Prediction of Dynamic Forces on Lumbar Joint Using a Recurrent Neural Network Model

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***Abstract*— We propose a modified recurrent neural network model which establishes the relationship between kinematics and the dynamic forces on lumbar joint. By doing that we can have the forces predicted directly from kinematic variables while bypassing the costly procedure of measuring EMG (electromyography) signals and avoiding the use of biomechanics model. In the proposed model, we introduce the EMG signal as an intermediate output and loop it back to the input layer, instead of looping back the ultimate output, the forces. Since the EMG signal is a direct reflection of muscle activity, the most valuable point of this model is that the back-looping of the intermediate output has physical meaning. It 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.**

I. Introduction

A. Predicting Forces on Lumbar Joint

Manual materials handling tasks in industry often cause occupationally-related low back disorders. Studying the forces applied to a joint is fundamental to the understanding of joint injury [1]. Therefore the forces on the lumbar joint during manual lifting are very useful in judging if such a task is risky or not. However such forces can not be measured directly. The conventional way is that first we measure the EMG signals during the motion then obtain forces through a biomechanics model, as shown in Fig. 1 (A). Measuring the EMG signals is because the EMG is a direct reflection of muscle activity and the transfer function between EMG and muscle force has been found by system identification techniques [2].

Researches have been done to use a neural network model to improve or replace the biomechanics model in Fig. 1 (A). In [3], 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. Because the muscle activation could not be measured, a Hill-type muscle-tendon model that transforms the muscle activations to muscle forces was used. The ANN model represented the relationship between EMG signals and joint moments well. Luh et al. built a three-layer feed-forward neural to model the relationship between the EMG activity and elbow joint torque [4]. Liu et al. created a neural network to predict dynamic muscle forces from EMG signal [5].

All the above researches concentrate 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 costly and time consuming.

The objective of this paper is to develop a model involving manual lifting tasks that would translate kinematics data (and other auxiliary data) into forces on lumbar joint while bypassing the costly procedure of measuring EMG signals and at the same time, avoiding the use of biomechanics model. Task variables, subject variables (anthropic characteristics) and kinematics variables are used as the input data. The model diagram is shown in Fig. 1 (B).

B. Recurrent Neural Network (RNN)

Recurrent neural network is basically a feedforward network with added feedback connections. The back-looping makes it possible to take past information into account. The output of the model is computed by the current data which is presented as input as well as the preceding data. Time delay is incorporated in the feedback connections. It serves to preserve the historical information so that the RNN is able to handle the dynamics [6].

One commonly used RNN model is the Elman model, which has feedback connections from its hidden neurons back to its inputs [7]. Besides looping back the hidden layer, feeding back the output layer to the input is also widely used [8][9].

It was shown that the recurrent neural network is suitable for dynamic time series prediction and can provide satisfactory results [10] [11] [12].

In this paper, a modified recurrent neural network model is proposed for the prediction of dynamic forces on lumbar joint. In the proposed model we do not loop back the hidden layer or the actual output layer. We introduce the EMG signal as an intermediate output and feed it back to the input layer, instead of feeding back the forces.

II. Methods

A. Model Construction

To avoid measuring the EMG signal and build a direct load prediction system, we can construct a neural network that

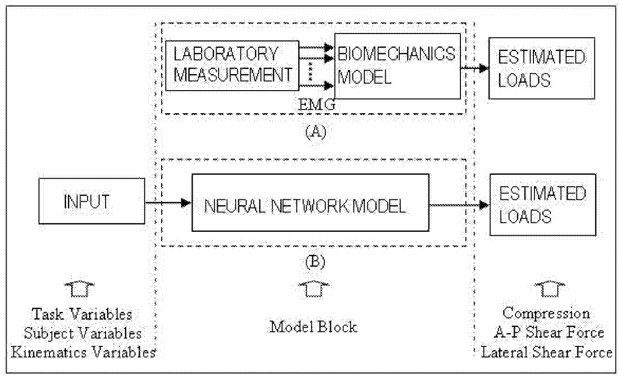

Fig. 1. EMG-drive load prediction system and neural network based direct load prediction system A) Conventional EMG-drive load prediction system method B) Neural network based direct load prediction system (laboratory measurements of EMG and biomechanics model are avoided)

takes kinematics data as input and predicts the corresponding dynamic forces.

This is not a conventional EMG-drive load prediction system. One problem of this model is that the physical connection between the kinematics and the forces on lumbar joint is not as direct and explicit as the connection between the EMG signal and the forces. As stated before the EMG signal is a direct reflection of muscle activity. Although the information of the connection with forces may exist in the kinematics data, it might be best to utilize the direct relationship between EMG and muscle force.

EMG signal is also related with the kinematics variables. Kinematics variables, together with the anthropic characteristics of the subject and requirements of the lifting task have a dominant influence on the EMG signals of the trunk muscles. Thus it is obvious that we can build a neural network to predict EMG using those variables as input.

Having those in mind, we can come up with the following neural network models to predict forces:

Model 1:
Kinematics $\longrightarrow$ forces

Model 2:
Kinematics $\longrightarrow$ EMG $\longrightarrow$ forces

Model 3:
Kinematics + EMG (back-looping) $\longrightarrow$ forces + (EMG)

The first model predicts forces directly from the kinematics data. It is simple and easy to realize. The training is also fast. However, the relationship between the input and output is indirect. The prediction quality is unsatisfactory.

The second model has direct relationship between the input and output in both the two neural networks. The same procedure as the biomechanics method is followed. But this model is complicated and the error may accumulate through the whole procedure. At the same time, the training is time consuming.

The third model is the proposed model. It overcomes the shortcomings of both Model 1 and Model 2 while having the advantages of both of them. It is simple, trains fast, and has a clear physical meaning which is coincident with the conventional method.

B. The Modified Recurrent Neural Network Model

1) Structure overview: Kinematics variables, task variables and subject variables are the system inputs. Forces on the lumbar joint are the system outputs. EMG signals of ten trunk muscles are introduced into the system as the intermediate output. They are delayed once and twice respectively by the unit delay operator, and then are looped back to the input layer. These delays of EMG signals are used to represent the muscle activation dynamic properties better. The interaction between muscles influences the EMG and the forces on the lumbar joint a lot. By presenting the previous EMG of muscles to the input, the system can take such interaction into account. The EMG signals at the output side have normalized values range from zero to one. It is better to rescale them before loop them back to the input layer so that they have the same range as the input variables. Otherwise, their importance will be reduced.

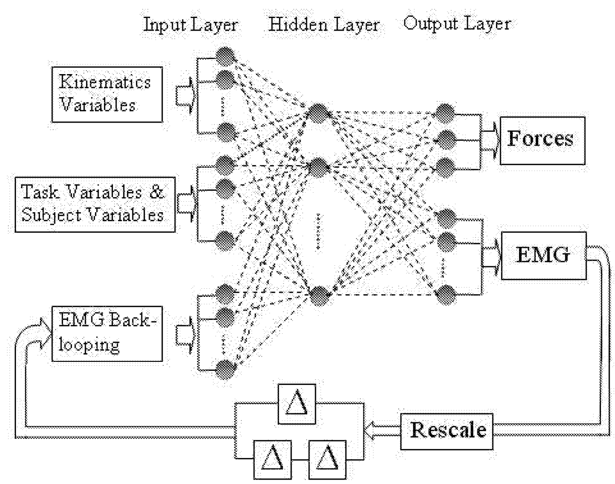

Fig. 2. The proposed recurrent neural network structure (Δ is a unit delay operator)

2) Description of the input/output variables: The input and output variables are described as follows.

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.

Subject variables which describe the characteristics of the subjects are selected as part of the input. These variables include gender, height, arm length, spine length, trunk depth (pelvis), trunk breath (pelvis), trunk depth (xyphoid), and trunk breath (xyphoid).

Task variables describe the requirements of the lifting task. They are weight of object, lifting height, handedness, and lifting style.

The intermediate 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).

The lumbar joint forces to be predicted are Lateral Shear Force, A-P Shear Force and Compression. 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.

3) Algorithm: The proposed load model for lumbar force prediction can be represented as a nonlinear mapping:

$$\mathbf{O}_{force}^{t} = f(\mathbf{W}^{t}, \mathbf{X}^{t}, \mathbf{O}_{EMG}^{t-1}, \mathbf{O}_{EMG}^{t-2})$$

where

$\mathbf{O}_{force}^{t}$ is the predicted forces for time t.

$\mathbf{O}_{EMG}^{t-1}$ is the predicted EMG for time $t-1$.

$\mathbf{O}_{EMG}^{t-2}$ is the predicted EMG for time $t-2$.

$\mathbf{X}^{t}$ is the system input for time t. It includes kinematics variables, subject variables and task variables.

$\mathbf{W}^{t}$ is the wight matrix of neural network for time t.

f denotes the nonlinear function representing the neural network.

The forces predicted for time t depend on not only the inputs at time t, but also the predicted EMG at time $t-1$ and $t-2$, 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 neural network.

In order to train the recurrent neural network, a modified dynamic back-propagation learning algorithm is used. The error function is defined as

$$E = \frac{1}{2}\|\mathbf{D}_{force} - \mathbf{O}_{force}\|^2$$

Where $\mathbf{D}_{force}$ and $\mathbf{O}_{force}$ represent vectors of the actual and predicted forces, respectively.

The output vector of the network is

$$\mathbf{O}_{all}^{t} = f_u(\mathbf{V}^{t} * \mathbf{Y}^{t})$$

where $\mathbf{O}_{all}^{t}$ is the vector of the whole output at time t. It includes the forces ($\mathbf{O}_{force}^{t}$) and the intermediate output EMG ($\mathbf{O}_{EMG}^{t}$).

f_u is the unipolar sigmoid activation function:

$$f_u(v) = 1/(1 + exp(-\beta v)$$

β is the slope of the sigmoid function.

$\mathbf{V}^{t}$ is the weight matrix between the hidden layer and the output layer at time t.

$\mathbf{Y}^{t}$ is the output of the hidden layer at time t. It is calculated as:

$$\mathbf{Y}^{t} = f_{tanh}(\mathbf{W}^{t} * \mathbf{X}^{t} + \mathbf{W}_{d}^{t} * \mathbf{O}_{EMG}^{t-1} + \mathbf{W}_{dd}^{t} * \mathbf{O}_{EMG}^{t-2})$$

where f_{tanh} is the hyperbolic tangent activation function.

$\mathbf{X}^{t}$ is the input vector at time t.

$\mathbf{W}$, $\mathbf{W}_{d}$ and $\mathbf{W}_{dd}$ correspond to the weights associated with the input $\mathbf{X}^{t}$, delayed output $\mathbf{O}_{EMG}^{t-1}$ and the delayed output $\mathbf{O}_{EMG}^{t-2}$, respectively.

Since the unipolar sigmoid activation function is used in the output layer, the range of the predicted EMG is from zero to one. To make them have the same range as the input variables, they can be rescaled before they are looped back to the input layer.

III. SIMULATIONS

A. Model Parameters

The input includes twelve kinematics variables, eight subject variables, four task variables, and two groups of back-looped EMG signals of ten trunk muscles (for different delay time). Including one timing variable, there are totally forty five input neurons in the first layer.

The output includes three forces and ten EMG signals, totally 13 output neurons in the output layer.

From eight to fifty, different number of hidden neurons have been tried. According to the performance, thirty five hidden neurons are used in the model.

Simulations have been done with a variety of different learning rates. Finally 0.2 was selected as the system learning rate. The momentum was set to equal 0.6.

B. Data Preprocessing

Data synchronization and normalization were performed before the original data were used as input/output training pairs of the neural network.

The motions done by different subjects were normally not synchronized very well. That means the motions were not recorded at the same starting point and ending point. Incorrect timing would make the prediction more difficult. Thus having the motions synchronized as good as we can is one of our goals in data preprocessing.

The forces to be predicted have quite different ranges. The Lateral Shear Force ranges from about -200 to 100. The A-P Shear Force ranges from about -200 to 600 and the Compression ranges from -3500 to -1000. They can not be used before normalization. Otherwise they will make the neurons saturate. Since they are outputs, we normalize them to the range from 0.1 to 0.9, avoiding the saturate regions of the unipolar sigmoid activation function. The raw kinematics data also have different scales of numbers. Since they are the inputs, they were normalized to the range of -2 to 2. Subject variables were normalized similarly.

IV. RESULTS

We evaluated the performance of the proposed recurrent neural network with two kinds of data. One is the sagittal symmetric motions, while the other one is unsymmetrical motions.

A. *Prediction for Sagittal Symmetric Motions*

In a sagittal symmetric lifting motion, the subject does not turn his body. The motion is done sagittally. This kind of motion is simple and easy to model. Fig. 3 gives an example of predicted such motion. The dotted curves are the targets, while the solid curves are the predicted forces.

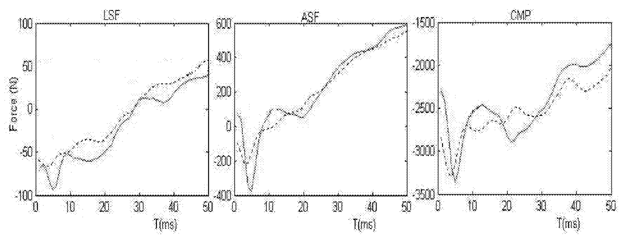

Fig. 3. Prediction of sagittal symmetric motion

Description of the forces:

LSF: Lateral Shear Force
ASF: A-P Shear Force
CMP: Compression

Descriptions of the tasks and the subjects for this prediction are listed in the "Sag. Sym. Motion" column of Table I and Table II, respectively.

TABLE I
DESCRIPTION OF THE TASKS

Task Variables	Sag. Sym. Motion	Unsym. Motion
Weight of Object	30 lbs	30 lbs
Lifting Height	30 cm	30 cm
Handedness	both	both
Lifting Style	Stoop	Stoop

As we can see that the prediction is satisfactory. This modified recurrent neural network can model the kinematics-EMG-force relationship and give an acceptable prediction.

B. *Prediction for Unsymmetrical Motions*

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

One example of such predictions is shown in Fig. 4. As we expected, the predicted curve does not fit the target curve as well as predicting sagittal symmetric motions. The statistic information is given in the section "Statistic Results". Considering the complexity of such motions, the prediction quality of the unsymmetrical motions is still acceptable.

TABLE II
DESCRIPTION OF THE SUBJECTS

Subject Variables	Sag. Sym. Motion	Unsym. Motion
Gender	male	male
Height	176.6 cm	180.2 cm
Arm Length	83.6 cm	88.7 cm
Spine Length	58.8 cm	62.5 cm
Trunk Depth(pelvis)	19.7 cm	20.1 cm
Trunk Breath(pelvis)	28 cm	32 cm
Trunk Depth(xyphoid)	20.5 cm	22.5 cm
Trunk Breath(xyphoid)	30 cm	31.6 cm

Descriptions of the tasks and the subjects for this prediction are listed in the "Unsymmetrical Motion" column of Table I and Table II, respectively. To make the results comparable, similar task variables and subject variables are selected for the sagittal symmetric motion and the unsymmetrical motion.

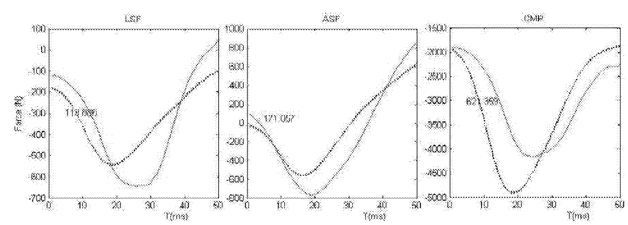

Fig. 4. Prediction of unsymmetrical motion

C. *Improvements*

There is a problem that most predictions have an offset at the beginning of the motion, as shown in Fig. 5. The offset is very severe that sometimes it is up to one third of the whole range of the forces. But we found that the offset has nothing to do with the motions themselves. It is actually caused by the lack of history EMG data at the beginning of the prediction. As stated before, if the recurrent neural model predicts the forces at time t, it needs the EMG data at $t-1$ and $t-2$. But when we are predicting the first sampling point, that is to say, at time $t=0$, the EMG data at $t=-1$ and $t=-2$ are not available. We initialized them as zeros. Of course this could be far from the actual values. Remember that we rescale the EMG signals before looping them back to the input layer. This will make the error between the initialized value and the actual value even bigger. That is the reason for the offset at the beginning of the prediction.

To solve this problem we need the EMG data at time $t=-1$ and $t=-2$. But there is no way to obtain them because we only have the kinematics data from $t=0$. One method that can alleviate the problem is that we initialize those history EMG data as 0.5, instead of zero. Because the normalized

EMG data are in the range from zero to one, 0.5 is in the middle of this range. From the statistics point of view, it is closer to the actual value than zero. At least the error will not be too bad. After doing this (initializing history EMG data as 0.5), the prediction of the same trial shown in Fig. 5 was greatly improved (see Fig. 6). Statistic results also show that this remedy works very well.

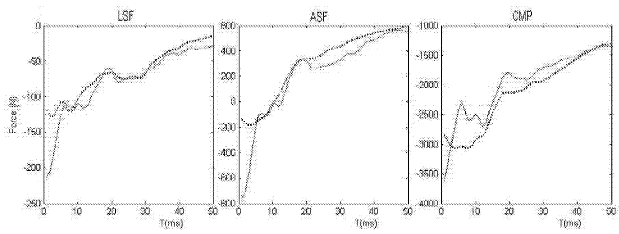

Fig. 5. The prediction has an offset at the beginning because the history data before the first sampling point are not available

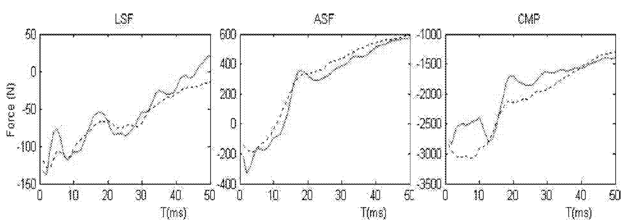

Fig. 6. Offset at the beginning of the prediction is alleviated after proper initialization of the history data

D. Statistic Results

Statistic 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 Fig. 7. As we said, the forces have different ranges. The variations of Lateral Shear Force, A-P Shear Force and the Compression are around 300 Newtons, 800 Newtons and 2500 Newtons, respectively. The MAEs are out of such ranges. From the figure we can see that the MAEs of the predicted sagittal symmetric tasks are much smaller than those of the predicted unsymmetrical tasks. It is reasonable since the muscle activities are much more complicated in the unsymmetrical tasks.

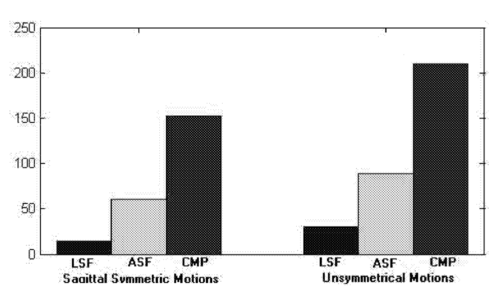

Fig. 7. Overall Mean Absolute Errors (force in Newtons) of different types of tasks

We also can compare the overall MAEs of the different models listed in the section "Model Construction". The results shown in Table III indicate that in all the three force prediction neural network models, the proposed recurrent neural network has superior performance.

TABLE III
OVERALL MAEs OF DIFFERENT MODELS FOR SAGITTAL SYMMETRIC TASKS

Force Names	Model 1	Model 2	Model 3
LSF	27	22.2	14.5
ASF	86.5	79.4	60.3
CMP	201.1	178.5	152

The values in Table III are forces in Newtons. Model 1, Model 2 and Model 3 are described in the section "Model Construction".

V. CONCLUSIONS

In this paper a adequate and parsimonious recurrent neural network is built to predict forces on lumbar joint from kinematics data. The uniqueness of this recurrent neural network is that the ultimate output is not looped back. Instead, we introduce an intermediate variable, the EMG, into the model and loop it back to the input. The back-looping of the intermediate output acts as a bridge connecting the input and the output, making their physical relationship explicit and strong, hence improves the prediction quality.

The multi-delayed EMG back-looping represents the muscle activation dynamics better. At the same time, the advantages of recurrent neural network are utilized. The model predicts forces directly from kinematics data, avoiding EMG measurements and the use of biomechanics model. This makes it a convenient and reliable tool.

The model proposed can be used to analyze the forces generated in a particular task and judge if such a task is risky or not. Also, it will be very useful in understanding the joint injury in manual lifting tasks and find out how it is related with the anthropic characteristics of the subject and the requirements of the task. More EMG-force related studies could be done with this model.

ACKNOWLEDGMENT

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