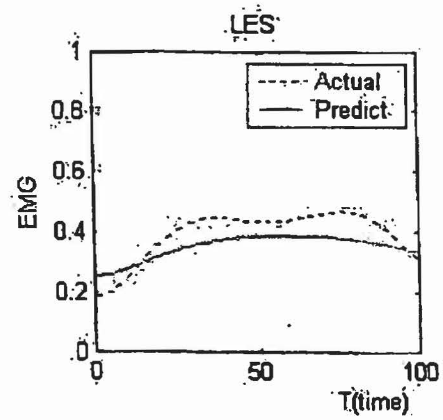

Fig. 2. Prediction of the network without regional connections -bad locality

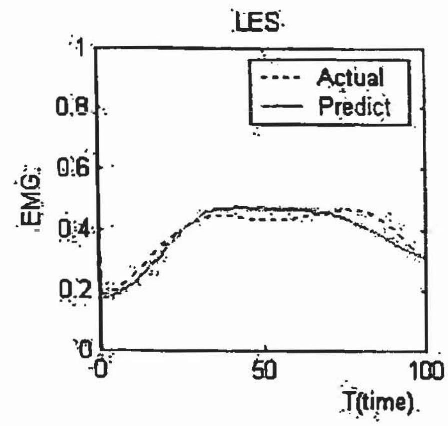

Fig. 3. Prediction of the network with regional connections - good locality

B. The model does not suffer from incorrect timing

As mentioned before, the network without regional connections suffers from incorrect timing. This is demonstrated on Fig. 4. The dotted line is the actual EMG signal of muscle "Left Erector Spine". It was generated in a lifting motion. But the rear part of the motion is missing. That means the recorded data start from the beginning of the motion, but end before the motion is finished. If data of other subjects (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. In Fig. 4 the incomplete motion does not follow such trend. But when we are trying to predict this motion, the neural network will take it as complete. As shown in Fig. 4, the predicted curve (solid curve) goes down as if the motion is 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. Fig. 5 shows the improved prediction.

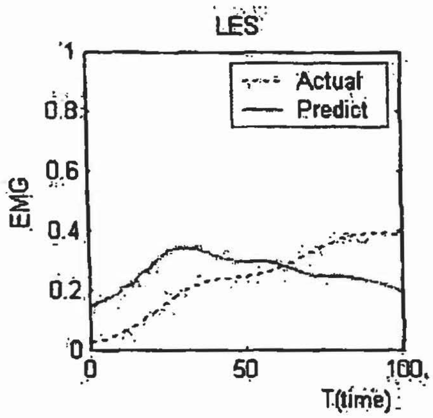

Fig. 4. The network without regional connections suffers from incorrect timing

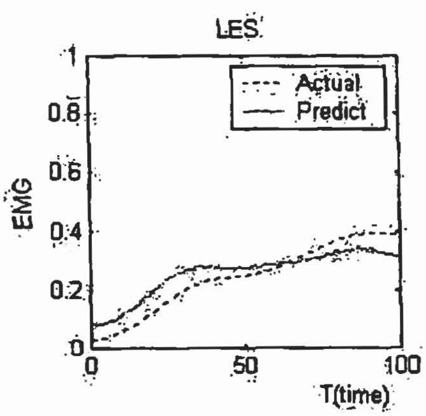

Fig. 5. The network with regional connections does not suffer from incorrect timing

C. *Statistics results*

The model gives good prediction quality in most situations. Table II shows some examples of the Mean Absolute Errors (MAEs) of the prediction. The first row is the subject name, and the first column is the trunk muscle name. The MAEs are given in percentage. They are calculated by using the following formula.

$$MAE = \frac{\sum_{1}^{K} |Actual\_EMG - Predicted\_EMG|}{K(Number\_Of\_Evaluated\_Data)}$$

In Table II, The first four subjects are males and the last four are females. The MAEs of females are normally bigger than that of males. That maybe indicate that the muscles of females have more complex activities than males. And this makes the prediction more difficult.

Fig. 6 and Fig. 7 show the MAEs for different muscles in the same motion. It is obvious that the result of proposed network has smaller errors (the "traditional model" refers to the basic model stated in part II). For different muscles, we can see 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 can find that the MAEs of the left muscles often bigger than MAEs of the corresponding right muscles. The possible reason is that the muscles in the left side have higher levels of muscular activity.

TABLE II
MAEs OF SOME PREDICTIONS

	AM	BH	BM	CL	BF	CD	DP	HS
RLD	4.2	2.1	5.2	2.7	5.2	3.2	2.5	3.7
LLD	5.1	4.0	4.9	3.9	4.2	4.1	2.0	5.4
RES	5.6	9.1	8.3	7.9	8.3	9.0	8.3	8.4
LES	6.1	10.7	8.4	8.3	9.5	9.7	11.1	9.8
RRA	1.2	3.7	3.3	4.5	3.5	4.7	1.5	3.2
LRA	1.3	4.6	3.5	3.4	5.0	3.4	4.3	2.6
REO	0.9	4.1	2.2	1.6	2.8	2.7	4.1	2.8
LEO	1.9	5.3	2.2	1.5	5.2	2.9	2.2	3.2
RIO	4.0	8.6	8.3	5.2	10.7	5.8	7.4	9.8
LIO	6.8	7.5	8.8	8.9	9.4	10.5	8.3	9.5

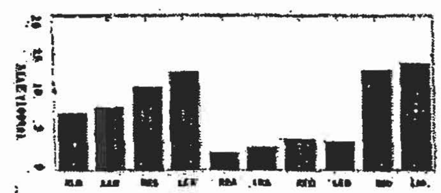

Fig. 6. Overall MAEs of each trunk muscle (result of the traditional network)

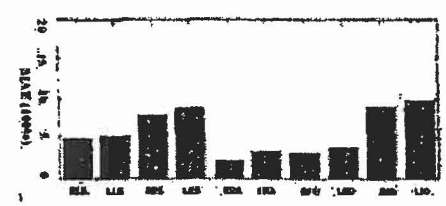

Fig. 7. Overall MAEs of each trunk muscle (result of the proposed network)

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.

More EMG related studies can be done with this model.

V. Conclusions

The architecture of the neural network model proposed and used in this paper ensures a robust and reliable 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 subject variables are fed to the second hidden layer of the global connections. These direct feedforward connections can alleviate the curse of dimensionality and enhance the importance of subject variables. The learning efficiency is also improved by doing so.

The additional connections can reduce the adverse influence of the incorrect timing problem, because they only connect regionally from the inputs to the outputs, inside the range of one sampling point.

One drawback of this model is that it needs "tuning" of the learning process of the global connections and the regional connections, to make both of them trained at the same time.

The subject variables are supposed to play an important role in EMG prediction. We have already employed many methods to increase their importance in the input vector, but in the simulation their influence on the output is less significant than was initially expected. The possible reason is that some subject variables are not important at all. The inclusion of variables in the input vector that have no underlying relationship with the output does not improve the performance of the model. We may improve it by selecting proper subject variables.

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