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Application of a Neural Network to Dynamic Draft Model

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Abstract: A dynamic draft model is necessary to analyze mechanics of tillage and to design optimal tillage tools. In order to deal with draft dynamics, a neural network paradigm was applied to develop dynamic draft models. For the development of the models, three kinds of tillage tools were used to measure drafts in the soil bin and a time lagged recurrent neural network was developed. The neural network had a structure to predict dynamic draft, having a function of one-step-ahead prediction. A procedure for network prediction model identification was established. The results show promising modeling of the dynamic drafts with the developed neural network.

Keywords: Draft prediction, Neural network, Tillage, Dynamic draft model

Introduction

One of the major objectives of tillage is to provide optimum environmental conditions for plant grows. More than 2 million hectares are stirred or turned each year in Korea. To plow this soil once requires 8~12 million liters of diesel or gasoline fuel. It is apparent that the improvement of tillage tool design can enable to reduce mechanical energy and labor requirements and to optimize the soil conditions.

There has been a marked upsurge in tillage tool design of research since about 1950s. However, no reliable attempt for tillage tool design has been made to describe soil failure patterns or the mechanisms of soil failure because soil has ununiformity and different characteristic according to fields. Most studies on the tillage tool design have focused mainly on reporting experimental findings under certain conditions with specific parameters.

The soil reaction to the forces applied by tillage tools is affected from compression resistance, shear resistance, adhesion, and frictional resistance. These are all dynamic properties that change through movement of the soil. In analyzing draft, mean value has been usually used to represent the draft measured over an entire experimental range. If dynamic draft model is available, predicted force acting on tillage tools during soil failure can be used for the analysis of tillage mechanics and the optimal design of tillage tools. A large number of models have been developed for the prediction of draft to engaging tillage tools (Hettiarachi and Reece, 1965; Mekyes and Ali, 1977; Perumpral and Grisso, 1983; Stafford, 1984). A dynamic model for soil cutting by blade and tine was reported by Dechao and Yusu (1992). Shear rate effect was taken account of both on soil shear strength and soil-metal friction.

Of the tillage-tool design factors, tool shape is a main factor for the designer because forces acting upon a tillage tool are determined with respect to the tool shape. Actually, the forces are affected by the tool shape and soil condition as well. Draft is the component of pull in the direction of travel and may involve information about mechanics of tillage. Because of fluctuation in measured signal, draft is usually calculated by averaging the values within a run. However, the draft shows periodic variation as soil fails in the form of furrow slices. So, a dynamic draft model is necessary for the analysis of the relation between draft and the tool shape. A neural network can be effectively used for the nonlinear mapping such as the modeling of dynamic draft.

Objectives

The main objective of this study was to develop a neural network model for the prediction of the dynamic draft of tillage tool. Specific objectives of this study were to measure drafts of tillage tools and to apply a neural network to the dynamic prediction of tillage tool drafts.

Materials and Methods

1. Tillage tools

Shearing force and cone index are widely used to represent physical property of a soil in predicting draft. It is known that soil failure in measuring shear force and cone index is different from failures by tillage tools. In order to predict draft closely to actual draft, it is necessary to develop new measuring device whose mechanics of soil failure is similar to the mechanics by tillage tools. A model tool was tested as a new measuring device. All drafts of tillage tools have

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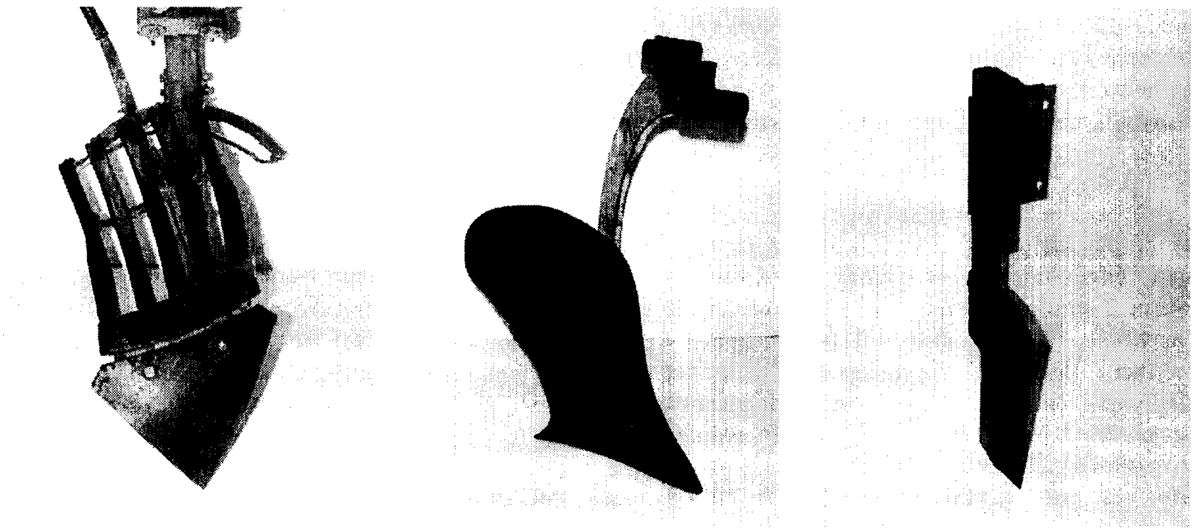
Table 1. Specifications of the tested tillage tools (Janggi and Plow)

Implement	Max. shear lift angle (degree)	Setting angle		Width of shear (cm)	Weight (N)	Moldboard type
		Shear (degree)	Wing (degree)			
Janggi	51.3	40.9	63.0	23.4	171.5	5-fork
Plow	21.3	42.2	55.3	15.5	73.5	Cylindrical



(a) janggi (b) moldboard plow (c) model tool

Fig. 1 View of the tillage tools.

acceptable linear relations to the model tool draft. (Lee, 1996).

Tillage tools used in this study were a moldboard plow, a janggi(Korean plow), and a model tool. Table 1 gives the specifications of the moldboard plow and the janggi. Figure 1 shows the view of the tillage tools used in this study.

2. Soil bin

Measurements of tillage tool drafts were carried out in the soil bin installed in the Soil-Machine System Lab at the Bio-mechatronic engineering department of Sungkyunkwan university. This soil bin is 1m wide, 0.7m deep, and 12m long. A tool carrier, pulled by a steel cable wound on a motor-driven pulley, moved the tillage tools. A track for the carrier was installed on the walls of the soil bin to maintain constant width and depth of cut. Tillage tools were attached to the carrier according to the hitch types. Tested soil was sandy loam. Table 2 gives physical properties of the tested soil.

3. Data acquisition system

The main components of data acquisition system were a load cell, a rotary encoder, a strain amplifier, and a microcomputer (100MHz Pentium processor) with PC Lab card. The load cell (Kyowa Co.) with nominal rating of 5kN could measure tensile or compressive forces. The rotary encoder (E6A-CS100) was used to measure the tillage speed and generated

Table 2. Physical properties of tested soil

Composition			Texture	Internal frictional angle (degree)	Cohesion (N/cm^2)	Adhesion (N/cm^2)
Sand (%)	Silt(%)	Clay(%)				
54.4	51.3	8.8	Sandy loam	57.1	82.3	37.2

Soil-metal friction angle (degree)	Moisture content (%, d.b.)	Cone index (N/cm^2)	Bulk density (g/cm^3)
41.7	11.7	10.8	1.4

100 pulses per one revolution. The strain amplifier (DPM-311A, Kyowa Co.) was used to amplify the signal come from the load cell and its output voltage was ±5V. The PC Lab card had an A/D converter and a counter for counting pulses generated from the rotary encoder. The A/D converter had a resolution of 12 bit, and its A/D conversion time was 9μs.

4. Draft measurement

Before the run of each experiment, the following preparations were made to ensure that the same soil conditions were maintained in all tests: the soil was pulverized, stirred, and leveled by the soil processing carriage. The soil processing carriage had a rotary tiller, a leveler, and a roller. First preparation was done to pulverize the soil with the rotary tiller at the depth of 20cm, which was approximately equal to the maximum tillage depth in fields. Second preparation was done to level the soil with the leveler. Last, the soil was compacted twice with the roller. Order and the number of times for the preparations were same in all experiments.

Drafts were measured at the level of tillage depth of 12cm, which is practical depth in Korea. The tillage speed was 0.49m/s. And all tests carried out three times with sampling time of 0.14sec.

5. Neural network structure

In order to develop the dynamic draft model, a time lagged recurrent neural network (TLRNN) was constructed so that the model can process time series data. The TLRNN developed in this study is identical to a feedforward neural network (FFN) in structure, but is trained by using the backpropagation through time algorithm as stated by Werbos, et al (1992). Backpropagation through time modifies the conventional backpropagation algorithm by viewing a network's recall of a time sequence as a cascaded neural network where each cascade step represents one time step in the time series.

Neural networks are "model free" estimators, so they can be used to directly approximate the function f() directly as follows:

$$\underline{\hat{y}}(t)=\hat{f}[\underline{y}(t-1),\underline{y}(t-2),...,\underline{y}(t-p),\underline{u}(t-d-1),\underline{u}(t-d-2),...,\underline{u}(t-d-q),\underline{\hat{W}}] \quad (1)$$

Where $\underline{u}(t)$ is input vector of $\underline{y}(t)$. $\hat{f}()$ is the approximation of the function f(), $\underline{\hat{y}}(t)$ is the output vector of the neural network model, and $\underline{\hat{W}}$ is the set of weights and bias terms in the network model. Equation (1) can be extended as a predictor if the past values of output $\underline{y}(t)$ are used as input vector for the prediction of $\underline{\hat{y}}(t+1)$. Equation (1) can be written in the form of a one-step-ahead predictor:

$$\underline{\hat{y}}(t+1 \mid t)=\hat{f}[\underline{y}(t),\underline{y}(t-1),...,\underline{y}(t-p+1),\underline{u}(t-d),\underline{u}(t-d),...,\underline{u}(t-d-q+1),\underline{\hat{W}}] \quad (2)$$

Where $\underline{\hat{y}}(t+1 \mid t)$ is the one-step-ahead prediction of $\underline{y}(t)$. The weights and bias terms in a network can be adapted to minimize the squared errors of the network outputs as follows:

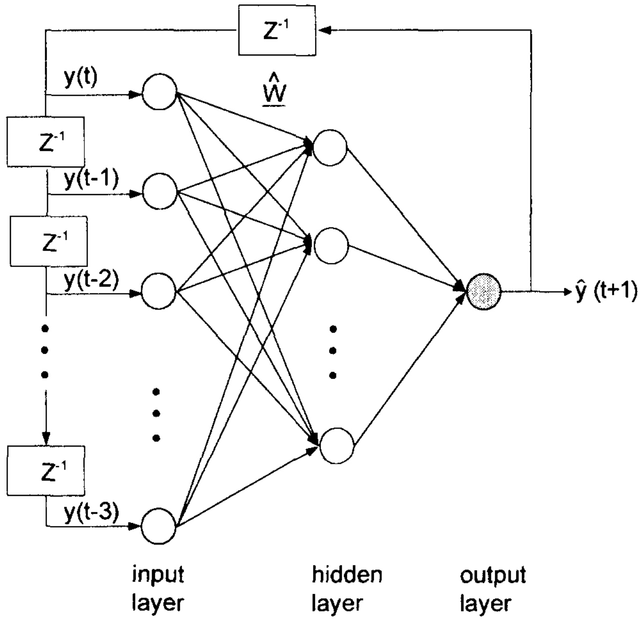


Fig. 2 Architecture of TLRNN.

$$J=\frac{1}{2}\sum_{t=1}^{N}[\underline{y}(t)-\underline{\hat{y}}(t)]^T[\underline{y}(t)-\underline{\hat{y}}(t)] \quad (3)$$

Where N is the number of observations. The function J represents a total error over considered time sequence. In this study, only previous values of $\underline{y}(t)$ are used to predict $\underline{\hat{y}}(t+1 \mid t)$ as inputs. So, $\underline{\hat{y}}(t+1 \mid t)$ is only a function of $\underline{y}(t)$ and W. N is the number of previous values of $\underline{y}(t)$. Since the TLRNN is identical to the FFN in structure, the FFN was used as a starting point for training the TLRNN. This greatly reduced training time to convergence. Figure 2 shows the construction of TLRNN. For the case of this study, $\underline{y}(t)$ had one variable. Therefore, the procedure for implementing TLRNN was as follows:

1. Starting with an initial weight set and initializing the network with real values of inputs (if necessary) and output y(t), y(t+1) was predicted. Then, the predicted value of y(t+1) was used to predict y(t+2), and so on to the end of the time sequence. This prediction is called one step ahead prediction and is expressed simply as follows:

$$\underline{\hat{y}}(t+1)=\hat{f}[y(t),y(t-1),y(t-2),...,y(t-n),\underline{\hat{W}}] \quad (4)$$

2. At each time step, weight updates were calculated based on backpropagation algorithm.
3. Weights were updated by averaging all the weight updates over time and multiplying a very small learning rate.

Results and Discussion

1. Dynamic draft

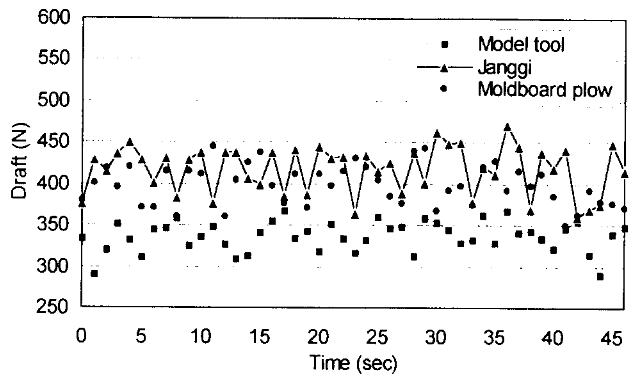


Fig. 3 Variation of draft to time.

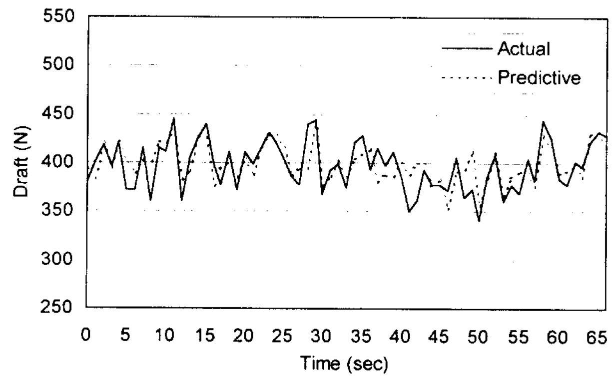


Fig. 4 Prediction of moldboard plow draft.

Many researchers have reported that periodical soil failure and the peak of draft appear as a tillage tool advances (Kepner, 1972. Osman, 1964), and the draft varies within the range of ±30~50% for its mean value.

The drafts, measured at the tillage depth of 12cm and the tillage speed of 0.49m/s, were plotted in Figure 3 in order to represent the dynamic changes in drafts. The figure shows the janggi draft had similar peaks to the moldboard plow draft; however, the model tool draft was different. Results indicated that soil failure by the model tool was different from the failures by the moldboard plow and the janggi. It was considered the difference was caused from the shapes of the tools. Comparing to the moldboard plow and the janggi, the model tool was symmetric in shape and had a narrow tillage width. Even though the peaks of the drafts were appeared periodically, it was difficult to verify the forces acting upon the tillage tools or the mechanisms of soil failure from the measured drafts.

2. Neural network draft model

For training the neural network, the initial weight values were selected randomly and determined by regular backpropagation at initial stage of the training. Then the weights of the neural network were modified with the way of backpropagation through time. To speed training, several modifications were made to the network as suggested by Fahlman(1990). First, in order to eliminate "flat spots" that occurs during training because of a small derivative value for the sigmoid functions, a constant offset of 0.1 was added to the calculation of the derivative. This modification has been shown to cut learning time almost in half. Second, a tangent function was performed on the mean squared at the output before being backpropagated. This improved training speed by putting more emphasis on training patterns with large errors over small errors. Last, the weights to the network were averaged over all training patterns (batch learning). All inputs and outputs were scaled to between 0.1 and 0.9 before training.

The data measured for three replications were randomly split up into the three groups, keeping sequences of time in order to evaluate continuous prediction: one for parameter modification, one for termination of training, and one for determining the performance of the neural network. Mean squared error (MSE) was used to evaluate the performance of the trained neural network. MSE is defined by

$$MSE = \frac{1}{N}\sum_{t=1}^{N}[y(t) - \hat{y}(t)]^2 \qquad (5)$$

Moldboard plow draft: The number of nodes in input layer determines how many inputs are necessary for the best draft prediction, explained in equation (2). Optimal number of nodes helps to understand the frequency of the draft. The number of nodes in the hidden layer determines only a performance of the network. In order to find the effect of the number of nodes in input layer and hidden layer, the performance of the network was evaluated based on MSE after the

Table 3 Effect of the number of nodes in layers on the neural network (moldboard plow)

	Case 1	Case 2	Case 3
Node no. in input layer	4	6	8
Node no. in hidden layer	9	8	12
Learning rate	0.10	0.10	0.10
MSE	0.0155	0.0193	0.0207

Table 4 Results of trained neural networks for draft models

	Moldboard plow	Janggi	Model tool
Node no. in input layer	4	7	4
Node no. in hidden layer	9	12	9
Learning rate	0.10	0.15	0.10
MSE	0.0155	0.0287	0.0145

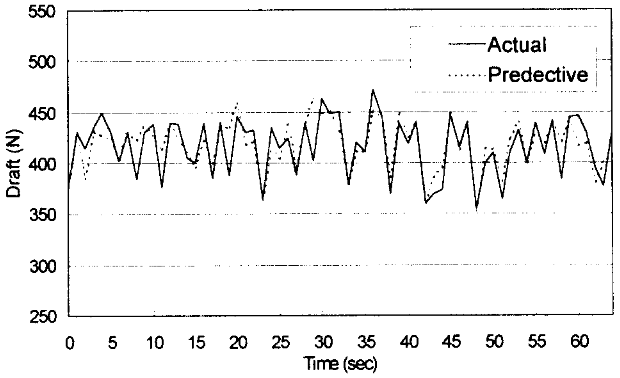


Fig. 5 Prediction of janggi draft.

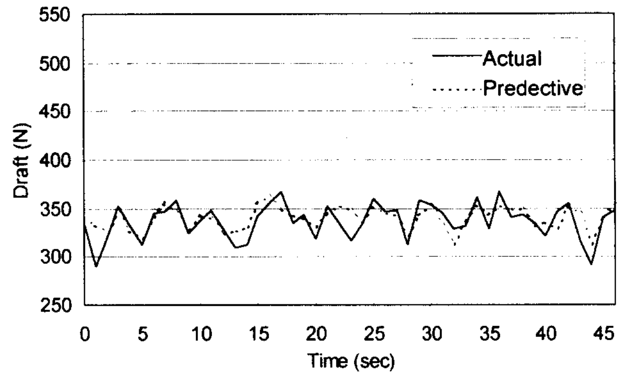


Fig. 6 Prediction of model tool draft.

same training iteration. Table 3 gives the results after 16,000 iterations for the moldboard plow draft. As shown in the table, minimum MSE appeared when the number of nodes in the input layer and the hidden layer were 4 and 9, respectively. Further training proceeded with the selected structure until MSE reached at an acceptable value. Figure 4 shows the result of one-step-ahead prediction by the trained network. MSE after 56,000 iterations was 0.0108. The change of draft predicted by the network was very similar to that of the measured draft. This result indicated it was possible to model the dynamic draft of the moldboard plow by the TLRNN. The frequency of the measured draft was not corresponding to the number of furrows. In moldboard plow draft, mean values of the measured draft and the predicted draft were 397N and 398N, respectively.

Janggi draft: Table 4 gives the results after 5,000 iterations for the selection of the number of nodes in case of the janggi draft. Minimum MSE appeared when the number of nodes in the input layer and the hidden layer were 7 and 12, respectively. The network was well trained when the number of node was more than the number of the moldboard plow model in the input layer. It was observed from this result that the period of soil failure by the janggi was longer than the period by the moldboard plow. Figure 4 shows the result of one-step-ahead prediction after 80,000 iterations. Mean values of the measured draft and the predicted draft were 416N and 413N, respectively. Also, MSE after training was 0.0102.

Model tool draft: For the case of model tool, the network with 4 and 9 nodes in the input layer and the hidden layer was chosen. The network with 8 nodes in the input layer had lower MSE than the selected network; however, it was thought 8 nodes could not reflect real period of the draft. It was observed that the period of soil failure by the model tool was similar to the period by the janggi. Figure 6 shows the result of one-step-ahead prediction after 35,000 iterations. Mean values of the measured draft and the predicted draft were 336N and 339N, respectively. Final MSE for the model tool model was 0.01.

Conclusions

This article has developed the neural network one-step-ahead prediction model for the prediction of dynamic draft. The architecture and training algorithm of the model, the time lagged recurrent neural network (TLRNN), were established. In order to get the training data, drafts were measured for three kinds of tillage tools (the moldboard plow, the janggi, and the model tool) with the load cell in the soil bin. Results showed that the neural network acceptably modeled the dynamic drafts. Even though the results showed the application of the neural network to the specific tillage tools and the soil condition in this study, the developed neural network can be directly applied to the modeling of other dynamic drafts.

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