A Note on Prediction of Road Surface Condition Based on Two LSTMs Using Weather and Road Surface Data in Winter Road

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1. Introduction

Road surfaces become icy or snowy/icy in snowy and cold regions as shown in **Fig 1**. The severe road surface conditions often result in traffic accidents because controlling the vehicle's movement is difficult. To enable autonomous driving in snowy and cold regions, it is necessary to set the driving system such as braking control system adaptively depending on road surface conditions. It is also important to avoid the route with severe surface conditions. Providing look-ahead information on road surface conditions to automated vehicles contributes to optimizing the driving system and route selection of automated vehicles.

As related works, the authors previously proposed an edge-computing system to store driving images recorded by an onboard video camera and to estimate the road surface condition simultaneously based on recorded images [1]. Furthermore, the authors previously proposed a method for predicting road surface conditions [2] (hereinafter referring to the previous method). Specifically, the previous method conducted prediction by a Long Short Term Memory [3] (LSTM) -based model that learns spatial direction series data, which is composed of data obtained by edge-computing systems and weather data. Here, not only spatial direction but also temporal direction has transition trends of road surface conditions. Thus, the prediction performance is expected to be improved by introducing prediction using temporal direction series data into the previous method.

Thus, this paper proposes a method for predicting road surface conditions using a series of data on spatial and temporal directions. Specifically, the proposed method constructed two LSTM-based models that learn spatial direction series data and temporal direction series data, respectively. The proposed method conducts tentative prediction via each model and late fusion of tentative prediction results. Also, the LSTM-based model used in the previous method and the edge-computing system classify road surface conditions into 6 labels. These methods are assumed to be used to optimize the amount of salt that is spread to the road for preventing road surfaces from being icy. Therefore, road surface condition is required to be grasped in detail, and the number of labels set to be 6. However, the method proposed in this paper is assumed to be

Fig 1 Icy or snowy/icy road surfaces in snowy and cold regions.

used for autonomous driving in snowy and cold regions. Thus, it is important to understand the friction of the road surface, and it is important to predict whether the road surface is dry, wet, or icy/snowy. Therefore, the proposed method finally merges 6 labels to 3 labels (dry, wet, snow).

2. Prediction of Road Surface Condition Using Two LSTM-based models

The road surface data $l_{i,j}^{6}$ were obtained in area j at day i by the edge-computing system [2] that data were evaluated into 6 labels of dry, semiwet, wet, slush, fresh, and ice. When the proposed method are utilized at day i, the proposed method combines road surface data $l_{i,j}^{6}$ and weather data $w = (w_1, w_2, \cdots, w_k,)$ as $\vec{D}_{i,j} = \left(w_1, w_2, \cdots, w_k, l_{i-1,j}^{6},\ l_{i,j}^{6}\right)$. By using the above $\vec{D}_{i,j}$, the proposed method constructs spatial direction series data S and temporal series data T as follows.

$$S = \left(\vec{D}_{1,1,}, \vec{D}_{1,2,} \cdots, \vec{D}_{1,m,},\ \vec{D}_{2,m,} \cdots, \vec{D}_{2,1,}, \vec{D}_{3,1,}\right) \tag{1}$$

$$T = \begin{pmatrix} \vec{D}_{1,1,} & \cdots & \vec{D}_{1,m} \\ \vdots & \ddots & \vdots \\ \vec{D}_{n,1} & \cdots & \vec{D}_{n,m} \end{pmatrix} \tag{2}$$

The proposed prediction method trains two LSTM-based models by using S and T, respectively. The architecture of the prediction models is shown in **Table I**. Each model accept data $\vec{D}_{i+1,j}$ as input data and obtain probability for each label. $\vec{D}_{i+1,j}$ is composed by road surface of day i on area j and weather data of day i and $i + 1$. The proposed method sums the probabilities of tentative prediction from two models in each label and obtains the label that corresponds to the maximum value. Finally, the proposed method merges 6 labels to 3 labels (dry, wet, snow).

Table I The architecture of the prediction models.

Layer Number	Name	Units	Parameters	Activating Function
1	LSTM	64	16,896	-
2	LSTM	64	33,024	-
3	Dense	32	2,080	ReLU
4	Dense	6	198	SoftMax

3. Experimental Results

In this section, the effectiveness of the proposed method is verified by using actual obtained data based on the edge computing system. In this experiment, we use two comparative methods which are a method using only spatial direction series data (CM1) and a prediction method using only temporal direction series data (CM2).

This experiment uses actual obtained data in "Horotomi Bypass" which is located in the north side of Hokkaido, Japan . The road surface data are 20Km length in "Horotomi Bypass". In this experiment, 20Km length was divided in 90 areas. These data were 350 days from the period of between 2021/09/01 to 2023/03/15. The train data are 230 days and the test data are 120 days. Weather data in this experiment are 4 types of air temp.(◦C) of day i and $i+1$, snow depth(cm) and rainfall amount of day $i+1$ (mm). This experiment evaluates the predicted results of each method by using the following criteria.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

The experimental results are shown in **Table II**. Here PM means the proposed method. From **Table II**, the proposed method outperforms CM1 which uses only spatial direction series data in F-measure of all labels. Furthermore, the proposed method outperforms CM2 which uses only temporal direction series data in Recall of snow label which is most dangerous conditions. Thus, the effectiveness of the cooperative use of spatial and temporal prediction is confirmed.

Table II Recall, Precision and F-measure of PM, CM1 and CM2

	PM (Spatial and temporal)			CM1 (Only spatial)			CM2 (Only temporal)		
	Dry	Wet	Snow	Dry	Wet	Snow	Dry	Wet	Snow
Recall	0.63	**0.66**	**0.87**	0.57	0.43	0.85	**0.68**	0.56	0.84
Precision	**0.85**	0.35	0.90	0.70	0.38	0.78	0.71	**0.44**	**0.92**
F-measure	**0.73**	0.46	**0.89**	0.63	0.40	0.81	0.70	**0.49**	0.87

4. Conclusions

This paper proposed a novel method for predicting road surface conditions. The proposed method first conducts tentative prediction via two LSTM-based models using spatial and temporal direction series data. Then, the final prediction results are obtained by late-fusion of tentative prediction results. The effectiveness of the proposed method was confirmed by an experiment using actual data captured in Hokkaido, Japan. The look-ahead information on road surface conditions is obtained by utilizing the proposed method. The proposed method contributes to realizing automated vehicles in snowy and cold regions.

Acknowledgement

This work was partly supported by the Committee on Advanced Road Technology under the authority of the Ministry of Land, Infrastructure, Transport, and Tourism in Japan (Project name "Technological development of digital twin-oriented transportation management system in winter road", Principal Investigator: Assoc. Prof. Sho Takahashi, Hokkaido University). Also, this work was partly supported by JSPS KAKENHI Grant Numbers JP23K22877 too.

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