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An SVM Based Algorithm for Road Disease Detection using Accelerometer

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Abstract

A signal processing algorithm based on the principle of support vector machines as well as the analysis to the characteristics of road surface diseases is proposed to detect pavement disease. Measurements from vehicle-mounted sensors (e.g., accelerometers and Global Positioning System (GPS) receivers) are properly combined to produce higher quality road roughness data for road surface condition monitoring. By using the proposed algorithm to identify the measurements, the test results show that this algorithm is suitable for pavement disease detection and is an efficient algorithm.

Keywords: *pahavement distress detection, support vector machine, signal processing*

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1. Introduction

The road is an important part of the highway. When the road is built and put into use, due to repeated rolling under the wheels, and rain, snow and other natural factors, the road will definitely lead to produce a variety of diseases, which affect the quality of highway driving. If the diseases are not found on the road timely, it will lead to a threat to safe driving and the need to spend a lot of maintenance costs. Therefore, to maintain the road level of service, we must strengthen the monitoring of highway management and conservation.

There are technical and systematic solutions known, as vision systems [1-3], ground penetrating radars [4], or devices assembled in cars consists of GPS and 3-axis accelerometer [5, 6]. Usually, the latter is considered as a low cost solution. The processing and classification of data collected from GPS and accelerometer are done onboard of the device. The device records only spot locations being locally classified as potholes or other road defects. The reliable results of pavement disease detection depend on the signal-processing methods captured from accelerometer.

Since road surface roughness is the main external excitation source of vehicle vibration, especially road surface diseases emerge high-energy events in the acceleration signal. Therefore, the algorithm of detecting some special diseases such as bumps, potholes, etc., from a number of measurements is a topic of this paper. The contribution of this paper is organized as follows. In Section 2, the preliminary algorithm is presented. The data models and the signal-processing methods proposed to solve the related issues are given in Section 3. In Section 4, the test results are shown. Conclusions are given in Section 5.

2. Preliminaries

When the vehicle is running, vehicle vibrations mainly from three aspects: (a) vibration of automobile suspension system caused directly by road irregularities, (b) body vibration caused by vehicle acceleration in direction of motion, and (c) vehicle vibration induced by torsional vibration of driveline through coupling. Meanwhile surface roughness is the main external excitation source of automotive suspension vibration. The vibrations from (b) and (c) are difficult to analyze because of the relevant parameters and the complex mechanism. Thus, the vast majority of performance analysis of vehicle dynamics takes road roughness as the external input stimulus of whole vehicle system.

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Road surface input excitation can generally be divided into two categories: the impact vibration and the continuous vibration. The impact vibration means the discrete events which occur in a relatively short time, and having high vibration intensity, for example, bumps and potholes on road surface. The continuous vibration refers to continuous excitations along the road direction. They are long time discrete events, such as asphalt pavement, concrete pavement. Therefore, the measurements of acceleration and displacement of body vibration in vertical caused by road excitation will reflect the characteristics of road surface.

To take the dynamical analysis of vehicle suspension systems, one should establish the appropriate vehicle model. This paper uses 1/4 vehicle model with 2 degrees of freedom, which is the basic dynamics model for design of vehicle suspension system as shown in Figure 1. It can basically reflect the characteristics of acceleration, velocity, Displacement of body vibration in vehicle suspension system with excitation. Compared with the complex full-vehicle model, 1/4 vehicle model with 2 degrees of freedom has less design and performance parameters to simplify the system input.

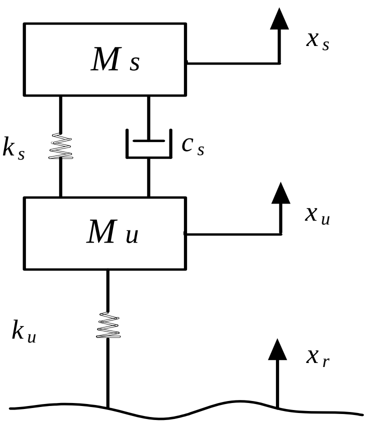


Figure 1. Model of quarter-vehicle

According to Figure 1, the quarter-vehicle kinetic equation is given as the following:

$$\begin{cases} M_s\ddot{x}_s = -k_s(x_s - x_u) - c_s(\dot{x}_s - \dot{x}_u) \\ M_u\ddot{x}_u = k_s(x_s - x_u) + c_s(\dot{x}_s - \dot{x}_u) - k_u(x_u - x_r) \end{cases} \quad (1)$$

Where M_s and M_u are sprung mass and non-sprung mass respectively. k_s and k_u are suspension spring stiffness and tire stiffness respectively. x_r , x_u and x_s are vertical surface displacement, the sprung mass displacement and non-sprung mass displacement respectively. c_s is damping coefficient.

Laplace transform of (1)

$$\begin{cases} (M_sS^2 + c_sS + k_s)X_s(S) - (c_sS + k_s)X_u(S) = 0 \\ (M_uS^2 + c_sS + k_s + k_u)X_s(S) - (c_sS + k_s)X_s(S) = k_uX_r(S) \end{cases} \quad (2)$$

Thus we have:

$$\begin{cases} X_s(S) = k_u(c_sS + k_s)\cdot\dfrac{X_r(S)}{\Delta S} \\ X_u(S) = k_u(m_sS^2 + c_sS + k_s)\cdot\dfrac{X_r(S)}{\Delta S} \end{cases} \quad (3)$$

Where,

$$\Delta S = M_u M_s S^4 + (M_s c_s + M_u c_s)S^3 + (M_s k_s + M_s k_u + M_u k_s)S^2 + k_u c_s S + k_s k_u$$

Sprung mass acceleration relative to the road input transfer function can be expressed as:

$$H(S) = \frac{X_s(S)}{X_r(S)} = \frac{k_u(c_s S + k_s)S^2}{\Delta S} \tag{4}$$

Then we can get the mathematical model which the road vertical displacement as the input, sprung mass acceleration as the output.

$$\begin{aligned} & M_u M_s \ddddot{y}(t) + (M_s c_s + M_u c_s)\dddot{y}(t) + (M_s k_s + M_s k_u + M_u k_s)\ddot{y}(t) \\ & \quad + k_u c_s \dot{y}(t) + k_s k_u y(t) = k_u c_s \dddot{x}_r(t) + k_u k_s \ddot{x}_r(t) \end{aligned} \tag{5}$$

Where $y(t) = \ddot{x}_s(t)$.

Time domain responses of the suspension system model (5) under impulse input are showed as in Figure 2.

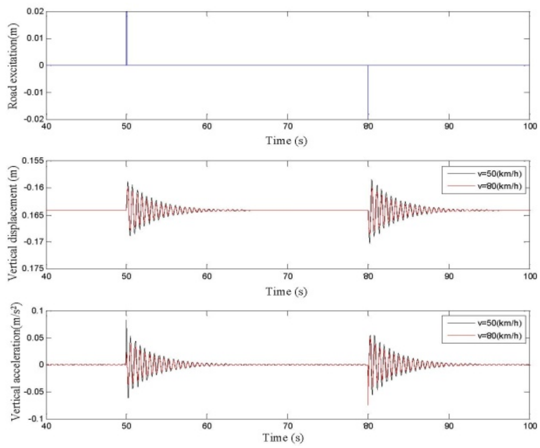


Figure 2. Time Domain Response of the Suspension System Model under Impulse Input

In Figure 2, the change of acceleration and displacement in vertical direction of the suspension system model can be clearly observed when the vehicle passes over pothole or bump.

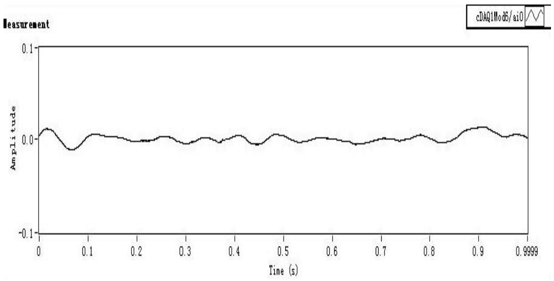
3. Disease Detection Algorithm

In this section, we describe the algorithm we have developed to detect road disease in streams of acceleration data.

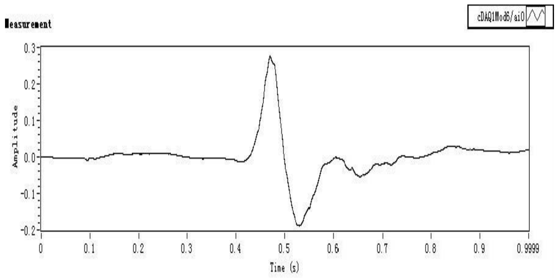
The intuition behind our algorithm is that anomalous road conditions are reflected in features of the acceleration data. Though the problem of identifying diseases from accelerometer data is challenging because of the broad variation in road conditions and driver behavior, most anomalies, fortunately, can be characterized as high-energy events in the acceleration signal. Further, the pavement disease detection algorithm proposed in this paper is based on support vector machine (SVM) [7-9]. The main idea of the algorithm is to find the best compromise between the complexity of the model and earning ability, according to limited sample information, so as to obtain the best generalization ability.

It is then important to extract feature of road anomalies from the acceleration signal because it affects the sample classifier design and performance. It is also related to determine the signal output characteristics and reduce the dimension of input space for reducing the computation difficulty and improving training efficiency. The correct extraction of feature parameters is also beneficial for better decision-making function to improve the forecast accuracy.

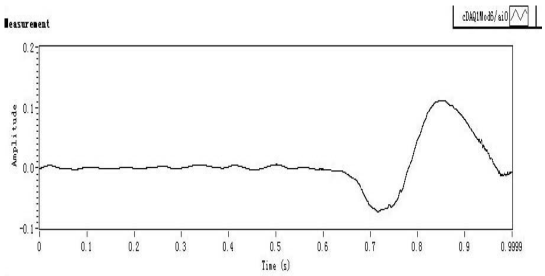
By analysing acceleration signals of the different road surface, it can be divided into three types: smooth road, bump and pothole. Figure 3 shows the three kinds of acceleration signal after digital filtering. Therefore, the characteristics of acceleration signal of anomaly road are relatively intuitive on time domain. The feature vector dimension on frequency domain is too high, and contains a variety of invalid components needed to be removed. To simplify data processing and calculation, sample training vectors choose the following characteristics: mean, range values, standard deviation, maximum peak, histogram statistics.



(a) Response of smooth road



(b) Response of bump



(c) Response of pothole

Figure 3. Acceleration Signals of Roads

In this paper, support vector machine algorithm is realized by LIBSVM software [10]. LIBSVM is an SVM pattern recognition and classification regression package. The structure of LIBSVM is simple and it is easy to use, fast and effective. This paper involves a one-to-one multi-class pattern recognition problem. The general implementation of LIBSVM is described as follows:

(a) formatted data

Convert the sample data into training data and test data with LIBSVM format data file

<label> <index l>: <value l> <index 2>: <value 2>. . .

where <*label*> is the training data target set, and is used to identify integer with certain types in classification problems; <index> is integer beginning with I which is expressed as the serial number of features, and it may be discontinuous. <*value*> is real number, which shows the characteristic values or independent variables. Data format conversion operations on the data include: removing redundant attributes, meeting or removing the default value.

(b) item data scaling

It is very important to scale the data before training, which is designed to avoid the range of some of the characteristics is too large while others characteristics range is too small, resulting in inundation of large numbers to inundate small numbers. There are some difficulties in numerical calculation caused by calculating the kernel function in the training process to reduce the computational complexity. Kernel function computation is the inner product of two feature vectors, such as linear kernel and polynomial kernel. The large data without scaling may result in calculation disaster. One thus should scale the feature attribute data into range $[-1,1]$ or $[0,1]$ according to certain rules. In this paper we use range $[0,1]$.

(c) determine the kernel function

LIBSVM provides a variety of commonly used kernel functions. We use radial primary kernel function. Kernel parameters required are calculated by the definition and training of the formula.

(d) find the optimal parameters for training

After determining the sample training model, we can do sample training and set parameters in the training process, such as the penalty factor and so on.

(e) predict the data collection according to the trained model

We can get a model file with suffix model after completing the sample training, which is used as the input sample data to predict and classify the total data collection.

LIBSVM is usually given in source code and executable files. Here we use the LabVIEW version executable file LIBSVM for the data training and forecasting as shown in Figure 4.

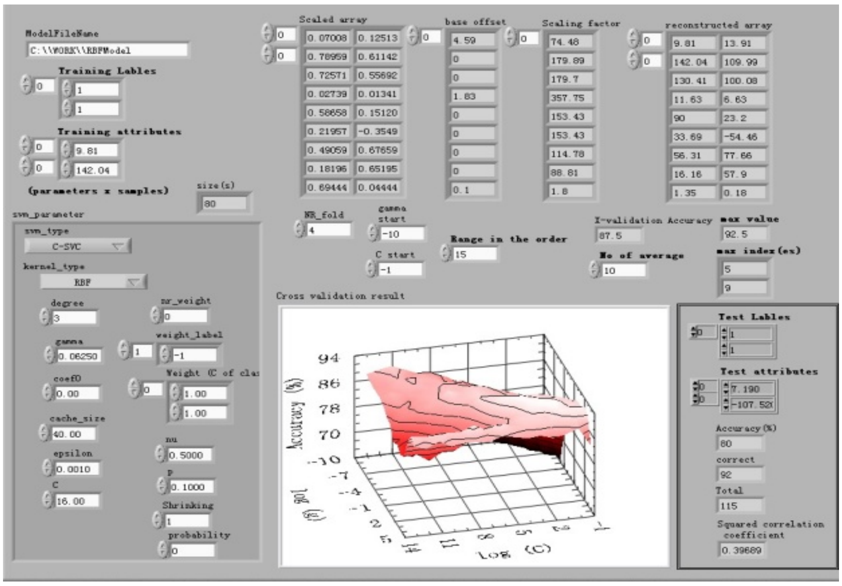


Figure 4. The Front Panel of LabVIEW LIBSVM

4. Test Results

To test the proposed algorithm, the accelerometer should produce consistent results for a given pothole, and have accurate localization of events from the on-board GPS. In test, for simplicity, only one acceleration sensor is fixed on the slide bar of saddle by the screw in TAXI car, as illustrated in Figure 5.

Figure 5. The Vehicle-mounted Detection Device

The sensor is connected to PC by a high-speed USB interface to make data acquisition and save. The sampling frequency set to 100Hz. On the same road, the system sample acceleration signals under two vehicle speed conditions at 20km/h and 30km/h, and try to keep a uniform speed during sampling time. GPS receive terminal is also connected to PC by the serial port, and send a standard format packet contained latitude and longitude information per second to determine vehicle location.

The test road with noticeable characteristics of road surface is selected for verifying the algorithm, where has 15 road diseases include bump (concave) and pothole (convexe) by means of visual observation. Measurement signals are divided into multiple samples. Each sample has 100 acceleration data in experiment. Then, it converts these data into data file format which correspond with SVM as shown in Table 1. 200 samples are taken to do SVM training. The model obtained from training is used to make predictive classification for all samples. Table 2 shows the experimental results.

Table 1. Sample Data

1:	0.565855	2:	0.456215	3:	0.678332	4:	0.285555	5:
1:	0.125674	2:	0.242345	3:	0.555556	4:	0.552435	5:
	…		…		…		…	
	…		…		…		…	
1:	0.158953	2:	0.256892	3:	0.472145	4:	0.333356	5:
1:	0.656214	2:	0.567575	3:	0.582468	4:	0.896542	5:

Table 2. Training Results of SVM

speed	M	N	α	β
20 km/h	13	12	92.3%	80.0%
30 km/h	17	14	82.4%	86.7%

In Table 2, M and N represent the number of diseases of the road surface detected by SVM predictive classification before and after SVM is trained, respectively. T is the number of all diseases known by visual observation, $T = 15$. $\alpha = N/M$ α and $\beta = N/T$ are respectively defined the accuracy and precision when the proposed SVM is used. Table 2 shows that the accuracy of system is more than 80%, which satisfies detection requirement. For ensuring the integrity of the road information, the running speed of vehicle impacts the accuracy of detection results. The faster the vehicle speed, the higher the accuracy of detection, while the higher the false rate caused. Therefore, we need to select the appropriate speed to measure according to the actual road conditions. Figure 6 shows the typical road surface disease detected and its marked point on electronic map.

Figure 6. Pavement Disease and Position

4. Conclusion

Since pavement roughness is the main external stimulation source of vehicle vibration, this paper proposes a accelerometer-based road surface disease detection system, which make use of acceleration sensor to detect vibration signals of vehicles on the road, indirectly reflect the road conditions, achieve the automatic detection of the pavement performance. The detection algorithm based on SVM is designed and used for experimental validation, the results show that this method can detect the anomaly road surface by SVM training and classification.

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