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EVALUATION OF ROAD SURFACE IRREGULARITY USING ACCELERATIONS RECORDED BY SMARTPHONE

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The infrastructure in Japan, which was mostly constructed in the 1960s, is facing aging problems. Higher priority has been given to the maintenance of infrastructure. The Road Committee of the Panel on Infrastructure Development recommended full-scale maintenance of aging roads in 2014. According to their recommendations, pavements may be inspected or replaced based on an appropriate renewal period depending on their deterioration level. This study aims to develop a numerical model to evaluate road surface irregularity using acceleration time histories recorded by smartphones. The records of the vertical component of acceleration of the automobile are employed to detect road sections with an international roughness index (IRI) of 12 mm/m or above. To achieve this objective, the IRI was measured with an interval of 10 m in the cities of Yokohama and Chofu. The authors employ logistic regression analysis and support vector machine to detect the road sections with an IRI of 12 mm/m or above. The discrimination accuracy is investigated, and a proper numerical model is proposed in this study.

Keywords: international roughness index (IRI), logistic regression analysis, support vector machine, smartphone.

1 Introduction

The infrastructures in Japan were mainly constructed in the 1960's, and they are facing aging problems. The ceiling panels inside the Sasago Tunnel collapsed on December 2, 2012, and nine people were killed by this accident. The Road Committee of the Panel on Infrastructure Development (2014) recommended full-scale maintenance of aging roads.

The roads in Japan are classified into the national expressways, national highways, prefectural roads, and municipal roads. According to the Ministry of Land, Infrastructure, Transport and Tourism (MLIT 2015), the total length of Japanese roads including narrow roads is approximately 1.21 million km as of April 2013. The length of municipal roads is approximately 1.02 million km, and it shows 84% by ratio. The number of road maintenance engineers in the municipal governments is very limited, and the budget for road maintenance is reducing these years.

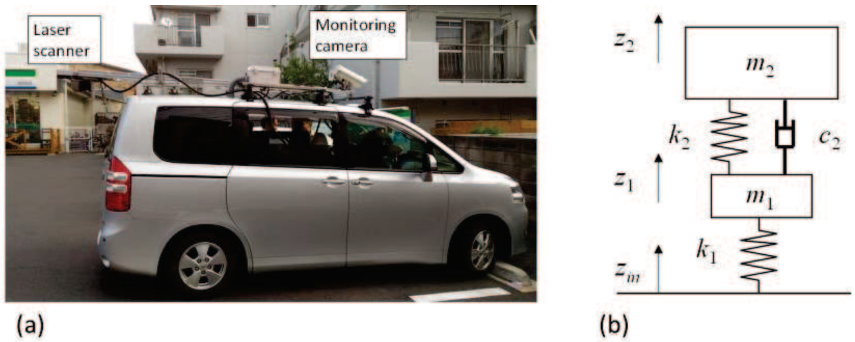

Figure 1. (a) Road-surface-condition survey (RSCS) vehicle and (b) quarter car model.

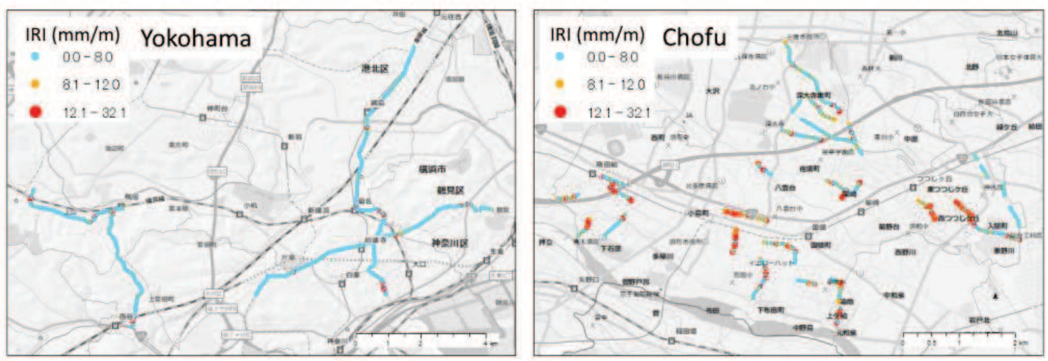

Figure 2. Observed international roughness indices in Yokohama and Chofu Cities.

In Japan, road-surface-condition survey (RSCS) vehicles are often employed to monitor the asphalt pavements. Maintenance Control Index (MCI), which was proposed the Ministry of Construction of Japan in 1981 (Omoto *et al.* 2003), is measured by RSCS vehicles. However, it is difficult to employ the RSCS vehicles for all of the municipal roads because of the expense involved. Hence, a new, low-cost measure to monitor the pavements is required by municipal governments.

Based on these backgrounds, this study evaluates the road surface irregularity based on the accelerations recorded by a smartphone. A smartphone was installed in an automobile to observe the accelerations during driving. The locations of the automobile were recorded by a global positioning system (GPS) unit equipped with the smartphone, and the velocities were also calculated during driving. The vertical accelerations were compared with the international roughness index (IRI), which is the road roughness index used most commonly in the world (Sayers *et al.* 1986). Numerical models to detect road sections with an IRI of 12 mm/m or above were considered based on logistic regression analysis and support vector machine.

2 Datasets Employed in This Study

2.1 *International Roughness Index (IRI)*

A RSCS vehicle belonging to Kajima Road Co., Ltd. (Fig. 1(a)) was employed to observe IRI. The longitudinal profiles were recorded by a laser scanner installed in the RSCS vehicle. The IRIs were calculated with an interval of 10 m assuming the quarter car model as shown in Fig. 1(b) (Sayers *et al.* 1986). The IRI is calculated by Eq. (1).

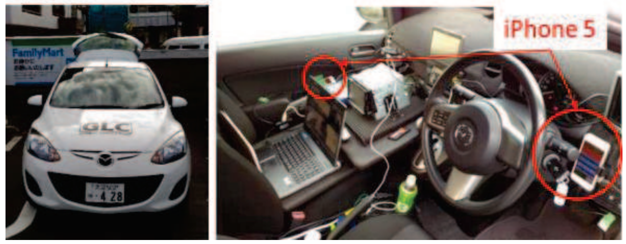

Figure 3. Smartphones installed in an automobile which followed the RSCS vehicle.

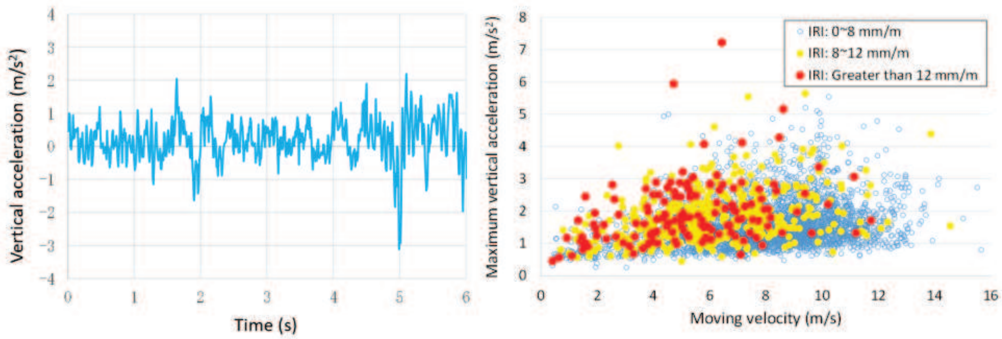

Figure 4. Example of the vertical acceleration time history recorded by the smartphone and the relationship between the maximum vertical acceleration and the moving velocity of the automobile.

$$IRI = \frac{1}{L}\int_0^{L/s} \left|\dot{z}_2 - \dot{z}_1\right| dt \qquad (1)$$

where z_1 and z_2, which are the responses against the road profile (z_{in}), are the vertical displacements [mm] of m_1 and m_2, respectively; L is the length of each section (10 m); and s is the speed (80 km/h).

In the guidelines on the inspection of pavements, compiled by the MLIT, heavy pavement distresses are associated with an IRI of 11–12 mm/m. The IRI measurements were performed in Yokohama on September 29, 2015, and in Chofu on October 9, 2015. Figure 2 shows the IRI values measured in this study.

2.2 *Acceleration Time History Recorded by a Smartphone*

Two smartphones (iPhone 5) were set as shown in Fig. 3 in another automobile which followed the RSCS vehicle. The accelerations recorded by the smartphone set at the passenger's door were employed in this study. The sampling frequency of the acceleration was set to be 100 Hz, and the locations of the automobile were also recorded by a GPS unit equipped with the smartphone.

The accelerations were compared with the IRI which was calculated with an interval of 10 m. Figure 4 shows an example of the vertical acceleration time history recorded by the smartphone, and the relationship between the moving speed of the automobile and the maximum vertical acceleration. The maximum accelerations are defined in terms of the absolute accelerations. The data points are depicted with different colors, which correspond to different IRI ranges. Larger maximum accelerations are observed as the moving velocity of the automobile gets larger. In addition, larger maximum accelerations are associated with larger IRI.

		Prediction	
Observation		IRI ≥ 12 mm/m	IRI < 12 mm/m
	IRI ≥ 12 mm/m	True Positive (TP)	False Negative (FN)
	IRI < 12 mm/m	False Positive (FP)	True Negative (TN)

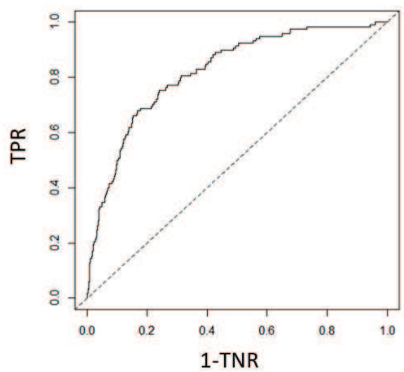

Figure 5. Example of the receiver operating characteristics (ROC) curve and definitions of the different fractions to draw ROC curve.

3 Evaluation of Road Surface Irregularity

3.1 *Logistic Regression Analysis*

A series of logistic regression analyses was performed to detect the sections with an IRI of 12 mm/m or above. Eq. (2) was assumed in this study.

$$p = 1/[1 + \exp\{-(b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3)\}] \tag{2}$$

where x_1 is the average speed of the automobile [m/s] in an interval of 10 m. x_2 and x_3 are the average and maximum vertical accelerations [m/s^2], respectively. b_0, b_1, b_2, and b_3 are the parameters determined by maximum likelihood method. The accelerations were not included in the calculation while the automobile was stopped. p is the probability defined as

$$p = \Pr(Y = 1 | x_1, x_2, x_3) \tag{3}$$

$$1 - p = \Pr(Y = 0 | x_1, x_2, x_3) \tag{4}$$

where the random variable Y = 1 when the section is associated with an IRI of 12 mm/m or above. Y is set to 0 for the section with an IRI of less than 12 mm/m.

The discrimination ability of the model was evaluated on the basis of the receiver operating characteristics (ROC) curve (Fig. 5). In the ROC curve, the true positive rate (sensitivity) is plotted as a function of the false positive rate (1-specificity) by changing the threshold value of p (Hanley and McNeil 1982). The definitions of different fractions are also given in Fig. 5. The area under the curve (AUC) is calculated based on the ROC curve to evaluate the discrimination ability (Metz 1978). The best cut-off probability to maximize both true positive rate (TPR) and true negative rate (TNR) is also obtained from the ROC curve.

3.2 *Support Vector Machine*

Support vector machine (SVM) is a pattern classification technique (Amari and Wu 1999). SVM aims at minimizing an upper bound of the generalization error through maximizing the margin between the separating hyperplane and the data. The authors employed a radial basis function (RBF) kernel to solve a nonlinear classification problem.

$$K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^{\mathrm{T}} \phi(\mathbf{x}_j) = \exp(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2) \tag{5}$$

where $\mathbf{x}_i$ is an input vector of the i-th data with a label of y_i ($y_i \in \{-1, 1\}$), and γ is a parameter which influences the result of classification.

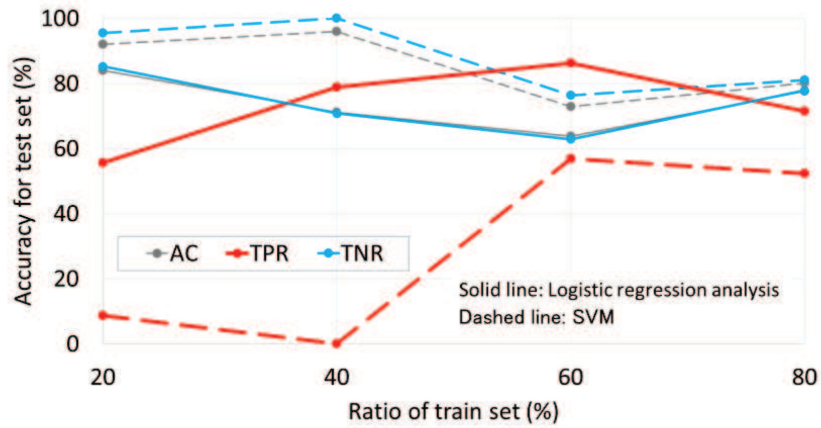

Figure 6. Comparison of the accuracies for test set obtained from the numerical models based on logistic regression analysis and weighted support vector machine.

Table 1. Summary of the logistic regression model to detect the road section with the IRI of 12 mm/m or above.

b_0	b_1	b_2	b_3	AUC	cut-off	TPR/TNR	AC
-2.043	-0.507	3.630	0.278	0.82	0.045	0.76/0.76	0.76

The nonlinear classifier $f(\mathbf{x})$ is expressed as

$$f(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\phi(\mathbf{x}) + b \tag{6}$$

w and b are obtained by solving an optimization problem shown below.

$$\min_{w,b,\zeta} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_i \zeta_i \quad \text{s.t. } y_i f(\mathbf{x}) \geq 1 - \zeta_i,\ \zeta_i \geq 0 \tag{7}$$

where C is a regularization parameter which influences the result of classification. The two parameters γ and C were determined based on k-fold cross validation. The dataset was divided into 10 subsets in this study. One of the 10 subsets was used for evaluation, while other 9 subsets were used for machine learning to estimate the best sets of parameters.

3.3 Evaluation of the models

The total number of observed IRI by this study is 3,581. The dataset was divided into training and test sets. The ratios between the number of training set and that of available data were sequentially changed, and the true positive rate (TPR), the true negative rate (TNR), and the accuracy (AC) were examined using the test set. The AC is calculated as in Eq. (8) using the fractions shown in Fig. 5.

$$AC = (TP + TN)/(TP + FN + FP + TN) \tag{8}$$

This study considered the two types of the numerical models based on logistic regression analysis and support vector machine. Figure 6 shows the TPR, TNR and AC with respect to the ratio of training set. The number of data with the IRI of smaller than 12 mm/m (3,442) is approximately twenty-five times larger than that of data with the IRI of 12 mm/m or above (139). Since the dataset employed by this study is imbalanced, the authors considered the weights of 25 in SVM classification (Abidine *et al.* 2013). According to the result, the logistic regression model shows the accuracy of approximately 75% if the ratio of training set is larger than 40%. As for the weighted SVM classification, the TPR is lower than that of logistic regression model.

Based on these findings, this study proposes the numerical model to detect the road section with the IRI of 12 mm/m or above based on logistic regression analysis. All of the available data was employed for regression analysis to complete the model. Table 1 summarizes the result of the logistic regression model. The model shows the accuracy of 76%, and fair discrimination ability based on the value of AUC.

4 Conclusions

This study aims to develop numerical models based on logistic regression analysis and support vector machine to detect road sections with the IRI of 12 mm/m or above using vertical accelerations recorded by smartphone. The logistic regression model showed a better result than the model based on support vector machine. The model showed the accuracy of 76%, and fair discrimination ability.

In a future study, the model will be applied for road inspection performed by local governments. Smartphones are installed in automobiles of road administrator, and road surface irregularity will be evaluated by the numerical model proposed by this study.

Acknowledgments

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