Predicting Slipperiness of Road Surface in Winter with a Neural-Kalman Filter

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An artificial intelligence method was developed to predict the slipperiness of a road surface in winter by emulating the prediction process of experienced drivers. To realize this method, a neural network model was integrated into the Kalman filter. First, the state equation that defines how the slipperiness varies with time and the observation equation that relates the slipperiness to the road surface temperature were described by using a multilayered neural model. Then, a prediction procedure similar to the conventional Kalman filter was developed. The introduction of the neural network model made it possible to formulate complicated phenomena mathematically, and the Kalman filter made it possible to predict slipperiness indirectly through the road surface temperature. Precision of the new method was examined through a comparison with actual measurement data. The kind of weather data needed to predict road surface slipperiness was also investigated.

Road surface conditions in winter undergo complex changes. They are strongly affected by many factors, such as weather, traffic, and other peripheral factors. They also vary greatly with time and space. Therefore, mathematical formulation and precise prediction of changes in road surface conditions are difficult. Several attempts have been made to predict ice formation and temperature on the road surface. Some approaches are analytical, based on energy balance theory (*1,2*), and others are statistical, based on regression analysis (*2–6*). However, none of these methods deals with slipperiness of the road surface.

Although several indexes represent road surface slipperiness, a friction coefficient is considered to be the best index because it directly indicates the degree of slipperiness. Precise predictions of the degree of road surface slipperiness would provide useful information not only to road maintenance officers but also to drivers. However, although the coefficient is not difficult to measure, special equipment, such as a skid-resistance tester, is required. Also, many testers or much time is necessary to measure the degree of slipperiness over a given road section because a friction coefficient greatly varies with time and space.

Drivers who live in a snowy region and have experience driving on snow- or ice-covered roads are very sensitive to changes in road conditions. Such drivers can often predict the slipperiness precisely by combining their past experience with the weather forecast information data, although they have no information concerning the friction coefficient. To emulate this forecasting process of experienced drivers, a new prediction method was developed by integrating a neural network model into the Kalman filter. First, indirect estimation of the degree of slipperiness through the use of a weather condition variable was considered. Air temperature is easy to measure but is not always correlated to the degree of slipperiness. Road surface temperature is more difficult to measure but is more closely related to the degree of slipperiness than is air temperature. Therefore, road surface temperature was used as the indirect variable. The Kalman filter is a mathematical technique for estimating unmeasurable state variables indirectly through some measurable observation variables. However, to apply the Kalman filter, both the state equation that describes how the state variables vary with time and the observation equation that relates the state variables to the observation variables must be defined analytically. Unfortunately, variations of road surface are too complex to be used to define these equations mathematically. To deal with this difficulty, a multilayer neural network model was introduced. To establish the relationship between the state and the observation variables, another neural network model was used. Both neural network models were integrated into the Kalman filter to establish a new prediction method, the neural-Kalman filter. The effectiveness of the neural network model in predicting the slipperiness on a road surface is discussed in this report.

NEURAL-KALMAN FILTER

Kalman Filter

The Kalman filter is a technique for indirectly estimating some state variables (*7,8*) that cannot be directly measured through the measurement of the other variables. It consists of two equations: the state equation and the observation equation. The former defines how state variables vary with time:

$$\mathbf{x}_{k+1} = A_k \cdot \mathbf{x}_k + \mathbf{v}_k \tag{1}$$

where $\mathbf{x}_k$ denotes the state variable vector at time k, and $\mathbf{v}_k$ denotes the white noise vector. The observation equation describes how state variables are related to observation variables:

$$\mathbf{y}_k = C_k \cdot \mathbf{x}_k + \mathbf{w}_k \tag{2}$$

where $\mathbf{y}_k$ is the observation variable vector at time k and $\mathbf{w}_k$ is also the white noise vector. When the new values of the vector $\mathbf{y}_k$ at time k are obtained, the state vector $\mathbf{x}_k$ at time k can be estimated according to the theory of the Kalman filter:

$$\hat{\mathbf{x}}_k = \tilde{\mathbf{x}}_k + K_k(\mathbf{y}_k - \tilde{\mathbf{y}}_k) \tag{3}$$

$\tilde{\mathbf{x}}_k$ and $\tilde{\mathbf{y}}_k$ are the one-step predictors of $\mathbf{x}_k$ and $\mathbf{y}_k$, respectively, and $\hat{\mathbf{x}}_k$ is the estimator of $\mathbf{x}_k$ at time k:

$$\begin{aligned} \tilde{\mathbf{x}}_k &= A_{k-1}\hat{\mathbf{x}}_{k-1} \\ \tilde{\mathbf{y}}_k &= C_k\tilde{\mathbf{x}}_k \end{aligned} \tag{4}$$

where K_k is termed the Kalman gain, which is a function of both coefficient matrices A_k and C_k and also the covariance matrices of noise vectors $\mathbf{v}_k$ and $\mathbf{w}_k$. Equation 3 corrects the estimate $\tilde{\mathbf{x}}_k$, which was predicted without the observed data $\mathbf{y}_k$ at time k, in proportion to the error between the actual vector $\mathbf{y}_k$ and the predicted vector $\tilde{\mathbf{y}}_k$.

Extended Kalman Filter

The preceding filtering technique is applicable only to linear systems. In many dynamic problems, the state and the observation equations are often described nonlinearly:

$$\mathbf{x}(k+1) = f[\mathbf{x}(k)] + \varphi(k) \tag{5}$$

$$\mathbf{y}(k) = g[\mathbf{x}(k)] + \zeta(k) \tag{6}$$

where $\varphi(k)$ and $\zeta(k)$ are noise vectors. Expanding the right sides of Equations 5 and 6 in the vicinity of $\hat{\mathbf{x}}(k)$ and neglecting the higher-order terms yields

$$\mathbf{x}(k+1) = A(k)\cdot\mathbf{x}(k) + \mathbf{b}(k) + \varphi(k) \tag{7}$$

$$\mathbf{y}(k) = C(k)\cdot\mathbf{x}(k) + \mathbf{d}(k) + \zeta(k) \tag{8}$$

where

$$\mathbf{b}(k) = f[\hat{\mathbf{x}}(k)] - A(k)\cdot\hat{\mathbf{x}}(k) \tag{9}$$

$$\mathbf{d}(k) = g[\hat{\mathbf{x}}(k)] - C(k)\cdot\hat{\mathbf{x}}(k) \tag{10}$$

$$A(k) = \frac{\partial f}{\partial \mathbf{x}} \quad C(k) = \frac{\partial g}{\partial \mathbf{x}} \tag{11}$$

Now we can estimate the state variable $\mathbf{x}(k)$ in the same manner as linear systems.

Neural Network Model

Figure 1 shows the multilayer neural network model used in the present analysis (*9,10*). It consists of five layers: an input layer, three intermediate layers, and an output layer. Neurons in each layer are mutually connected to neurons in adjacent layers, except for those in the input layer. The strength of the connections is called synaptic weight. The synaptic weights for both intermediate and output layers are adjusted. The input layer serves only as a normalizer. First, the synaptic weights are initialized randomly. The raw variables x_i^A are input into the input layer and normalized. If the normalized signals are transmitted in sequence from the input layer to the output layer, the output signals may be obtained during the neural operations:

$$y_m^E = h\left(\sum_k w_{km}^{DE}\, h\left\{\sum_j w_k^{CD}\, h\left[\sum_i w_{ij}^{BC}\, h\left(x_i^B\right)\right]\right\}\right) \tag{12}$$

where h is an activation function that represents the input-output relationship for each neuron. The sigmoid function is used as the activation function. The ability of neural network models to describe nonlinear behavior comes from this nonlinear function. This represents the foreword signal process in Figure 1. Next, the synaptic

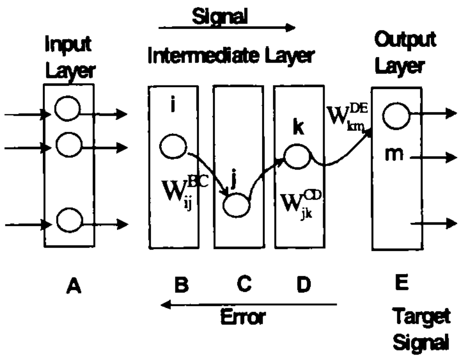


FIGURE 1 Mutilayer neural network model for describing state and observation equations.

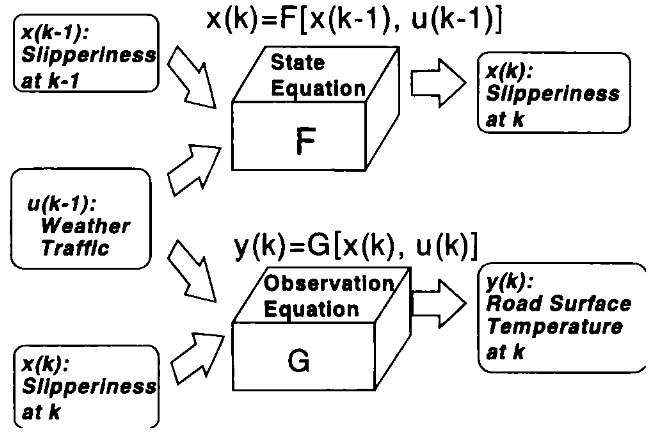


FIGURE 2 Basic concept of neural-Kalman filter for estimating slipperiness on a winter road surface.

weights are adjusted so that the error between the output signals and the target signals is minimized. The back-propagation method is used to adjust the synaptic weights. The errors are corrected and the weights are modified backward from the output layer to the input layer. Iterative adjustment of synaptic weights by using many training patterns produces a stable input-output relationship between input and output signals, even for a nonlinear system. In other words, the neural network model is very effective in accurately describing nonlinear phenomena.

Neural-Kalman Filter

Because of the difficulty of measuring slipperiness of road surfaces in winter, an attempt was made to estimate slipperiness indirectly through other variables that are closely related to slipperiness but are easily measurable, such as road surface temperature. Air temperature was another promising variable because it is very easy to measure, but it was not used because it is not as closely correlated to slipperiness as is road surface temperature. Application of the Kalman filter theory is possible with prior knowledge of how slipperiness varies with time and how closely it is correlated with road surface temperature. As shown in Figure 2, slipperiness varies according to weather and traffic conditions. This transition process is too complex to formulate analytically, that is, it is too difficult to physically or mathematically define the state equation. Therefore, the process is described as using a multilayer neural network model, which inputs the slipperiness as well as data on weather and traffic conditions at time k, and outputs the slipperiness at time $k + 1$. The relationship between slipperiness and road surface temperature is also very complex, and is almost impossible to describe analytically. Thus, another multilayered neural network model is introduced for establishing a steady nonlinear relationship between them. The input signals are the same as those of the state equation, and the output signal is the road surface temperature. Thus, an estimation method was developed by incorporating the neural network model into the Kalman filter. This artificial intelligence method was named the neural-Kalman filter. Figure 2 shows a conceptual representation of this method.

Since the proposed method is essentially a Kalman filtering technique, it consists of two equations: the state equation that defines how the slipperiness varies with time, and the observation equation that describes how the slipperiness is related to the road surface temperature. First, each equation is identified by using a multilayer neural network model. This simply requires the preparation of a large volume of measurement data on slipperiness, weather, and traffic conditions. The synaptic weights are then adjusted. This is the training phase in establishing the neural networks. The completion of the training makes it possible to estimate or predict the degree of slipperiness for unknown weather and traffic situations. The fundamental algorithm is identical to that of the conventional Kalman filter. First, on the basis of the estimate at the previous time k, the slipperiness $\tilde{x}(k + 1)$ at time $k + 1$ is predicted by using the neural function F. Then the road surface temperature $\tilde{y}(k + 1)$ is estimated by using the neural function G, before the actual temperature $y(k + 1)$ at time $k + 1$ is measured. At the same time, the derivative matrices $A(k)$ and $C(k)$ given by Equation *12* are calculated and the Kalman gain is evaluated. Finally, the slipperiness $\hat{x}(k)$ may be estimated from Equation 3 after the actual temperature $y(k)$ is measured. By repeating these procedures, the degree of slipperiness in real time may be estimated and predicted successively.

Field Measurements

To obtain fundamental data on road conditions in winter, field measurements were carried out at an intersection in a suburb of Sapporo over several days in December 1994, 1995, and 1996. Weather conditions such as air temperature, total solar radiation, and net radiation also were measured as were traffic conditions, such as traffic volume. Table 1 shows the items measured. The measurements were carried out from early in the morning to late in the evening because road conditions changed greatly during the daytime. To evaluate the degree of slipperiness on the road surface, the friction coefficient (skid number) was measured by using a bus-type skid tester with a test wheel mounted in the center. The effect of sunshine was evaluated through both total solar radiation and net radiation, cumulated every 30 min. Road surface temperature was measured on the surface of two tire ruts in the road that were covered with snow or ice by using a portable thermistor. Humidity data were not used here because they had little influence on prediction precision. Traffic volume was measured by counting the number of vehicles passing by the intersection every 30 min.

Numerical Experiments

Structure of Neural Network Model

By using the measurement data, the neural network models for both state and observation equations were determined. Table 2 presents the input and the output signals for neural networks F and G in Figure 2. For the neural State Equation F, the skid number at time k was input together with weather conditions and traffic volume at time k, and the skid number at time $k + 1$ was output. Similarly, for the neural Observation Equation G, the same data as those used in the state equation were input, and the road surface temperature at time k was output.

To clarify the weather data necessary for precise estimation of the degree of slipperiness, the weather data were classified into two groups: ordinary data that can be measured without any special equipment, and special data that require special equipment (Table 3). Ordinary weather data were obtained through the SNET system, which is a weather information system in Sapporo. However, some items of weather data required special equipment for measuring, because the SNET system does not measure total solar radiation or net radiation. Two cases were simulated, one using only ordinary weather data and the other including the special weather data. The number of neurons in the input layer was eight for Case 1, in which solar radiation data were used, and six for Case 2, in which these data were not used. The number of neurons in the intermediate layers was empirically determined—the same number of neurons for the first intermediate layer, and half that number of neurons for the second intermediate layer. Naturally, the number of neurons in the output layer was one for both equations in this analysis.

Training of Neural Networks

To determine the neural networks precisely for both equations, measurement data for extensive road and weather conditions are needed. Also, to examine the validity of the models, checking data for which the neural models are not yet trained are needed. Unfortunately, the number of measurement data sets here is restricted. Excluding the incomplete data caused by the failure in the measurement, the measurement data for 8 days were used as the training data. The training procedure was simple. First, the initial synaptic weights were set. Then the input signals into the input layer were set, and the output signals were calculated. These signals were then compared with the actual measured signals (target signals), and the synaptic weights were adjusted to minimize the difference between the output signals and target signals. This procedure was repeated until the error

TABLE 1 Field Measurements of Winter Road Conditions

Date	December 1994	19(Mon), 20(Tue), 21(Wed), 22(Thu), 23(Fri)	7:00 to 20:00
	December 1995	14(Thu), 18(Mon), 20(Tue), 27(Wed)	15:00 to 20:00
		15(Fri), 19(Tue), 21(Thu), 28(Thu)	6:00 to 20:00
	December 1996	18(Wed), 19(Thu), 20(Fri), 21(Sat), 22(Sun)	6:00 to 20:00
Items	Weather Conditions	Air Temperature, Snowfall Intensity, Snowfall Depth, Total Solar Radiation, Net Radiation, Humidity	every 30 minutes
	Road Conditions	Skid Number, Road Surface Temperature Pavement Surface Temperature	every 30 minutes
	Traffic Conditions	Traffic Volume, Heavy Traffic Volume	every 30 minutes

TABLE 2 Input and Output Signals of Neural Network Models for State and Observation Equations

	State Equation	Observation Equation
Input Signals	Skid number at time k Weather condition data Traffic volume Pavement surface temperature	Skid number at time k Weather condition data Traffic volume Pavement surface temperature
Output Signals	Skid number at time k+1	Road surface temperature

became sufficiently small for all the training patterns. In general, the estimation ability of a neural network model can be evaluated by the estimation precision for checking data that are not trained yet. The measurement data for 3 days were used as the checking data. After the completion of training, the input signals of the checking data were set, and the corresponding output signals were calculated by using Equation 12. These signals were then compared with the actual measured signals.

Figure 3 shows the root mean square (RMS) errors for both the training and the checking data sets for each case. The errors for Case 1 in Figure 3(*a*), for which the solar radiation data as well as the ordinary weather data were used, were around 5 percent for both state and observation equations except for a few data sets. The errors for the checking data were larger than those for the training data. In particular, the errors of the state equation for the data sets on December 22, 1994, and December 19, 1995, exceeded 15 percent. This means that the number of training data sets is not sufficient yet. That is, the neural model did not experience weather and road conditions similar to those of the checking data in the training process. The errors for the data set on December 21, 1996, were less than 10 percent for both equations.

The errors for Case 2 shown in Figure 3(*b*), for which the solar radiation data were not used, were larger than those for Case 1 for both state and observation equations. The errors of the state equation were more than 10 percent for half of the training data sets. This means that there is no definite relationship between the input and output signals. In other words, any other weather condition data, such as solar radiation data in Case 1, may be needed to accurately describe the degree of slipperiness on roads in winter. The errors of the checking data for Case 2 were better than those for Case 1. However, the errors of the state equation were more than 10 percent for all checking data sets.

Prediction Precision

Training Process

To determine how precisely the neural network model represented the state and the observation equations, the skid numbers predicted by the neural-Kalman filter were compared with the actual measured skid numbers. For this purpose, the skid numbers were calculated by following the procedure of the neural-Kalman filter already explained. Figure 4 shows variations in skid number with time for the training data on December 19, 1996. The skid number was predicted 30 min in advance at 30-min intervals. It can be seen that the values predicted with solar radiation data trace the measured values better than do the values predicted without solar radiation data. This reflects the results of the training process for both cases shown in Figure 3. Similar results were obtained for the other training data.

Checking Process

The results in Figure 4 can be expected because the synaptic weights had been adjusted so that the estimated variables agreed with the measured variables. As mentioned, the true estimation ability of the new method can be evaluated by the estimation precision for checking data. Figure 5 shows a comparison of the skid number predicted for the checking data on December 21, 1996, with the measured skid numbers. As shown in Figure 5(*a*), the level of prediction precision obtained by using the neural-Kalman filtering method was not bad for Case 1, except for the initial period from 7:00 to 9:00 a.m. This outcome reflects the effect of solar radiation data in both state and observation equations. If the initial skid number were estimated more precisely at the beginning of the prediction, the errors could be decreased for the initial period. On the other hand, the

TABLE 3 Weather Condition Data

CASE	Ordinary Weather Data	Special Weather Data
1	Air temperature, Moisture, Snowfall depth	Total solar radiation, Net radiation
2	Same as Case 1	None

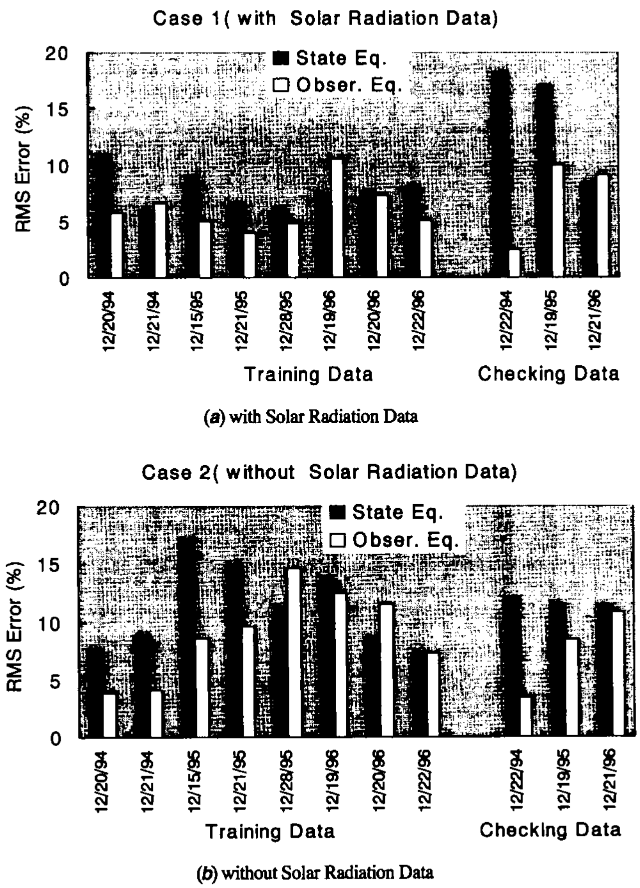


FIGURE 3 RMS errors for training and checking data.

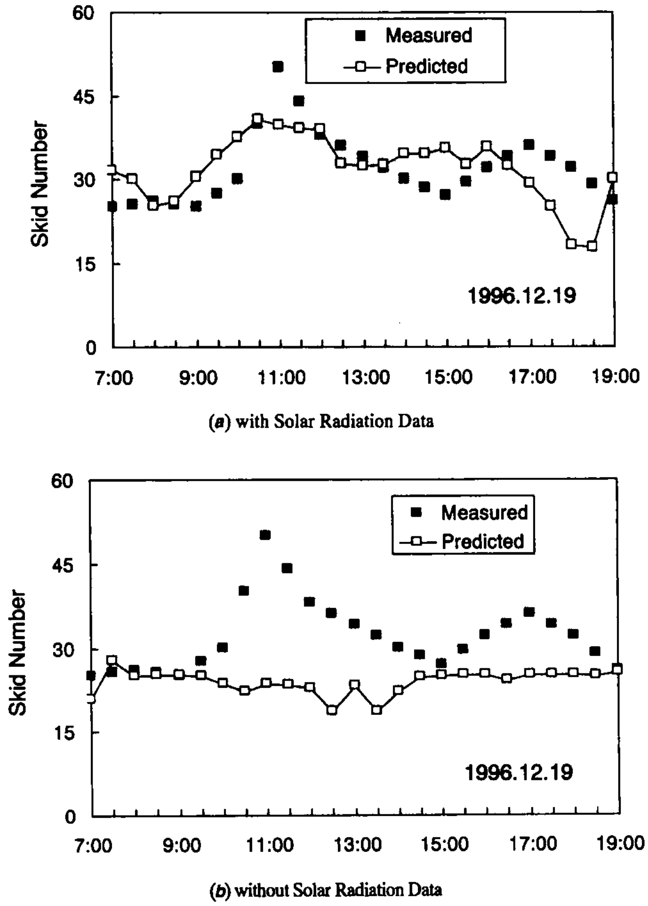


FIGURE 4 Skid numbers predicted by neural-Kalman filter in comparison with measured numbers for training data.

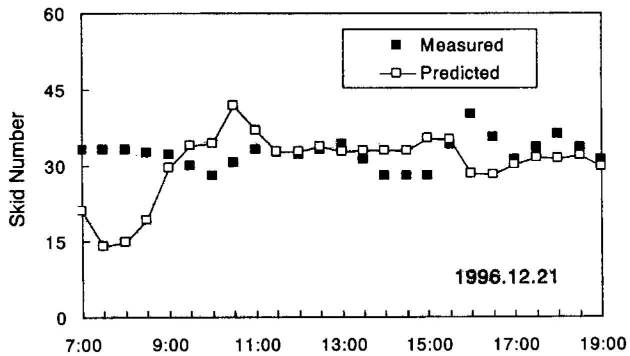
prediction in Case 2, in which solar radiation data were not used, gave very poor results. This is partly because of insufficient training of the neural networks as well as the lack of solar radiation data. Because a neural network model has the promising characteristic of being able to flexibly adjust synaptic weights regardless of the number of training data sets, the neural-Kalman filter could predict more precisely by training the neural networks with more measurement data sets.

CONCLUSIONS

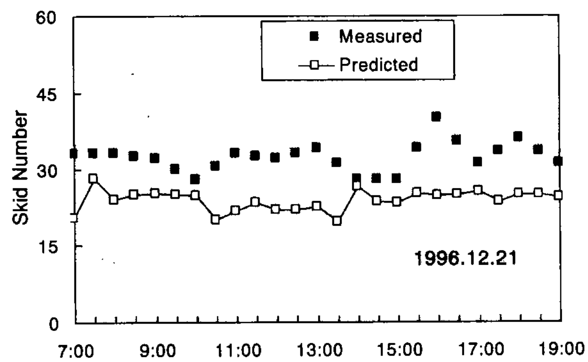
Information on the degree of slipperiness on road surfaces is very important for efficient snow and ice control. It is also useful for drivers using unfamiliar roads in winter. However, the transition of slipperiness is too complex to formulate mathematically. Slipperiness is difficult to measure because it varies greatly with time and space. To emulate the prediction process of experienced drivers, an artificial intelligence method for predicting the degree of slipperiness was developed. The major findings were as follows.

1. A multilayer neural network model was proposed to describe the nonlinear behavior of how slipperiness varied with time and how it was related to road surface temperature and weather conditions.
2. A method that could indirectly predict the skid number through road surface temperature was developed by integrating a neural network model into the Kalman filter.
3. The weather data that represent solar radiation activities were effective in constructing the neural network system and predicting the skid number.
4. The road surface temperature may not be sufficient to accurately represent the observation equation. Other weather condition variables may be needed.

This study is only the first step to predicting the slipperiness of road surfaces in winter. Many problems remain to be resolved. First, training precision of the neural network models must be improved. The estimation precision for checking data is not yet satisfactory. Also, what input signals are influential in the transition of road conditions in winter must be assessed



(*a*) with Solar Radiation Data



(*b*) without Solar Radiation Data

FIGURE 5 Skid numbers predicted by neural-Kalman filter in comparison with measured numbers for checking data.

quantitatively. Fortunately, because it is easy to differentiate the output signal y_m^E of Equation 12 with respect to any input signal x_i^B, the effect of each input signal is easily evaluated. Although comparison with other statistical approaches is another problem, it is too early to evaluate the new method because much has yet to be improved.

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