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Research Paper

Road profile reconstruction using connected vehicle responses and wavelet analysis

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ABSTRACT

Practitioners analyze the elevation profile of a roadway to detect localized defects and to produce the international roughness index. The prevailing method of measuring road profiles uses a specially instrumented vehicle and trained technicians, which usually leads to a high cost and an insufficient measurement frequency. The recent availability of probe data from connected vehicles provides a method that is cost-effective, continuous, and covers the entire roadway network. However, no method currently exists that can reproduce the elevation profile from multi-resolution features of the vehicle inertial response signal. This research uses the wavelet decomposition of the vehicle inertial responses and a nonlinear autoregressive artificial neural network with exogenous inputs to reconstruct the elevation profile. The vehicle inertial responses are a function of both the vehicle suspension characteristics and its speed. Therefore, the authors normalized the vehicle response models by the traveling speed and then numerically solved their inertial response equations to simulate the vehicle dynamic responses. The results demonstrate that applying the artificial neural network to the wavelet decomposed inertial response signals provides an effective estimation of the road profile.

1. Introduction

As pavement roughness accelerates vehicle wear, affects ride quality and transportation safety, expedites pavement deterioration, and increases fuel consumption, it has long been used as a major criterion to assess the road condition and guide the road maintenance and rehabilitation (Zhang et al., 2015; Kong et al., 2017; Qin et al., 2019). The prevailing method of roughness measurement uses a vehicle instrumented with an inertial profiler to collect road profile data (Spangler and Kelly, 1966). The inertial profiler collects the road profile information at a highway speed and a sampling rate sufficient for further analysis of the profile's spectral composition. Despite its worldwide popularity, the profiling method has high cost and labor intensity that prevents agencies from measuring many roads more than once per year. As a result, the decisions on road maintenance and rehabilitation are usually made using outdated road roughness information. Moreover, infrequent road condition monitoring precludes the detection of severe immediate road distresses such as the frost heaves that occurs and vanishes within a year. This situation leads to information gaps of roadway safety and thus increases the liability of administrative bureaus (Zhang et al., 2016).

The response-type method of roughness evaluation uses the dynamic responses of a probe vehicle traversing uneven roads, including the displacements, velocities, and accelerations of multiple components of the vehicle, to assess the road roughness severity indirectly. Compared with inertial profiling, the response-type method is less expensive because it reduces labor and equipment costs. Hence, this method allows more frequent and timely measurement and evaluation of road roughness conditions by agencies. Mostly, the response-type method yields an indirect roughness evaluation index through statistical analysis and signal processing on the collected data of vehicle responses, which is usually comparable to the widely used international roughness index (IRI) (Bridgelall, 2014; Bridgelall et al., 2016). Recently, the response-type method has also been used to estimate the road profile by analyzing the collected data using advanced signal processing and system identification techniques (Ngwangwa et al., 2010; Kong et al., 2014; Qin et al., 2018). The literature review finds that there is limited research on road profile estimation using probe

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vehicle responses. All the existing studies use the collected signal series as the input to their estimating algorithms without discriminating its frequency composition. Vehicle responses, the output of a vehicle under the roughness excitation when travelling across a road section, reflects the road information as well as the vehicle characteristics, which compromises its representation of the roughness information if without appropriate signal decomposition and filtering.

Wavelet analysis provides a multi-resolution decomposition of a signal in the time or spatial domain. It is widely used for road profile and pavement surface analysis and evaluation. Qin et al. used wavelet analysis to extract features from vehicle responses for road roughness classification (Qin et al., 2017). Wei and Fwa characterized road roughness using the wavelet energy statistics developed from a wavelet transform and found that it has a high correlation with IRI for both asphalt and concrete pavements (Wei and Fwa, 2004). De Pont and Scott used wavelet analysis to find local roughness features by comparing the magnitude of a certain component with a reference value at that decomposition level (De Pont and Scott, 1999). Papagiannakis et al. used wavelet analysis to decompose the pavement roughness and a truck's dynamic axle load and compared their relative energy within different wavelet sub-bands (Papagiannakis et al., 2007a, 2007b). Shokouhi et al. used wavelet-based multi-resolution decomposition as a diagnostic tool to determine the location and extent of various frequency features of the road profile including pavement defects and surface anomalies (Shokouhi et al., 2005). Wei et al. used wavelet analysis as a tool to provide in-depth insights into the road profiles including the correlation of the IRI with the energy within the subbands, the energy distribution difference for profiles with close values of IRI, the effect of local features on IRI, and the identification of patterns of pavement roughness deterioration (Wei et al., 2005). Zhou et al. used wavelet transform together with Radon transform to analyze pavement images for the purpose of pavement distress classification (Zhou et al., 2005).

Daubechies' wavelet family is widely used for signal processing due to their ease of implementation and their orthogonality that yields stable mathematical behaviors. Among the Daubechies' wavelet family, DB3 is the most widely used wavelet for road profile analysis (Wei and Fwa, 2004; Wei et al., 2005; Papagiannakis et al., 2007a, 2007b) because of its good resolution in both the spatial and frequency domains as well as its orthogonality and maximal flatness. These are desirable characteristics to support iterative decomposition in discrete wavelet transforms (Daubechies, 1988). Researchers also use other wavelets from the Daubechies' family to analyze road roughness such as DB4 (De Pont and Scott, 1999) and DB6 (Shokouhi et al., 2005).

Machine learning technique is an effective tool for data analysis and information extraction. It has been widely used to assess road condition by processing and analyzing the data collected from connected vehicles. Ngwangwa et al. used a Bayesian-regularized nonlinear autoregressive exogenous model (NARX) neural network to reconstruct road profiles (Ngwangwa et al., 2010). Qin et al. used a probabilistic neural network (PNN) classifier to determine the road roughness class for a semi-active suspension system (Qin et al., 2017). Guarneri et al. used a recurrent neural network to predict the dynamic behavior of vehicles traversing road irregularities by training the network with outputs from a simulated tire-suspension model (Guarneri et al., 2008). Attoh-Okine aimed at predicting the IRI and conducted a detailed study on the influence of momentum-term and learning rate in the back-propagation algorithm (Attoh-Okine, 1999). Tai et al. detected road anomalies, such as potholes and rutting, by processing the data collected from a motorcycle-mounted tri-axial accelerometer using the support vector machine (Tai et al., 2010). Hoffmann et al. developed an online road roughness classification system using bicycles instrumented with smartphones imbedded with the Naive Bayes algorithm (Hoffmann et al., 2013). Ward and Iagnemma used support vector machines to process the measured acceleration signal from a passenger vehicle to classify terrains after removing the impulses from anomalies including ruts and potholes (Ward and Iagnemma, 2009).

Practitioners use the elevation profile data to characterize network-level roughness, estimate the spatial wavelength composition of a road segment, localize anomalies, and forecast maintenance needs. Therefore, the availability of roadway elevation profiles from widely available connected vehicle data sources will provide transportation agencies and users with efficient means to collect road condition data continuously, and network-wide. The literature review indicates a lack of research that addresses the estimation of a road elevation profile from connected vehicle data. This research contributes to this field by applying the NARX artificial neural network to the wavelet decomposed inertial responses from connected vehicles to estimate the road elevation profile. The organization of the paper is as follows: Section 2 describes the mathematical models used for the roughness generation and the vehicle response analysis. Section 3 describes the wavelet decomposition of the normalized vehicle responses that serve as inputs to the NARX network of road profile reconstruction. Section 4 reconstructs the road profiles by applying the NARX network to the wavelet decomposed signal components. Finally, Section 5 presents the conclusions and outlines the future work.

2. Model description

2.1. Vehicle roughness interaction

Fig. 1 illustrates the dynamic model of a vehicle and a single dimension road profile. The vehicle model is a quarter car that contains a sprung mass m_s, an un-sprung mass m_u, a suspension spring k_s, a tire spring k_u, a suspension damper c_s, and a tire damper c_u. Studies of vehicle dynamics and ride quality use the quarter car model extensively because of its simplicity and effectiveness [29–32]. IRI is defined as the integrated relative difference between the sprung mass velocity and the un-sprung mass velocity over the distance traveled, assuming that the model travels at a simulated speed of 80 km/h over the measured road profile with roughness (Sayers, 1995). In particular, IRI is a function of the sprung and un-sprung mass motions of a special quarter car that the international standard specifies to represent all vehicles, regardless of their actual parameter equivalents.

Suppose that y_s^t and y_u^t are the absolute displacements of the sprung and un-sprung masses, respectively. Let y_s and y_u denote the relative displacement of the sprung mass and the un-sprung mass, respectively, such that

$$y_s = y_s^t - y_u^t \quad \text{and} \quad y_u = y_u^t - \xi. \tag{1}$$

Expressing the equations of motion of the dynamic system in the matrix form yields [33]:

$$M\ddot{Y}(t) + C\dot{Y}(t) + KY(t) = R(t) \tag{2}$$

where $M = \begin{bmatrix} m_s & m_s \\ 0 & m_u \end{bmatrix}$, $C = \begin{bmatrix} c_s & 0 \\ -c_s & c_u \end{bmatrix}$, $K = \begin{bmatrix} k_s & 0 \\ -k_s & k_u \end{bmatrix}$, $Y = \begin{Bmatrix} y_s \\ y_u \end{Bmatrix}$, $\dot{Y} = \begin{Bmatrix} \dot{y}_s \\ \dot{y}_u \end{Bmatrix}$, $\ddot{Y} = \begin{Bmatrix} \ddot{y}_s \\ \ddot{y}_u \end{Bmatrix}$, and $R = \begin{Bmatrix} -m_s\ddot{\xi} \\ -m_u\ddot{\xi} \end{Bmatrix}$.

Solving Eq. (2) for a given road profile produces the absolute displacements of the sprung and un-sprung masses such that