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Consistent haul road condition monitoring by means of vehicle response normalisation with Gaussian processes

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ABSTRACT

Suboptimal haul road management policies such as routine, periodic and urgent maintenance may result in unnecessary cost, both to roads and vehicles. A recent idea is to continually access haul road condition based on measured vehicle response. However the vehicle operating conditions, such as its instantaneous speed, may significantly influence its dynamic response resulting in possibly ambiguous road classifications. This paper proposes vehicle response calibration by means of Gaussian process regression, so that a severity metric which is more robust to fluctuating operating conditions may be obtained.

1. Introduction

Various road maintenance policies, such as routine, periodic and urgent maintenance (Burningham and Stankevich, 2005) have been investigated towards the goal of minimising both road and vehicle maintenance costs. To support maintenance decisions many road agencies collect data which are representative of the road condition, such as road surface monitoring (RSM) which is based on laser technology, falling weight deflectometer (FWD) measurements, and ground penetrating radar (GPR) measurements (Ruotoistenmäki and Seppälä, 2007). Some indices, such as the pavement condition index (PCI) which requires manual surveying of roadways, and the present serviceability index (PSI) have also widely been investigated as indicators of the condition of roads (Ruotoistenmäki and Seppälä, 2007).

The aforementioned approaches are often expensive, time consuming or subjective so that they are not well suited to the frequent monitoring of haul roads. It has subsequently been proposed that vibration response, as measured directly on a vehicle, may be used to assess the condition of a road.

Thompson et al. (2003) investigate the use of on-board diagnostic data collection systems in conjunction with GPS coordinates to monitor open cast haul roads on a real-time basis. Based on field experiments they found that distinct vibration signatures are generated for different road defects. Theoretically these signatures can be used to identify road conditions. However, they also found that certain operating conditions (such as the speed of the vehicle, its acceleration and its payload) affect these vibration signals. Isolated interpretation of the vibration data, without considering the vehicle operating conditions, could result in ambiguous road classification. Thompson et al. (2003) propose that research should be conducted where artificial neural networks (NNs) are used to account for the effect of different operating conditions on the vehicle response.

Hugo et al. (2008) propose the use of an inverted model of a haul truck to estimate the road profile from the measured response. They implement a seven degree of freedom model, which consists of a set of coupled second order differential equations. These equations describe the interaction between the lumped masses, damping coefficients and stiffness constants of the vehicle. The condition of a section of road is estimated by converting its reconstructed road profile to a power spectrum which may then be assessed against the ISO 8608 road classification standards (International Organization for Standardization, 1995).

Ngwangwa et al. (2010) propose that a NN could be trained to directly model the inverse dynamics of a vehicle. This approach avoids the need to invert the vehicle model, rendering it possible to model the nonlinear characteristics of the vehicle, such as those exhibited by the wheels. This approach avoids the costly requirement to individually characterise vehicle components, by allowing the NN to learn the assembled vehicle characteristics from a set of training data. The training data are generated by measuring the response of the selected vehicle over different road profiles for different operating conditions. The estimated road

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profile is again classified according to the ISO 8608 standards (International Organization for Standardization, 1995).

The cost associated which generating the necessary experimental data to train the models in the aforementioned approaches can limit the practical feasibility of these techniques. The model described by Hugo et al. requires the characterisation of individual truck components, such as the suspension struts. The massive scale of these trucks renders this process both complex and expensive. Similarly the NN models require training data, where either manually classified road defects or measured road profiles must accurately be synchronised with the measured vehicle response.

Rather than basing maintenance decisions on an estimated road profile, it may be substantially simpler to perform maintenance based on some indication of the strain that a vehicle is subjected to when it traverses a section of road. The International Road Roughness Experiment (Sayers et al., 1986) comprises a large scale investigation into the feasibility of a variety of possible metrics to serve as an indication of the road roughness. One such vehicle response measure is the international road roughness index (IRI) which is based on the cumulative strut displacement of the vehicle (Sayers et al., 1986). The IRI exhibits a number of desirable characteristics, such as being easy to measure and being fairly well correlated with the actual road condition. It is found that these vehicle response type measures, including the IRI, are generally sensitive to both the road profile and the vehicle operating speed (Sayers et al., 1986). For this reason it is necessary to compare these vehicle response measures a standardised speed; the IRI for instance is specified at a constant speed of 80 km/h (Sayers et al., 1986; Kropáč and Múčka, 2005).

Rashid and Tsunokawa (2008) consider the practical limitations of measuring vehicle response on a vehicle which operates in traffic and hence cannot maintain a constant speed. They propose to improve the quality of vehicle response measures which are measured under fluctuating speeds by implementing speed calibration equations. It is however noted in the International Road Roughness Experiment (Sayers et al., 1986) that the dependency between the vehicle response and the vehicle speed is not static, but rather depends on the type and roughness of the surface which is traversed. This is because the vehicle responds to the presence of different wavebands and road signatures when operated at different speeds. It is subsequently difficult to implement a single calibration function.

This paper proposes a speed calibration methodology, where the underlying condition of the road is considered during the calibration phase. This renders it possible to obtain a dynamic calibration function which adjust itself to the instantaneous nature of the road which the vehicle traverses, hence allowing for more robust calibration.

A case study is performed on data which were measured on a utility vehicle at an underground coal mine. A severity metric is defined based on the instantaneous magnitude of the vehicle response as measured on a wheel axle. The dynamic calibration function is implemented by means of Gaussian process regression. The methodology may also be implemented with any of a number of standard regression analysis techniques, such as neural networks and support vector regression. This paper favour the use of Gaussian process regression due to its good generalization properties. The results indicate that the proposed methodology may potentially be of use as a generic, simple and cost effective approach to perform real time road condition monitoring.

2. Metric calibration for consistent road quality evaluation

2.1. Severity metric

Road quality may be interpreted as one, or a combination, of multiple criteria (Ruotoistenmäki and Seppälä, 2007). Some criteria which may be considered include how safe the road is, how much wear it causes to a vehicle, and how comfortable it is to drive on. Towards this goal it is reasonable that various types of vehicle response measurements may be used to assess road quality. Since the vehicle response is dependent on the operating conditions, such as the vehicle speed, it is required to calibrate the proposed metrics to a standardised operating condition which will allow for consistent road quality comparison.

The proposed calibration framework discussed in this paper is intended to be generic, and not specific to a selected metric. However, for the presented case study a single metric which is deemed relevant to the continuous monitoring of haul roads is investigated.

An accelerometer is attached to the wheel axle. The position on the wheel axle, which is an un-sprung mass, is selected to ensure good transmissibility. The envelope of the acceleration signal is subsequently computed. This is done by taking the point-wise absolute value of the acceleration signal and then using a low pass filter to remove the high frequency content. The obtained metric is instantaneous and reflect the presence of individual humps. The metric is representative of the magnitude of the acceleration, and thus the force, which is transmitted to the vehicle. The metric is also easy to implement, since it only requires the installation of a single accelerometer.

2.2. Dynamic calibration function

The focus of this paper is the implementation of a dynamic calibration function which adjust itself to the instantaneous nature of the road which the vehicle traverses so that more robust calibration may be performed.

The implemented dynamic calibration function rests on the assumption that if a vehicle traverses a section of road at a measured speed v_i so that vehicle response r_i is observed, then the combination of these two measurements contains information regarding the underlying condition of that section of road. These two variables may thus be used in some nonlinear manner to adjust the calibration function to better represent the specific section of road. The adjusted calibration function may subsequently be used to estimate the expected vehicle response r_j if the vehicle was to traverse the same section of road at a different (standardised) speed v_j. The process where an individual datum point from the continuous measurement is calibrated is presented in Fig. 1.

Nonlinear regression techniques may be used to learn the proposed calibration functions from training data. It will be shown how the required training data may be obtained in a cost effective manner, without the need for manual classification or profiling of the road surface.

Various regression techniques such as polynomial, spline or Neural Network (NN) regression analysis may be implemented. The results indicated in this paper are based on Gaussian process regression, since this is the technique which offered the best performance on our data set. Rasmussen (1996) examines a number of case studies where Gaussian process regression generalizes well and occasionally significantly outperforms other regression techniques, especially when limited training data are available. An empirical study by Wang et al. (2008) similarly found one of the main strengths of the Gaussian models to be

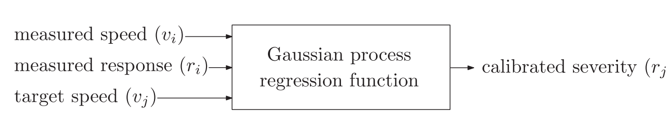

Fig. 1. Calibrating a single datum point from the continuous severity measurement to a specified target speed.