

Speed independent road classification strategy based on vehicle journal homepage: www.elsevier.com/locate/ymssp

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ABSTRACT

This paper presents a speed-independent road classification strategy (SIRCS) based on sole measurement of unsprung mass acceleration. The new method provides an easy yet accurate classification methodology. To this purpose, a classification framework with two phases named off-line and online is proposed. In the off-line phase, the transfer function from unsprung mass acceleration to the road excitation is firstly formulated, and a random forest-based frequency domain classifier is then generated according to the standard road definition of ISO 8608. In the online phase, unsprung mass acceleration and vehicle velocity are firstly combined to calculate the equivalent road profile in the spatial domain, and then a two-step road classifier attributes the road excitation to a certain level based on the power spectral density (PSD) of the equivalent road profile. Simulations are carried out for different classification intervals, varying velocity, system uncertainties and measurement noises. Road experiments are finally performed in a production vehicle to validate the proposed SIRCS. Measurement of only unsprung mass acceleration to identify road classification and less rely on the training data are the major contributions of the proposed strategy.

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1. Introduction

Road condition identification attracts much attention of vehicle manufacturers and government because of vehicle safety and comfort [\[1,2\].](#page--1-0) In America, about a quarter of major urban roads are in poor conditions, resulting in extra vehicle maintenance cost of nearly four hundred dollars per driver per year [\[3\]](#page--1-0). A report in 2013 revealed that annual road maintenance expenditure was about 20,000 million Euros in EU $[4]$, and roads with poor conditions decrease passengers' feeling and increase travel times [\[5\].](#page--1-0) Better road condition information can not only help drivers and advanced vehicle control systems [\[6–9\]](#page--1-0), but also assist in a better road maintenance scheduling.

Generally speaking, reported road estimation algorithms could be divided into three distinct types, i.e. contact measure-ment, non-contact measurement and system response based estimation [\[10\]](#page--1-0). The first type requires specially designed profilometer, which restricts its commercial application [\[11\]](#page--1-0). For the second method, Mono/Stereo cameras and LiDAR are applicable thanks to the vigorous development of autonomous vehicles. Although accurate estimation can be obtained with the non-contact measurement method, high cost of the instruments impedes its application in middle- to low-end vehicles.

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<https://doi.org/10.1016/j.ymssp.2018.07.035> 0888-3270/© 2018 Elsevier Ltd. All rights reserved. As a result, the third type becomes more and more popular with the help of sensors installed for advanced vehicle dynamics control in mass-produced vehicles [\[12\].](#page--1-0)

To date, various algorithms have been developed and introduced to the system response based method, which can be classified into two categories from the perspective of model formulation, namely data-driven and model based [\[13\]](#page--1-0). Data-driven method formulates black-box model/classifier based on the training data. Ward et al. used a well-trained support vector machine (SVM) classifier to classify real-world road types [\[14\].](#page--1-0) Qin et al. used adaptive neuro-fuzzy inference system (ANFIS) [\[12\]](#page--1-0) and deep neural network (DNN) [\[15\]](#page--1-0) for road classification and pointed out the unsprung mass is the most suitable system response because of its merits of measurable and relative high classification accuracy [\[16\]](#page--1-0). Although data-driven methodology can obtain satisfactory classification result, it still heavily relies on the training data and the accurate extrapolation can not be guaranteed [\[17\].](#page--1-0) Model based strategy thus attracts more attention in recent years, where system observer technique is one important component $[18–20]$. Rath et al. realized the simultaneous estimation of road profile and tire-road friction with a combined higher-order sliding mode and nonlinear Lipshitz observer [\[21\]](#page--1-0). Martinez et al. presented an adaptive observer based on Q-parameterizations for semi-active suspension system, which was also experimentally validated. Several attempts have also been made to reconstruct road profile with Kalman-based observer [\[22,23\]](#page--1-0). All the studies related to system observer reviewed so far, however, suffer from one common drawback that not all required response information is measurable. Transfer function based road estimation methodology thus emerges as an alternative. Gonzalez et al. used the transfer function from unsprung mass acceleration to road profile to estimate road power spectral density (PSD) [\[24\]](#page--1-0). Ward et al. and Wang et al. further extended this approach to varying velocity scenario and performed experiment validation [\[14,25\].](#page--1-0)

Since no detailed classification algorithm is proposed in $[24]$, and both $[14,25]$ require extensive training data prior to the classification which is impractical for mass-produced vehicles, this paper presents a general framework for road classification without prior training process and independent from the vehicle velocity. The proposed framework contains both online and off-line phases, In the off-line phase, both the inverse transfer function model and the well-trained road class classifier are obtained and stored for online application. As for the online phase, the equivalent road profile in the spatial domain is calculated based on unsprung mass acceleration and vehicle speed. Comprehensive analysis for different driving scenarios and road conditions are numerically investigated, and experimental studies have been conducted to validate the proposed method. The contributions of this paper are:

- A general road classification framework is proposed, which is robust to vehicle velocity and does not rely on extensive training data.
- The SIRCS is robust to system uncertainties and measurement noises. Methods to further improve classification accuracy in noisy environments are also discussed.
- Road tests for different scenarios on various road conditions are performed to validate the algorithm.

The rest of this paper is organized as follows. Section 2 introduces models of road profile and a quarter vehicle; Section 3 presents the classification algorithm and numerical simulation; Section [4](#page--1-0) details road experiments; and Section [5](#page--1-0) concludes the paper.

2. System modeling

This section presents a quarter vehicle transfer function, and details definition of various road levels.

2.1. Vehicle transfer function for road classification

This paper uses the transfer function of a quarter vehicle suspension system to formulate the proposed SIRCS. Despite its simplicity, both simulation and field test results show the quarter vehicle model has good accuracy for the presented algorithm. [Fig. 1](#page--1-0) depicts the structure of quarter vehicle model with the following dynamics:

$$
m_b \ddot{x}_b + k_s (x_b - x_w) + c_p (\dot{x}_b - \dot{x}_w) = 0 m_w \ddot{x}_w + k_t (x_w - x_r) + k_s (x_w - x_b) + c_p (\dot{x}_w - \dot{x}_b) = 0
$$
\n(1)

where m_b and m_w are sprung and unsprung mass; k_s and k_t denote the spring and tire stiffness; c_p represents the damper coefficient, and x_b , x_w and x_r stand for displacements of the sprung mass, unsprung mass, and road profile, respectively. Note that the tire is simplified to be a spring with only vertical stiffness. The reasons for such simplification are twofold:

 The tire is a complex system containing nonlinearity, time-delay, hysteresis, and uncertainty. Its dynamics have attracted the attention of both academia and the automobile industry, and much remarkable researches have been done on this topic in recent decades [\[26\],](#page--1-0) however, an accurate tire dynamic model is always unavailable in a real-world application. A simplified tire model is thus necessary for vehicle dynamics analysis.

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