IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 16, 2018, accepted May 13, 2018, date of publication May 23, 2018, date of current version June 20, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2839765

A Road Quality Detection Method Based on the Mahalanobis-Taguchi System

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This work was supported in part by the Natural Science Foundation of China under Grants 61172018 and 61771387, in part by the Scientific Research Program of Shaanxi Province under Grant 2016K TZDNY01-06, in part by the Scientific Research Program of Shaanxi Province Education Department under Grant 15JK1527, in part by the Project of the Xi'an Science and Technology Planning Foundation under Grant XALG033, in part by the Project of the Xi'an Social Science Planning Foundation under Grant 16J133, in part by the CERNET Innovation Project under Grants NGII20150707 and NGII20160704, and in part by the Xi'an BeiLin Science Research Plan under Grants GX1626 and GX1623.

ABSTRACT As an extremely complicated task, road detection is of vital importance for the traveling comfort and driving safety. While high-end automobiles are already equipped with road detection function, most mid-range cars can only detect and evaluate road conditions leveraging remodeled or additional hardware devices built on vehicles, thereby constraining the road quality detection. With the growing popularity of smartphones, detections based on built-in sensors emerge. Most detections on built-in sensors, nevertheless, are on the basis of Euclidean distance, thus neglecting the correlation between characteristics in road quality, i.e., the acceleration sensor and gyroscope have obvious fluctuations when the vehicle passes through the larger pothole, and there is a connection between them. In this paper, we propose a novel road detection approach based on Mahalanobis–Taguchi system (MTS), leveraging smartphones for data collection and involving the correlation between characteristics. We develop an application to collect and process the data, and then classify road quality conditions. The experimental test was carried out on city roads in Xi'an, Shaanxi. Experiment results reveal that the road surface conditions, including manhole cover, pothole, and speed bump, can be well differentiated with the method based on MTS. To a certain extent, the strategy of marking road conditions to the navigation map can effectively improve not only driving experience and traveling comfort but also driving safety, thereby providing more supports for the maintenance units.

INDEX TERMS Road quality detection, smartphone, Mahalanobis-Taguchi system (MTS), road surface condition, driving safety.

I. INTRODUCTION

Nowadays, road networks connecting buildings, villages, cities, and even countries, are becoming key parts of the transportation infrastructure in modern life. Due to the large increase in the number of cars, nevertheless, the traffic load is increasingly getting large and pavement damage is inevitable. Destructive roads that may damage vehicles (e.g., potholes) are sometimes hazardous to drivers and pedestrians, and even induce a significant loss of property [1]–[3]. Therefore, informing drivers of hazardous road conditions (e.g., bumps or other anomalies), is directly related to not only driving experience and comfort, but also safety. Meanwhile, awareness of road surface anomalies in the earliest manner possible is of vital importance toward prompt repair, thereby motivating municipal authorities to maintain and repair their roadways.

It is of great realistic significance to detect road conditions, which can be divided into the four following stages [4].

1) Manual detection. Manual measurements are with some disadvantages, such as high cost, long period, and low efficiency. Legacy methods (e.g., three-meter ruler or manual sand patch method), may deteriorate traffics and result in hazard for operators, due to unreliable data accuracy.
2) Semi-automated detection. Computers are responsible for controlling the part of mechanical motion, storing

the measured data in real time, and analyzing as well as calculating it at certain intervals. Nevertheless, besides continuous evenness apparatus testing, practical applications of low-efficiency and low-speed detection technologies are still very limited in this stage.

3) Automated detection. Ultrasonic, laser, ground-penetrating radar and other technologies are utilized for road detection. With ever-increasing computer technology, the integration of computer, electronics, machinery and mathematics makes detection equipment more intelligent and efficient. With the development of information technology, automated detection cannot meet the growing demand from expressway development. For example, car jolt cumulate apparatus testing or laser pavement evenness apparatus testing, usually relies on high cost and requires skilled operator.
4) Informatization detection. Communication, network, database and other information technologies are applied to the road quality testing. Information technology and information resource, highly developed and shared in each field, can greatly improve the test accuracy and provide great technical supports for promoting the human society. Although informatization detection can detect road conditions more efficiently, it also brings several issues, e.g., informatization testing still lies in the preliminary phase. In addition, the road detection is distributed to a large number of car drivers through the crowdsourcing-based model, whereby more information can be collected [5], [6].

In the process of informatization detection, existing works in [7]–[11] with machine learning, threshold-based heuristics, Euclidean distance, video, image or laser imaging are generally utilized to classify the road condition. There methods do not take into account the correlation of data features; for example, an Euclidean distance-based classifier measures the absolute distance of each point in the space, and is directly related to the coordinates where the points are located, equally treating all the differences between various discrete features. To improve the accuracy of road quality detection, this paper tries to propose a road quality detection model based on MTS [12], considering the interactions between the characteristics of road conditions, then distinguishing the test dataset. The general process of detection is shown in Fig. 1. To a certain extent, predicting the details of road quality could make the transportation system more safe, efficient and comfortable, and thus provide better data supports for the maintenance of build infrastructure.

The rest of this paper is organized as follows: In Section II, we briefly outline related works. In Section III, we put forward the road quality detection model based on MTS. In Section IV, we describe the proposed method for data processing and road condition classification. In Section V, we provide experimental results and analysis. We conclude this work in Section VI with future works.

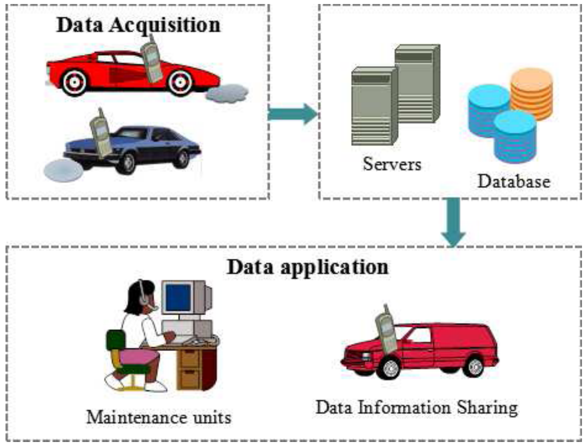

FIGURE 1. The general process of road detection.

II. RELATED WORKS

There have been some existing works on road surface detection at home and abroad, which can be totally categorized into two classes, i.e., on board equipment and on mobile devices.

Pothole Patrol, a taxi-based mobile sensing system studied by Eriksson *et al.* [1], was proposed for monitoring and assessing pavement conditions. In [1], a taxi is equipped with three-axis acceleration sensors, a Global Positioning System (GPS) receiver, and a laptop computer with the data aggregation and processing unit. By analyzing the hand-labeled data by repeatedly driving down several known stretches of road in the Boston area, they have been able to build a detector, which can misidentify good road segments as with potholes less than 0.2%. CRSM, a crowdsourcing based road surface monitoring system, was proposed in [5] for effectively detecting road potholes and evaluating road roughness using their hardware modules embedded in distributed vehicles. The proposed system uses low-end accelerometers and GPS devices to obtain vibration pattern, location, and vehicle velocity, and has been considered among the first few methods putting forward crowdsourcing mode in road quality detection. Yu and Salari [7] introduced an efficient and more economical approach for pothole and crack detection with laser imaging. The detection equipment consists of an active light source that projects a line pattern of laser beams onto the pavement surface, and a camera for image captures. Moreover, the proposed method is capable of discriminating the dark areas that induced by lane marks, oil spills, etc. In [8], two scenarios were considered, i.e., data collection already available on the CAN-bus using a fleet of ordinary cars or trucks, and one or more Time-of-Flight cameras (ToF) to be installed on a group of vehicles. Data on the CAN-bus is collected using either a CAN-logger transmitting data to a central server with GPRS, or an OBD scantool sending data to a mobile phone with Bluetooth that has processed data as detection events. Mednis *et al.* [16] proposed a methodology for pothole detection by measuring pothole induced sound signals using mobile vehicles equipped with off the shelf microphone and global positioning devices attached to an on-board computer. In [13], a recursive multiscale correlation-averaging approach to jointly filter and fuse spatially indexed measurements captured from many vehicles was proposed. Measurements from low-cost vehicle-mounted sensors (e.g., a vertical-axis accelerometer and a GPS receiver) are properly combined to monitor the pavement condition. Road Condition Monitoring with Three-axis Accelerometers and GPS Sensors (RCM-TAGPS) in [14], a low-cost vehicle-based solution, was presented to monitor the road condition by analyzing the Power Spectral Density (PSD) of pavement roughness, estimating International Roughness Index (IRI), and thus classifying the pavement roughness level into four levels according to a Chinese industry standard [15].

The aforementioned works [1], [5], [7], [8], [12]–[14] require either the transformation of vehicles to extract the required sensor data, or the additional on-board equipment, both of which would increase the application cost and data acquisition difficulties, thus restricting the project scale.

Yang [6] utilized the sensors built in mobile phones to collect various data in vehicles. In particular, the system can actively learn the knowledge of a vehicle and adopt one degree-of-freedom (DOF) vibration model to infer the depth and length of pothole when the vehicle is moving. Mohan *et al.* [9] focused specifically on the sensing component, using the accelerometer, microphone, GSM radio, and GPS sensors in cell phones to detect potholes, bumps, braking, and honking via simple threshold-based heuristics. It is proposed in [10] to leverage a smart-phone with a three-axis accelerometer to collect acceleration data when riding a motorcycle. Both supervised and unsupervised machine learning methods are used to recognize road conditions. Seraj *et al.* [11] introduced a method to detect road anomalies by analyzing driver behaviors via a simple machine learning approach as well as a clustering algorithm. Mednis *et al.* [16] described a mobile sensing system for road irregularity detection by a slightly more advanced Z-DIFF algorithm using android operating system based smart-phones. Focusing on the development of a sensing system monitoring the pavement quality, one algorithm is proposed in [17] based on the analysis of vertical acceleration impulse, i.e., the temporal derivative of acceleration absolute amplitude in one second. Some studies also demonstrated the linear relationship between acceleration data collected by sensors at different speeds and road surface roughnesses [18], [19]. Yi *et al.* [20] put forward a smart-phone probe car (SPC) system to monitor road pavement, and proposed a road anomaly indexing heuristic based on under-damped vibration model. Using sensors of smart-phones, SmartRoadSense monitors the vertical accelerations inside a vehicle, extracts a roughness index conveying information and studies the correlation of mobile phone vertical accelerations, the roughness index as well as vehicle speeds [21]. RoadScan in [22], compounded by a real-time responsiveness application and a crowdsourcing web page, is a crowdsourcing Android application that would determine pavements quality in a simple and lightweight way. Singh *et al.* [23] demonstrated that combining multiple streams (from accelerometer data of smart-phones using crowdsourcing and DTW) could increase the accuracy of pavement anomaly detection. In addition, DTW, which can automatically cope with time deformation and different speeds associated with time-related data, is simple in its implementation and its training procedure is even simpler than other two existing techniques. The average detection rates in [23] in case of potholes and bumps was found to be 88.66% and 88.89%, respectively.

Road quality detection using mobile devices is low-cost and portable, requiring little maintenance and relying on high popularity [6], [9]–[11], [16]–[23]. With the growing popularity of mobile phones, their associated groups become more large-sized, thus reaching a certain crowdsourcing scale, Therefore, compared with other existing detection approaches, the crowdsourcing model not only reduces the cost and increases the efficiency, but also breaks the geographical location and time limit, enabling communications more convenient.

By leveraging data collected by smart-phones, this paper tries to propose a road quality detection method based on MTS. MTS, due to its advantages in the quantitative pattern identification of polysystem, is an effective data classification method in the sensor system, face recognition system, voice recognition system, market forecast, economic forecast, etc. [24]–[26]. The detection method based on MTS fully considers the relationship between characteristics of road conditions, enabling a more accurate detection.

III. ROAD QUALITY DETECTION MODEL BASED ON MTS

A. SYSTEM MODEL

In the Mahalanobis-Taguchi system [12], Dr. Taguchi combined Mahalanobis distance (MD) with signal-to-noise ratio (SNR), and identified unknown samples in line with the constructed MD, measurement scale as well as given threshold. Taking into account the correlation between variables, MD is utilized to measure the anomaly degree of samples. Since the evaluation of road quality is typically based on multiple interrelated variables, the correlation between characteristic variables should be considered when calculating the distance between multivariate observation samples and normal ones. In addition, MD is not affected by the dimension, since the MD between two points has nothing to do with the measurement unit of original data. In other words, the MD between two points calculated by standardized data is the same as that of original data. Thus, the road quality classification and prediction prefer to leverage the road anomaly model based on MTS.

There exists a relationship between multiple characteristics of the road quality. For example, in three-axis acceleration sensors, the relationship between the three axes **XYZ** can reflect the driving state of the car. The MTS typically acts on the abnormal detection, with a flowchart shown in Fig. 2.

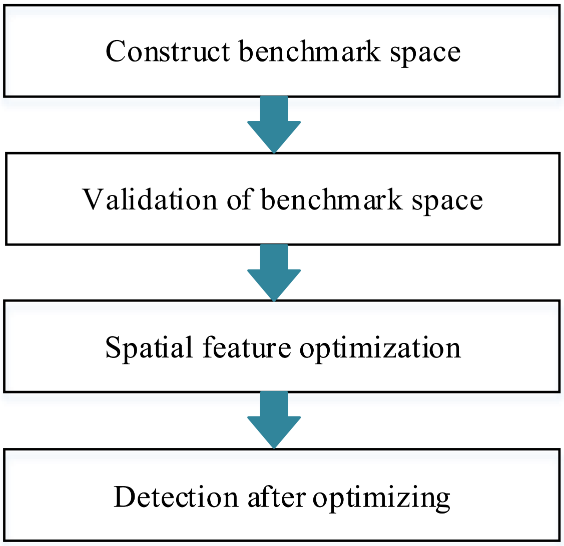

FIGURE 2. Flowchart of the road detection model.

In the MTS, MD is used as a classification criteria to measure the deviation degree between the road quality data and benchmark space, and classify the measured data by the threshold. The benchmark space is constructed through a predetermined flat road sample. For example, in three-axis acceleration sensors, the relationship between the three axes **XYZ** can reflect the driving state of the car. In the road quality detection, however, the abnormal road conditions need to be further subdivided to determine the irregularity of surface. Therefore, it is necessary to establish the MD range of various abnormal road conditions. Using the MD of the abnormal road condition to verify the validity of the benchmark space constructed, characteristics are filtered to optimize the space. Finally, by calculating the MD from the road data to various road conditions, the road data can be classified, diagnosed and predicted.

B. BENCHMARK SPACE

First, the window size of flat road data is h. It is assumed that the flat road sample space is m-dimensional and the sample data of flat road is $\mathbf{X}_i = (\mathbf{X}_{i1}, \mathbf{X}_{i2}, \cdots, \mathbf{X}_{im})$, with the collected data of the i-th feature in the j-th time as

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}_{11} & \mathbf{X}_{12} & \cdots & \mathbf{X}_{1m} \\ \mathbf{X}_{21} & \mathbf{X}_{22} & \cdots & \mathbf{X}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{X}_{n1} & \mathbf{X}_{n2} & \cdots & \mathbf{X}_{nm} \end{bmatrix}. \quad (1)$$

Then, the sample space of flat road is standardized as

$$\hat{\mathbf{X}}_{ij} = \frac{\mathbf{X}_{ij} - \bar{\mathbf{X}}_i}{\delta_i}(i = 1, 2, \cdots, n, j = 1, 2, \cdots, m), \quad (2)$$

where, $\bar{\mathbf{X}}_i$ is the mean of the i-th feature, and δ_i is the standard deviation of the i-th feature. As such, the normalized sample space of flat road turns out to be

$$\hat{\mathbf{X}} = \left[\hat{\mathbf{X}}_1 \;\; \hat{\mathbf{X}}_2 \;\; \cdots \;\; \hat{\mathbf{X}}_n\right]^T. \quad (3)$$

Next, the MD of the i-th feature of normalized flat road sample space is computed as follows

$$\mathrm{MD}_i = \sqrt{\frac{\hat{\mathbf{X}}_i C_x \hat{\mathbf{X}}_i^T}{m}}, \quad (4)$$

where C_x represents the correlation matrix of $\hat{\mathbf{X}}$. To ensure the existence of C_x, the sample volume is at least three times the dimension number of flat road sample space, namely, $n \geq 3m$.

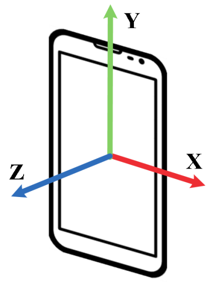

FIGURE 3. The smart-phone's 3-dimensional Cartesian coordinate.

C. VALIDATION OF BENCHMARK SPACE

To verify the validity of benchmark space, we need to collect some abnormal road data $\mathbf{Y}_i = (\mathbf{Y}_{i1}, \mathbf{Y}_{i2}, \cdots, \mathbf{Y}_{im})$, standardized as

$$\hat{\mathbf{Y}}_{ij} = \frac{\mathbf{Y}_{ij} - \bar{\mathbf{X}}_i}{\delta_i}(i = 1, 2, \cdots, n, j = 1, 2, \cdots, m), \quad (5)$$

where $\bar{\mathbf{X}}_i$ is the mean of the i-th feature of the benchmark space, and δ_i is the standard deviation of the i-th feature. Then the MD of normalized abnormal data $\mathbf{Y}_i$ can be described as

$$\mathrm{MD}_i = \sqrt{\frac{\hat{\mathbf{Y}}_i C_x \hat{\mathbf{Y}}_i^T}{m}}. \quad (6)$$

If the MD of abnormal data is obviously greater than that of the benchmark space, then the validity of space is proved; otherwise, the benchmark space needs to be refined.

D. SPATIAL FEATURE OPTIMIZATION

In general, the characteristic variables contain redundant information, thereby inducing a misjudgment and negative impact on classification results. Therefore, the filtering of effective variables is prerequisite for the improvement of classification accuracy. To simplify the calculation of MD, shorten the diagnostic time and improve the diagnostic accuracy, it is necessary to optimize the benchmark space and refine characteristic variables. Legacy MTS utilizes orthogonal table and SNR method to optimize features and refine

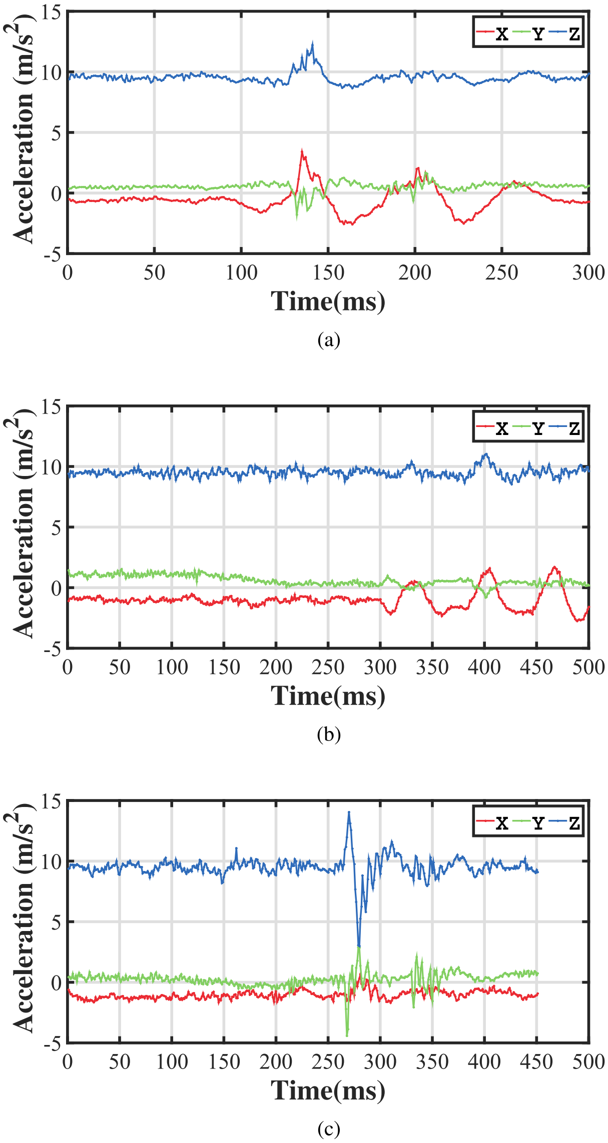

FIGURE 4. Three different cases with data obtained by the acceleration sensor. (a) Manhole cover. (b) Pothole. (c) Speed bump.

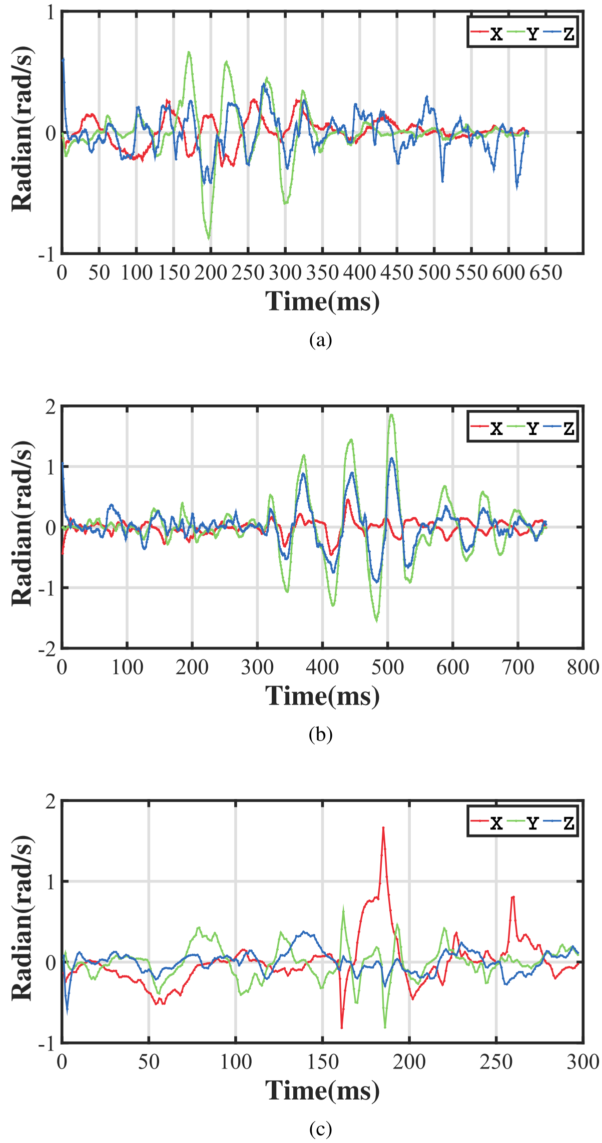

FIGURE 5. Three different cases with data obtained by the gyroscope. (a) Manhole cover. (b) Pothole. (c) Speed bump.

variables beneficial to classification results. In addition, feature optimization needs to collect as much data as possible. However, in view of only three kinds of road anomaly data (manhole cover, pit, speed bump) involved in this work, this step is ignored.

IV. DATA PROCESSING AND ROAD ANOMALY CLASSIFICATION

A. DATA ACQUISITION

In this work, we collect the driving data of vehicles through smart mobile terminals, leveraging sensors including GPS, accelerometer and gyroscope to glean information. Note that, a three-axis accelerometer is considered in Fig. 3, with a three-dimensional Cartesian coordinate, represented by **X**, **Y** and **Z**, respectively.

For three different cases (i.e., manhole cover, pit and speed bump), the diagrams in Fig. 4 and Fig. 5 depict the data received by acceleration sensor and gyroscope, respectively.

From Fig. 4(a)-(c) and Fig. 5(a)-(c), it follows that the phone can generate significant acceleration impulses and radian changes with varying road conditions. The road anomaly in Fig. 4 is characterized by peak acceleration in **Z**, while that in Fig. 5 is **Y**. In addition, the peak and valley values of aX, aY and aZ are captured by accelerometer, while those of rX, rY and rZ are obtained by gyroscope.

Next, for the improvement of accuracy, wavelet denoising, a kind of signal-based approach, is leveraged in our work.

B. DATA CLEANING

Data denoising is prerequisite since it would influence signal detection, analysis accuracy or result. With the emerging smart-phone measurements, it is important for us to

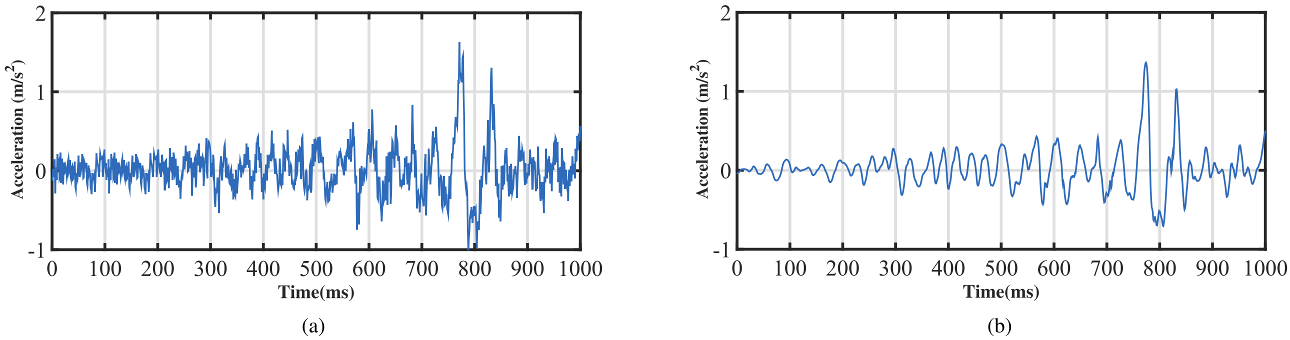

FIGURE 6. Data cleaning based on wavelet transform. (a) Raw signal. (b) Signal after wavelet transform.

reduce or eliminate noise. The traditional denoising method would increase the entropy, and thus the signal correlation could not be reached. Nevertheless, due to the superior time-frequency characteristics, the wavelet transform can be picked in line with signal characteristics and denoising requirements.

Given original signal $f(t)$, $\varphi(t) \in L(R)^2$ constitutes the fundamental wavelet. If $f(t) \in L(R)^2$ holds, then its continuous wavelet transform can be written as

$$W_f(a, b) = < f, \varphi(a, b) > = |a|^{(-\frac{1}{2})} \int_R f(t)\varphi(\frac{t-b}{a})dt. \quad (7)$$

In this paper, the Daubechies wavelet transform is used to decompose the signals in a multi-scale way. The scaling coefficients $C_{j,k}$ and the wavelet coefficients $d_{j,k}$ are given as

$$C_{j,k} = \sum_n C_{j-1,n} h_{n-2k} \quad (8)$$

and

$$d_{j,k} = \sum_n d_{j-1,n} g_{n-2k}, \quad (9)$$

respectively, where h and g are a set of quadrature mirror filter (QMF) banks. Then, given a specified decomposition layer p, for $p + 1$ or higher, all coefficients are retained. And for any $q(1 \le q \le p)$, coefficients with n_q largest absolute values are preserved as

$$n_q = M(p + 2 - q)^3, \quad (10)$$

with M representing empirical coefficient. Given each layered threshold, the signal denoising can be performed using the soft threshold method as

$$\hat{w}_{j,k} = \begin{cases} \text{sgn}(w_{j,k})(|w_{j,k}| - \boldsymbol{\gamma}, |w_{j,k}| \ge \boldsymbol{\gamma} \\ 0, |w_{j,k}| < \boldsymbol{\gamma}, \end{cases} \quad (11)$$

where $\hat{w}_{j,k}$ is the estimated wavelet coefficients, sgn() is the symbolic function, and $\boldsymbol{\gamma}$ is the threshold value. E_g is given as the signal energy after data cleaning as

$$E_g = \int |V(t)|\, dt \approx \Delta t \sum_i V\, |(t_i)|\,, \quad (12)$$

where, $V(t_i)$ represents magnitude of the signal collected at each point. Fig. 6(a) represents the raw signal, with its wavelet transform shown in Fig. 6(b). From Fig. 6, it is observed that the signal after the wavelet denoising, which has eliminated the signal burr, is smoother than the raw signal. In this case, the signal energy ratio is approximately 0.8704 and standard deviation is 4.3314. The experimental results conform to the smoothness and similarity criterion of signal denoising, since the deniosed signal retains basic characteristics of original signal well.

C. DATA SEGMENTATION

One typical data segmentation is the sliding window approach, with two control factors, namely, the window size and coverage. For decision makers, the selection of window size is of vital importance. If the window is too large, then noise may exist or redundant road condition information may be involved. Otherwise, only a small amount of data could be captured.

Fig. 7 shows the two different data segmentation scenarios, with a fixed window size of 30 ms without overlapping for Fig. 7(a) as well as 30 ms with 50% coverage for Fig. 7(b).

Identifying road anomaly from data is challenging due to the vast variation in road conditions (e.g., various types of road surfaces such as potholes, speed bumps) and smaller duration. Therefore, sliding window segmentation is then applied to this anomaly detection, with a window size of 0.03 s and an adjacent window covered by 50%, namely, 30 sampling points are included in each window.

D. FEATURE EXTRACTION

Feature extraction is utilized to distinguish data information that could categorize data. In this paper, the feature extraction involves the maximum, minimum, mean, variance and covariance in the time domain, shown in Table 1.

E. ROAD CONDITION CLASSIFICATION

While most non-flat roads can be characterized as abnormal ones in the detection, the road anomaly is not sufficient as an accurate classification, since each road classification is obtained by the MD within a certain interval, and different intervals are overlapping. Therefore, we define different abnormal spaces. The road anomalies can be roughly

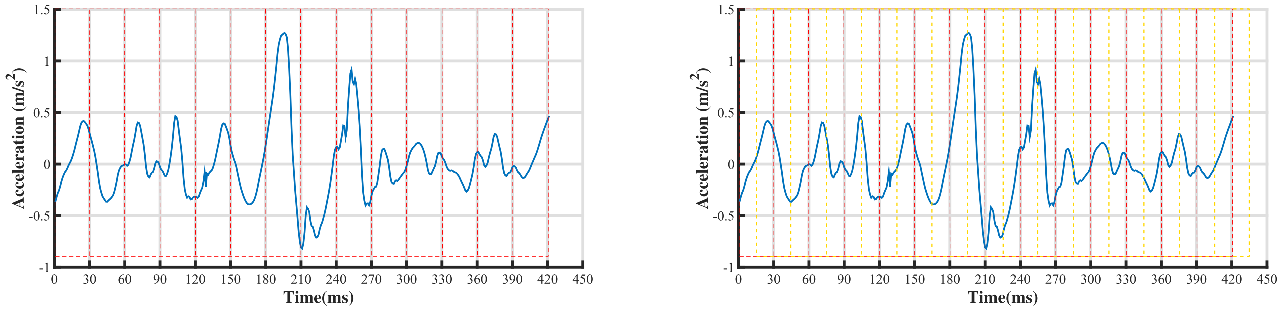

FIGURE 7. Schematic diagram of two data segmentation scenarios. (a) No overlapping data segmentation. (b) 50% coverage segmentation.

TABLE 1. Feature extraction formula.

Feature extraction	Formula
maximum	$\mathrm{MAX}(X_1, X_2, \cdots)$
minimum	$\mathrm{MIN}(X_1, X_2, \cdots)$
mean	$\bar{X} = \frac{1}{N}\sum_{i=1}^{N} x_i$
variance	$\mathrm{V(X)}=\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})$
covariance	$V(X)^{\frac{1}{2}}$

classified into three categories: manhole cover, pit, speed bump. Eq. 13, derived from Eq. 6, is given as

$$\begin{aligned}
\hat{\mathbf{S}}_{ij} &= \frac{\mathbf{S}_{ij} - \bar{\mathbf{X}}_j}{\delta_{X_j}} \\
&\quad (i = 1, 2, \cdots, n, j = 1, 2, \cdots, m), \\
\mathrm{MD}_{\mathrm{FlatRoad}} &= \sqrt{\frac{\hat{\mathbf{S}}_i C_x \hat{\mathbf{S}}_i^T}{k}}, \\
\mathrm{MD}_{\mathrm{SpeedBump}} &= \sqrt{\frac{\hat{\mathbf{S}}_i C_y \hat{\mathbf{S}}_i^T}{k}}, \\
\mathrm{MD}_{\mathrm{Pothole}} &= \sqrt{\frac{\hat{\mathbf{S}}_i C_p \hat{\mathbf{S}}_i^T}{k}}, \\
\mathrm{MD}_{\mathrm{ManholeCover}} &= \sqrt{\frac{\hat{\mathbf{S}}_i C_q \hat{\mathbf{S}}_i^T}{k}},
\end{aligned} \tag{13}$$

where, $\mathbf{X}_j$ is the mean of the j-th feature in the flat road space, δ_{X_j} is the standard deviation of the j-th feature in the flat road space, C_x, C_y, C_p and C_q represent the correlation matrix of flat road, speed bump, pothole and manhole cover, respectively. Next, the classification criteria is utilized to indicate the category of road anomalies, and the MD is leveraged to characterize. The smaller the MD, the greater the similarity between two samples, namely,

$$\begin{aligned}
&\text{if } (\mathrm{MD}_{\mathrm{FlatRoad}} < \cdots < \cdots < \cdots), \quad S = \mathrm{FlatRoad}, \\
&\text{if } (\mathrm{MD}_{\mathrm{SpeedBump}} < \cdots < \cdots < \cdots), \quad S = \mathrm{SpeedBump}, \\
&\text{if } (\mathrm{MD}_{\mathrm{Pothole}} < \cdots < \cdots < \cdots), \quad S = \mathrm{Pothole}, \\
&\text{if } (\mathrm{MD}_{\mathrm{ManholeCover}} < \cdots < \cdots < \cdots), \quad S = \mathrm{ManholeCover}.
\end{aligned} \tag{14}$$

FIGURE 8. Map of Xi'an with drive routes highlighted.

Different road anomaly detection methods have been proposed such as the distance-based, model-based, and statistical methods. In this paper, the distance-based method is picked, and the benchmark space is established to verify the validity. If the space is valid, then the classification, diagnosis and prediction of road data are realized based on MTS. Algorithm 1 describes the procedure of road anomaly detection on the basis of MD.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. EXPERIMENT SETUP

Our experimental works were conducted in Xi'an, gathering vehicle traveling data during several drives over 15 weeks, reaching 34895 data records. In addition, GPS-tagged anomaly data was collected on different routes over 6 days. Fig. 8 shows a map of Xi'an with four drive routes highlighted.

B. MODEL VALIDATION

With the detection model validation, we construct and then standardize a benchmark space, calculating the correlation matrix and the MD of space by 30 eigenvectors of flat road signal. From Table 2, it shows that the threshold value of benchmark space lies in the 0.31-0.31 region, proving the validity of reference space.

Algorithm 1 Road Detection Algorithm Based on MTS

Input: Four types of sample data: flatroadList data[1,...,n*m], manholecoverList data[1,...,n*m], speedbumpList data[1,...,n*m], potholeList data[1,...,n*m]

Output: The actual quality information of the road S_{type}

```
Initialize temp:intermediatevariable, max:maximum, min:minimum, mean:mean, std:standard deviation
/*CalculatestandardMatrixMDRange(flatroadList)*/
for j = 1 ← MD.size() do
    m_{i,g} ← (floatRoad(:, 1) − mean)/std
end for
for j = 1 ← MD.size() do
    /*H:StandardizedFloatRoad
    C:CorrelationCoefficient*/
    MD_i ← sqrt(H(1, :) ∗ C ∗ H^T(:, 1)/m)
end for
/*CalculateMDRange(flatroadList)*/
/*CalculateMDRange(speedbump,pothole,
    manholecover)*/
for j = 1 ← MD.size() do
    if temp > max then
        max ← temp
    end if
    if temp < min then
        min ← temp
    end if
end for
/*Arrive at the type of the smallest markov distance*/
if MD_X < MD_Y < MD_P < MD_Q then
    S_type ← X
end if
/*The type of Y, P and Q by analogy*/
Output S_type
```

Next, using the benchmark space, MD for each road anomaly (e.g., manhole cover, pit and speed bump) are shown in Table 2. In total, MD of the abnormal data is obviously greater than that of the benchmark space, and thus the validity of space is proved. To accurately classify the road anomalies, we improve the model based on MTS by constructing three kinds of road anomaly spaces (manhole cover, pit, speed bump). Finally, the abnormal data collected can be accurately identified.

C. EXPERIMENT RESULT

In the experiment, driving data on specific road sections (i.e., bumps, potholes, etc.) derived from 34895 sets of data is utilized to detect the performance of classifier, with its result shown in Table 3 (A: classification error rate, B: distance errors (m)).

There are several reasons why the error rate of pothole is as high as 2.33%-2.49%. When examining the experiment processes, we find that each of road anomaly actually corresponds to a certain interval. However, the interval of pothole often overlaps with manhole cover, since their properties are close to each other. On the contrary, the error rate of speed bump remains relatively low due to the speed and body motion of car crossing speed control humps. In addition, the error in GPS measurements (typically 5 meter median) stems from the mobile phone signal instability or the presence of magnetic fields and other factors, resulting in inaccurate positioning. In the case of road test site, the error rate was approximately 5.72% using the road detection algorithm based on MTS. It was found that a total of 34895 samples were classified, but with only 32899 correct ones. To verify the accuracy of road detection algorithm, we visited each

TABLE 2. Mahalanobis distance of four road conditions.

Trial	Flat road	Manhole cover	Pothole	Speed bump
1	0.85	3.96	4.54	6.00
2	2.09	4.12	4.44	5.97
3	.031	3.96	4.57	5.73
4	1.67	3.77	4.34	5.39
5	1.36	3.76	4.54	5.73
6	1.55	3.96	4.44	6.23
7	1.94	4.28	4.57	5.67
8	1.88	4.34	4.34	5.85
9	1.63	3.77	4.54	5.87
10	1.01	4.17	4.44	5.42
11	0.98	4.37	4.57	6.68
12	1.15	4.12	4.34	5.86
13	0.72	4.12	4.54	6.21
14	0.76	4.07	4.44	6.50
15	1.20	3.78	4.57	5.93
16	0.62	4.07	4.37	5.94
17	1.51	3.76	4.58	6.07
18	0.63	3.77	4.47	5.34
19	0.45	3.76	4.61	5.61
20	0.76	3.96	4.37	6.33
21	0.54	3.77	4.58	5.56
22	1.78	3.76	4.47	5.51
23	1.14	3.96	4.61	5.55
24	1.26	4.07	4.37	6.01
25	0.31	3.77	4.58	6.17
26	0.35	4.28	4.47	6.17
27	0.41	3.88	4.60	6.14
28	0.57	3.77	4.37	5.84
29	0.40	3.79	4.58	6.06
30	0.61	4.28	4.47	6.20

TABLE 3. Error rate & Distance error Comparison of Pothole, Speed bump and Manhole cover.

Trial	Pothole		Speed bump		Manhole cover	
	A	B(m)	A	B(m)	A	B(m)
1	2.33%	3	0.01%	3	1.87%	5
2	2.49%	5	0%	3	1.83%	4
3	2.41%	4	0.02%	3	1.89%	5
4	2.47%	4	0%	3	1.84%	3

TABLE 4. Error rate among different road detection methods.

	Detection Method Based On MTS	Classification Regression Tree	Support Vector Machine(SVM)
Pothole	3.26%	3.38%	3.33%
Manhole Cover	2.45%	2.52%	2.55%
Speed Bump	0.01%	0.02%	0.01%
False Positive Rate	5.72%	5.91%	5.89%

FIGURE 9. Test results of the highest degree of trust in driving route 1-4.

detected abnormal location. Vehicles were driven along the four routes setting in Xi'an scenario as illustrated in Fig. 9. The red circles, the blue cubes and the yellow triangles represent the event of manhole cover, pothole and speed bump, respectively.

To evaluate the performance of proposed method, a set of data of road detection was tested using Classification Regression Tree algorithm and Support Vector Machine algorithm, respectively, shown as in Table 4.

VI. CONCLUSION

In this paper, a method to detect anomalous regions based on MTS model is proposed. The crowdsourcing method that drivers place the mobile phone in their vehicles can obtain the basic data information to distinguish between different road conditions by the built-in sensor of smart-phones, i.e., acceleration, vibration amplitude, offset data, location data, etc. Meanwhile, a method for data preprocessing using wavelet transform is utilized to improve detection accuracy. As such, the pavement conditions, including manhole cover, pothole, and speed bump, can be differentiated with the method based on MTS in an efficient manner. The detailed information on road conditions (e.g., deceleration zone and potholes) is marked on the existing map navigation system providing services for the majority of drivers, reducing the incidence of traffic accidents, increasing driving safety, offering the possibility of data support for the road building plan, thus greatly reducing the cost of road quality detection.

In future work, we plan to further expand the scale of deployment, perform experiments on multiple types of vehicles, thereby improving the accuracy of road quality detection through the crowdsourcing-based data fusion.

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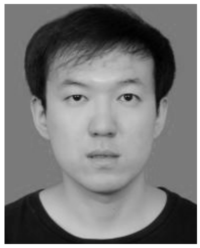

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