VEHICLE MODEL CALIBRATION IN FREQUENCY DOMAIN USING MULTIPLE OBSERVABLES AND ITS APPLICATION TO IRI ESTIMATION

Dept. of Civil Engineering, the University of Tokyo, Japan Student Member, º Zhao Bo Yu
Regular Member, Tomonori Nagayama

1. INTRODUCTION

The maintenance of ordinary road is important for the safety of drive and asset management. Instead of conventional profile measurement, which usually requires a special probe-vehicle, efficient approaches based on dynamic responses of ordinary vehicles have been developed. Dynamic response intelligent measurement system (DRIMS) estimates the International Roughness Index (IRI) by measuring vehicle's dynamic responses (Fujino et al. 2005). In order to achieve large-scale implementation, an iOS application named iDRIMS featuring accurate sampling timing, has been developed and integrated with DRIMS (Nagayama et al. 2013). Moreover, DRIMS has been improved to directly estimate road profile employing Unscented Kalman filter (UKF) and Kalman filter (KF) with acceleration and angular velocity responses of vehicle body as observable variables (Zhao et al. 2016). Half car (HC) vehicle model is adapted to account for the acceleration and angular velocity responses. However, its applicability is limited due to its poor robustness. The vehicle parameter identification through UKF is highly affected by inaccuracy in the drive speed and location estimation. As a result, the reliability of profile estimation through KF is low. In this paper, Genetic Algorithm (GA) is utilized in the vehicle's parameter identification to improve the robustness. As a numerical model of measurement vehicles, HC and quarter car (QC) models are compared with each other to examine the appropriateness of these models. A HC model calibrated through GA is shown to result in robust IRI estimation.

2. IRI ESTIMATION FLOW

The approach consists of two main steps, i.e., hump calibration and IRI estimation (See Fig.1). In the hump calibration step, vehicle models (i.e. HC or QC models) are calibrated by measuring vehicle's dynamic response when it passes over a portable hump with known shape at a specific speed. The difference between the measured responses and the simulated responses is minimized through GA with vehicle model characteristics as the parameters. Instead of minimizing the response difference in the time domain, the difference in power spectral density (PSD) of vehicle responses, which is not seriously affected by the error in speed and location, is chosen as the objective function of the minimization.

The QC model is optimized by minimizing PSD of vertical acceleration while HC model is optimized by minimizing the weighting summation of PSD of both vertical acceleration and pitching angular velocity. Using the identified parameters, the amplitude ratio function $TF(\omega)$ from measured acceleration to golden car responses is evaluated. The IRI estimation step is same as the previous algorithm. The acceleration response is measured when the vehicle drives over a target road. PSD of the acceleration response is converted to that of golden car by using amplitude ratio function and further converted to IRI (Nagayama et al 2013).

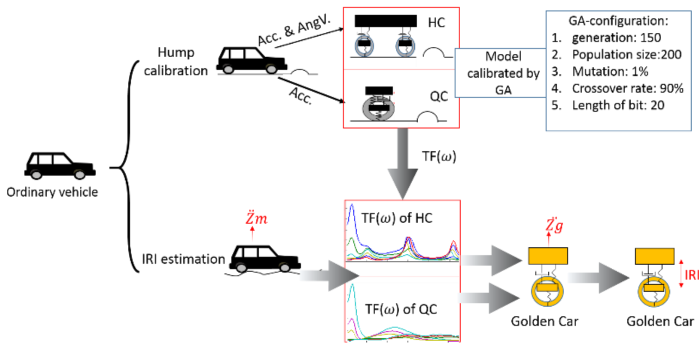


Fig. 1 Scheme of the proposed method

3. IRI ESTIMATION PERFORMANCE OF TWO VEHICLE MODELS

A numerical simulation of hump drive is performed using a reference HC model which represents real vehicle. Sensor installation location is 0.8 meter from the rear axle. Then the responses are used to calibrate the QC and HC model. $TF(\omega)$ of the estimated QC and HC models are shown in Fig. 2. The relative error of $TF(\omega)$ within 0-0.45 cycle/m is calculated by Eq. (1) and shown in Table 1.

$$C = \sqrt{\frac{\sum (TF(\omega) - TF(\omega)_{true})^2}{\sum TF(\omega)_{true}{}^2}} \tag{1}$$

As shown in Fig. 2 and Table 1, QC model cannot accurately reproduce amplitude ratio function. The reference HC model is then used to simulate the vehicle response of a 3km road. The IRI estimated by the calibrated QC model (see Fig. 3) shows poor accuracy and high dependency on drive speed due to its inability to reproduce the pitching motion. Note that the effect of pitching motion is small and QC model performs as good as HC model when the sensor is close to the axle. However, considering practical sensor installation, QC model does not perform as well as HC model. As shown in Fig. 4, HC model shows accurate IRI estimation with small speed dependency. The simulation result validates that IRI estimation based on HC model and GA is with high reliability. Therefore, HC model based approach is implemented in field test and the performance is examined next.

Keyword: Road condition evaluation, IRI, Half car model, Quarter car model, Genetic algorithm
Contact: Bridge & Structure Laboratory, Dept. of Civil Eng., The University of Tokyo, 113-8656, Japan, Tel: 03-58416009

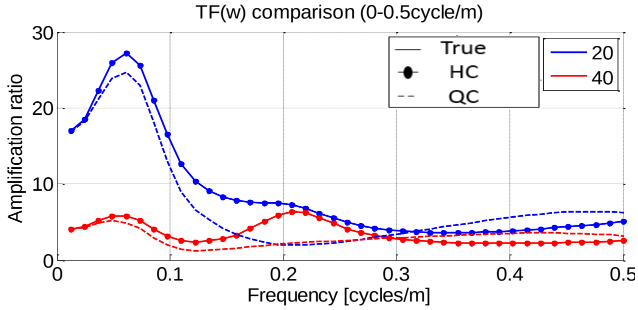


Fig. 2 Procedure of comparison between HC and QC model

Table 1 Relative error of $TF(\omega)_{acc.}$

Speed (km/h)	Quarter Car Model (%)	Half Car Model (%)
20	24.7	0.5
40	45.3	1.2
60	46.7	1.4
80	42.7	1.3
100	44.7	2.1

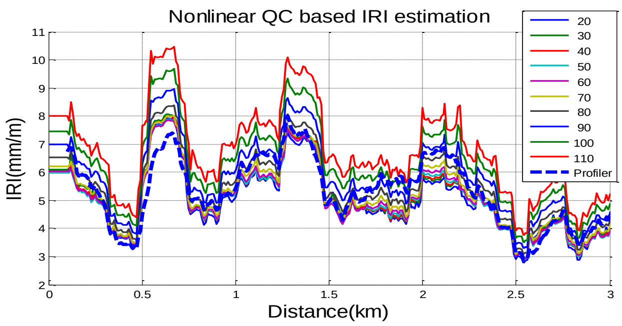


Fig. 3 IRI estimation based on QC model

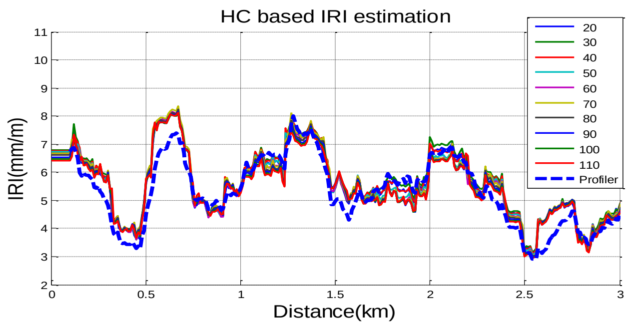
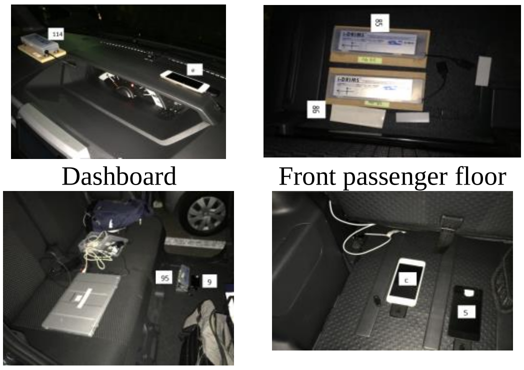


Fig. 4 IRI estimation based on HC model

4. IRI ESTIMATION IN FIELD TEST

Field test is performed on a 13km road in Chiba city. A light vehicle is implemented with multiple iPod touches at different locations (See Fig.5). The IRI estimation accuracy of the proposed method is examined by comparison with the road profiler. IRI estimation from sensors on dashboard is shown in Fig. 6. The IRI relative error is 12.77% at the dashboard; 13.49% at front passenger floor; 16.31% at rear passenger floor; and 13.30% at trunk. These results validate that the proposed method is able to achieve good IRI estimation even when sensor is installed at different locations.



Dashboard Front passenger floor

Rear seat floor Trunk

Fig. 5 Sensor layout

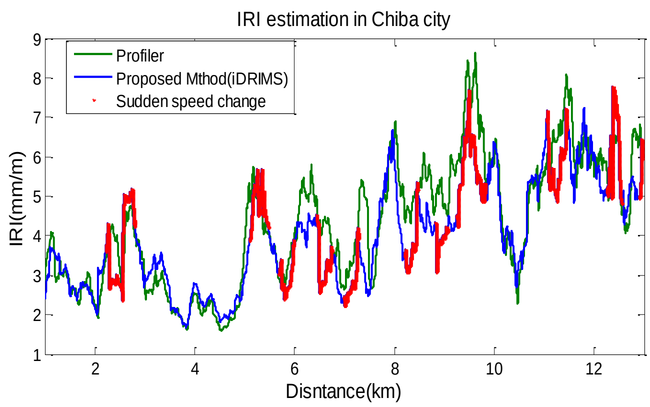


Fig. 6 IRI estimation of sensor on dashboard

5. CONCLUSION

A vehicle model calibration by optimizing vehicle body responses to a hump in the frequency domain using GA is examined based on QC and HC models. The calibration using HC model is shown to be accurate. The need of HC model is numerically validated by quantifying the error introduced by QC model. Both simulation and field test validate that the proposed method performs with a high accuracy and robustness for a variety of sensor installation locations.

REFERENCES

Fujino, Yozo, et al.: Development of vehicle intelligent monitoring system (VIMS). Smart Structures and Materials. 2005

T. Nagayama, et al.: Road condition evaluation using the vibration response of ordinary vehicles and synchronously recorded movies. SPIE Smart Structures and Materials+ Nondestructive Evaluation and Health Monitoring 2013: 86923A.

B. Y. Zhao, et al.: Development of response-based road profile estimation using multiple observables, Conference of Structural Engineering and Construction, Vietnam, 2015

ACKNOWLEDGMENT

This work was supported by Council for Science, Technology and Innovation, “Cross-ministerial Strategic Innovation Promotion Program (SIP), Infrastructure Maintenance, Renovation, and Management”. (Funding agency: JST)