Pothole in the Dark: Perceiving Pothole Profiles with Participatory Urban Vehicles

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Abstract—Accessing to timely and accurate road condition information, especially about dangerous potholes is of great importance to the public and the government. In this paper, we propose a novel scheme, called P^3, which utilizes smartphones placed in normal vehicles to sense and estimate the profiles of potholes on urban surface roads. In particular, a P^3-enabled smartphone can actively learn the knowledge about the suspension system of the host vehicle without any human intervention and adopts a one degree-of-freedom (DOF) vibration model to infer the depth and length of pothole while the vehicle is hitting the pothole. Furthermore, P^3 shows the potential to derive more accurate results by aggregating individual estimates. In essence, P^3 is light-weighted and robust to various conditions such as poor light, bad weather, and different vehicle types. We have implemented a prototype system to prove the practical feasibility of P^3. The results of extensive experiments based on real trace demonstrate the efficacy of the P^3 design. On average, P^3 can achieve low depth and length estimation error rates of 13 and 16 percent, respectively.

Index Terms—Pothole profile perception, smartphone, one degree-of-freedom, 3D accelerometer

1 Introduction

Poor road conditions, especially dangerous potholes, are most concerned by drivers, insurance companies and the government, which severely threatens the drive safety and causes enormous losses. For example, in 2011, the council of UK paid more than 22 million pounds for compensation to drivers whose cars were damaged by potholes on roads [1]. To detect and repair all those potholes in England and Wales, however, would cost more than ten billion pounds [2]. In America, nearly a quarter of major metropolitan roads have pavements in poor condition, which results in rough rides and an extra vehicle maintenance cost of around four hundred dollars per driver per year [16]. Furthermore, a tough road also brings uncomfortable trip experience to drivers [5]. Nevertheless, not all potholes are that serious and need to take urgent actions immediately. Knowing the precise road condition in advance can help drivers decide whether to alter their routes to avoid dangers and damages. Furthermore, it also helps the government to better evaluate when and where to fix or rebuild a road at a minimum cost. Therefore, such timely and precise road condition information is of great importance to both the public and the government.

To solve the pothole profile perception problem, which refers to obtain up-to-date and accurate profiles of dangerous potholes (i.e., the size and depth) in a metropolitan scale, however, is very challenging due to the labor-intensive nature of this problem. For instance, there might be thousands or tens of thousands of roads to be checked in a big city. The current solution of sending professional staff to drive on road and manually evaluate the road condition is neither cost-nor time-efficient. Recently, with the rapid development of mobile devices, especially smartphones, participatory sensing [8], [10], [17], [21], [22] is an appealing technique and can be leveraged to solve this problem efficiently. With this new paradigm, volunteer drivers can first help collecting sensory data while driving via their personal smartphones and then uploading their sensory data to a data center for further processing to perceive the final road condition information. Nevertheless, retrieving road condition information in this way poses two new challenges. First, as the sensors embedded in a smartphone are usually low-end products, the quality of the retrieved sensory data is usually low, which makes it very hard to accurately estimate the profiles of potholes based on such data. Second, it is possible to improve the accuracy of pothole-perception results by aggregating those low-quality sensory data. However, designing an effective aggregation scheme is non-trivial, which has to leverage the unique features of the specific problem and particular domain knowledge.

In the literature, a few works studied on the pothole detection but as far as our knowledge, no work on the problem of profiling the pothole. A few number of pothole detection schemes have been proposed. Dedicated sensors such as ground penetrating radar (GPR) [9] are installed on a vehicle and used to detect potholes. Using GPR can achieve

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high-resolution subsurface images by using high-frequency radio waves. However, to detect timely road condition, it would require a wide deployment of special vehicles with GPR installed, which would lead to a prohibitively high deployment cost and therefore is infeasible. Besides GPR, cameras [11] can also be mounted on vehicles for pothole detection. Although cameras are cheap and easy to deploy, the usage of camera is often limited by the light condition. In addition, it is possible to judge whether there is a pothole on road but quite challenging to obtain accurate pothole profiles (e.g., when full of water). Recently, there are several pieces of work using 3D accelerometers built in smartphones to collect vibration data and distinguish road condition (e.g., potholes, cracks, rails and bumps) [4], [13], [15], [23]. Similar with using camera, those schemes can easily detect potholes but fail to perceive accurate pothole profiles. Knowing the details of a pothole is of great significance as not all potholes are harmful and urgent to be repaired. As a result, to the best of our knowledge, there is no existing low cost solution to the pothole profile perception problem.

In this paper, we propose an innovative participatory sensing scheme, called Perceiving Pothole Profiles (P^3), which utilizes common vehicles to tackle pothole profile perception problem. The core idea of P^3 is for a driver to first collect 3D acceleration information via its own smartphone while driving and then infer the profile of a pothole based on the obtained sensory data. Individual perceptions about the pothole are further collected and aggregated to obtain a more accurate profile of this pothole by a data center. In designing P^3, we mainly solve two following challenges. First, it is not obvious to directly understand the underlying pothole from the raw acceleration readings of the smartphone as the vehicle is equipped with a suspension system to absorb shocks to the vehicle body. Especially, the characteristics of such a suspension system are different from vehicle to vehicle. Dealing with this challenge, we propose an active vibration recovery algorithm which can automatically learn the dynamic knowledge about the vehicle and recover the actual vibrations of wheels from raw acceleration readings regardless of the type, its mass, or the speed of the vehicle. With the vibrations of wheels, the profiles of the pothole can be precisely estimated. Second, individual estimates about the profile of a pothole can be rather inaccurate due to limited performance of low-end sensors available on smartphones. To tackle this challenge, we characterize the relationship between the underlying potholes and the retrieved individual estimates and design an individual perception aggregation algorithm, which assigns an appropriate weight to an individual perception according to the speed when the perception was made.

The main advantage of P^3 is four-fold. First, P^3 can infer accurate pothole profiles in metropolitan scale at very low costs, leveraging ordinary commuting vehicles. Second, P^3 is light-weight and can easily run on smartphones. Third, P^3 is also robust to various conditions such as poor light, bad weather, and distinct vehicle types. Last, P^3 requires no expensive dedicated hardware, which stimulates a wide deployment of P^3 and facilitates the performance of the system in return. Nevertheless, the limitation of P^3 can also be directly observed. Specifically, as volunteer drivers are not especially trained or required for the purpose of P^3, they may drive arbitrarily passing different parts of a pothole, which leads to different views about the same pothole and there is no way for P^3 to ever find out. As the potential harm of a pothole that might bring to driving safety is the major concern, we only consider the worst-case where the worst driving experiences on a pothole count and should be estimated by P^3 to represent the pothole. To evaluate the design of P^3, we implemented a prototype system and conduct intensive field studies and experiments. The real experiment results show that the average depth and length of error is less than 13 and 16 percent, respectively.

We highlight our main contributions as follows:

- We have proposed a self-learning vibration recovery algorithm, where the particular parameters of the vehicle can be first actively learned by the on-board smartphone and then adopted in inferring the actual vibrations of wheels. With this algorithm, P^3 can be used on different vehicles to perceive the profile of potholes.
- We have implemented an on-campus prototype system and conducted extensive field study the effectiveness of P^3 on different potholes, vehicle types and traversing speeds. The results demonstrate the feasibility and efficacy of the P^3 design.
- We have designed an individual perception aggregation algorithm to improve the individual estimates, showing its potential for the large scale pothole profile perception problem. The P^3 scheme needs no dedicated devices but only smartphones, handy to use and easy to gain a wide deployment.

The remainder of this paper is organized as follows. The related work is presented in Section 2. In Section 3, we define the pothole profile perception problem and present the system model and design goals. Section 4 elaborates the design of P^3 and analyzes its computational complexity. In Section 5, we discuss the potential issues when applying P^3 in practice. We introduce the prototype implementation of P^3 in Section 6. The methodology to evaluate P^3 and the experiment results are presented in Section 7. Finally, we give the concluding remarks and future directions of this work in Section 8.

2 Related Work

The existing work related to road condition perception can be categorized into two types in general as follows:

Dedicated-Sensors Based. Ground Penetrating Radar used in work [9] uses radar and operates in a wide radio frequency band from 0.05 to 6.0 GHz to detect tiny defects on roads. Furthermore, GPR can detect the potential potholes hidden under the ground. The defect of this system is that GPR is unrealistic to be widely deployed on ordinary vehicles. In work [11], the authors use an on-board vision system to capture the view of the road when driving, and use the image recognition technique to find out potholes. In their work, pothole larger than 2 feet in diameter can be detected. Using image recognition technique is mature and easy to deploy but has the problem of line-of-sight limitation. In addition, the performance of the scheme is also constrained by poor light conditions such as under bad weather or at night.

Vibration-Sensor Based. The Nericell project [15] utilizes acceleration information to detect car braking, stop-and-go traffic and bumping (caused by potholes or other uneven road surface). The detection algorithms are threshold-based. In work [13], the authors examine the vibration characteristics such as the maximum acceleration values and the variations when hitting potholes and propose thresholds to detect the potholes. The pothole patrol [4] is based on a machine learning approach using x- and z-axis acceleration information obtained from a 3D accelerometer and the velocity of a vehicle as inputs to identify potholes and other severe road surface anomalies. In [23], the authors investigate the variation of vertical vibrations of vehicles using neural network (NN). The approach proposed in [18] utilizes supervised and unsupervised machine learning methods to detect road anomaly. In [7], the authors extract features such as the mean, root mean square, standard deviation and variance of vibrations, and use Support Vector Machine (SVM) to detect potholes.

In general, both types of existing schemes conduct a qualitative analysis, which mainly focuses on the detection of an on-road obstacle and its type. However, they cannot tell the specific details of such an obstacle such as the size and the shape of a pothole. As not all potholes are harmful and should be informed to drivers, establishing the profiles of a pothole is of great importance. In P^3, though we also utilize the 3D acceleration information to perceive on-road potholes, our major effort is to further infer the specific profiles such as the depth and the length of potholes.

3 Problem Definition and System Model

3.1 Problem Definition

We aim to obtain the road condition information, especially about the distribution and the characteristics of potholes. in a metropolis where the number of roads needed to be checked is huge. Thanks to the popularity of mobile devices such as smartphones and tablets, crowdsourcing technique leveraging normal commuting drivers provides a cost-efficient and stunning solution. With crowdsourcing, drivers can first collect sensory data about potholes with their personal smartphones while driving, which can be collected and analyzed to perceive the demanded road condition information. In this paper, we study the accurate pothole profile perception problem, which refers to obtain the most important attributes, i.e., the length and the width, of potholes on hard-surface roads in a metropolis leveraging the 3D acceleration information collected by individual vehicles.

3.2 System Model

To solve the problem defined above, a practical system should consist of the following components:

- *Individual smartphones*: Every participating driver has a smartphone with a low-end 3D accelerometer and a GPS receiver embedded. The smartphone is required to be placed in the center of the top cover of the instrument panel of the vehicle where it is convenient for the driver to touch. It keeps sensing the acceleration and the current location information of the vehicle via the 3D accelerometer and GPS receiver, respectively. Moreover, it has sufficient computational capability to pre-process sensory data in situ.
- *The Data center*: In the system, the data center collects and aggregates individual perceptions of a pothole and disseminates the retrieved pothole information such as the global distribution and the refined profiles of potholes to the public as an information service.
- *Wireless communications*: Individual smartphones can send either raw sensory data or intermediate results to the data center via digital wireless communication channels such as GPRS and 3G/4G or free WiFi when available.

It should be noted that the power consumption of the smartphone is not critical under the vehicular environment. In this paper, we only consider sole potholes within a short range (e.g., at the scale of GPS localization errors). The reason is that, otherwise, it would be hard to distinguish whether individual perceptions collected for aggregation are about the same pothole or distinct potholes located in vicinity. As the localization technique progresses, different potholes in vicinity might be identified and estimated in future.

3.3 Design Goal

An effective scheme to solve the pothole profile perception problem should meet the following requirements:

- *Low deployment cost*: Considering the huge number of road in a metropolis, schemes relying on additional dedicated sensors or new infrastructure would introduce great deployment cost, which is infeasible. Therefore, a low cost pothole perception system without additional expensive dedicated hardware is preferred.
- *Good perception accuracy*: The profile including the depth and the length of a pothole can be used to evaluate the potential damages to moving vehicles and therefore is significant to driving safety. An effective scheme should not only be able to judge the types of surface anomalies but have the capability to infer the accurate profile of a pothole.
- *Robust to dynamic conditions*: A practical scheme should be able to work under complicated and dynamic conditions such as different weather, vehicle types, traversing speeds and light conditions.

4 System Design

4.1 Overview

It is common that a driver or a passenger can feel the magnitude of a pothole according to the intensity of vibrations made to the vehicle while crossing over a pothole on the road. Inspired by this intuition, P^3 is designed to utilize onboard smartphones to sense and further infer the details of a pothole. In addition, with the wide spread of smartphones, normal drivers or passengers can help build a whole pothole map of a big city by crowd sourcing. The system architecture of P^3 is shown in Fig. 1. In general, the system can be divided into four layers as follows.

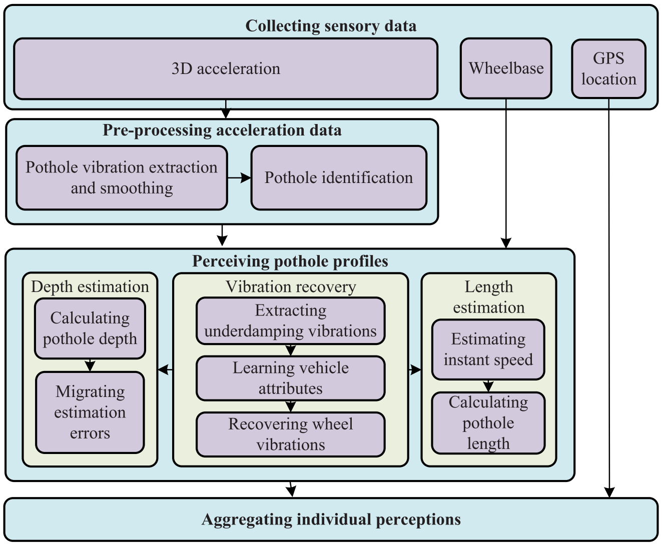


Fig. 1. The system architecture of P^3.

Collecting Sensory Data. In this layer, we utilize an on-board smartphone to sense the mobility status of the vehicle, including the acceleration information along the three perpendicular axes of the phone and the GPS location information. Furthermore, P^3 also need to know the wheelbase information of the vehicle which can be obtained by looking up a table given the type and brand of the vehicle. Note that P^3 requires a volunteer driver to specify the type and brand of its vehicle and put its smartphone at the center of the instrument panel of the vehicle. We will discuss more about these two requirements in the next section.

Pre-Processing Acceleration Data. While the vehicle is moving, besides a pothole, many other vibration stimuli, such as bumps, braking, making turns and slamming doors, can also lead to severe vibrations of the vehicle. In addition, the running engine and the unsmooth surface of roads may cause additional high-frequency noisy vibrations. In order to perceive the profile of a pothole, it is necessary to smooth the collected acceleration data and identify those vibrations caused by potholes.

Perceiving Pothole Profile. Given the observation that the vehicle would experience an underdamping vibration right after a wheel (called the probing wheel) has hit a pothole, P^3 extract such underdamping vibrations to learn the inherent attributes of the vehicle. With the particular knowledge about the vehicle, it can recover the vibration of the probing wheel by adopting an vibration model of one degree-of-freedom (DOF) [20]. After that, it is easy to roughly estimate the depth of the pothole. Considering the displacement of the smartphone from the probing wheel, P^3 corrects estimation errors according to a linear model. In addition to the depth, the length of the pothole can be estimated by multiplying the instant speed of the vehicle and the duration for the probing wheel from entering to leaving the pothole.

Aggregating Individual Perceptions. As individual perceptions about the same pothole might not be accurate or consistent, how to aggregate those individual perceptions so that an accurate result can be obtained at the data center is not trivial. To tackle this problem, we study the impact of a number of factors to the perception quality and find that the vehicle speed as well as the sampling rate of the embedded 3D accelerometer count most, i.e., a lower speed and a higher sampling rate can result in a better perception accuracy. With this observation, P^3 aggregates individual perceptions at the data center by increasing the weights of those perceptions obtained with low speeds and high sampling rates.

TABLE 1
Symbols Used in This Paper

Symbol	Description
m	the mass of the vehicle
k	the coefficient of the spring
c	damping coefficient of the damper
x	vertical shift distance of the vehicle body
y	vertical shift distance of the wheel
$\dot{x}$	the derivative of x
$\ddot{x}$	the second derivative of x
T	periodicity of underdamping vibrations
p	frequency of underdamping vibrations
η	amplitude attenuation rate in underdamping vibrations
δ	the natural logarithm of η

4.2 Background of One-DOF Vibration Model

As P^3 adopts a one-DOF vibration model [20] in perceiving the profile of a pothole with an arbitrary shape, we first briefly introduce this model before we elaborate the detailed design of P^3. To facilitate the understanding, we enumerate the symbols used in this paper in the Table 1.

The one-DOF vibration model is illustrated in Fig. 2 where the vehicle body is simplified as a box with the mass of m, connected to the suspension system. The suspension system can be simplified as a spring with a coefficient of k and a damper with a damping coefficient of c, connecting the vehicle body and a wheel. With this model, the relation between the vertical shift distance of the vehicle body, denoted as x, and the vertical shift distance of the wheel, denoted as y, can be formalized as follows:

$$c\dot{y} + ky = m\ddot{x} + c\dot{x} + kx, \tag{1}$$

where $\dot{x}$ and $\ddot{x}$ denote the derivative and the second derivative of x, respectively.

Equation (1) can be solved and deduced as follows:

$$\begin{cases} y = e^{-\frac{k}{c}t}[\int q(t)e^{\frac{k}{c}t}\,\mathrm{d}t + a] \\ q(t) = \frac{m}{c}\ddot{x} + \dot{x} + \frac{k}{c}x, \end{cases} \tag{2}$$

where a is a constant and can be assigned with value 0. Note that $\ddot{x}$ is the acceleration readings along z-axis of the smartphones. And $\dot{x}$ and x can be obtained by calculating the integrals of $\ddot{x}$ and $\dot{x}$ along time, respectively. As a result, the rest unknown parameters are the inherent attributes of the

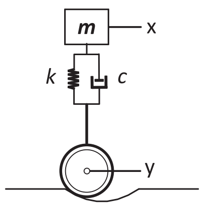


Fig. 2. The one-DOF vibration model.

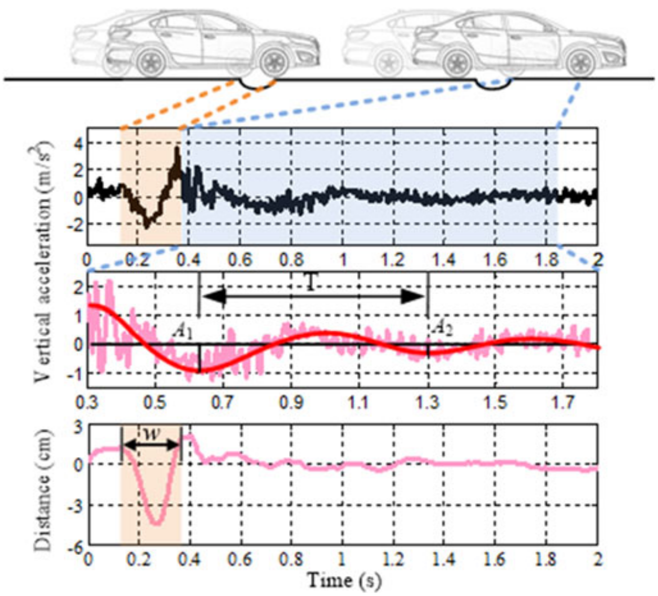


Fig. 3. Illustration of the forcing and underdamping vibrations caused when a car is passing over a pothole.

vehicle, i.e., $\frac{m}{c}$ and $\frac{k}{c}$, which need to be figured out before we can derive the vertical shift distance of the wheel y with the vertical acceleration readings $\ddot{x}$.

4.3 Pre-Processing Acceleration Data

With an on-board smartphone, we can continuously sense the status of a vehicle including its acceleration along three axes of the smartphone and GPS location information. As mentioned above, there might be other vibration stimuli which can cause obvious vibrations in addition to hitting a pothole. Furthermore, high-frequency noisy vibrations should also be removed from the acceleration signal. To this end, we need to pre-process the acceleration data first, which consists of two following components:

1) *Vibration smoothing and segmenting*: We first use moving average to mitigate the influence of noisy vibrations. Then, we cut the acceleration signal by using a sliding window to find a set of consecutive of vibration segments which exceed a predefined threshold value. Such consecutive segments are then combined to form a complete vibration signal caused by a particular vibration stimulus.

   We compare Fourier transform, wavelet transform and moving average to filter out the high frequency noise. The main cause of choosing moving average method is the lower computation cost compared to Fourier and wavelet transform and nearly the same result. The principle under moving average method is continuingly calculating the average of nearby m numbers.

   To set a proper threshold value, we found that the threshold set to be three times of the overall road variance is well balanced to segment.

2) *Pothole Identification*: To distinguish a potential pothole from other identified vibration stimuli such as door slamming, braking and making turns, we adopt the method proposed in [4] and check the duration of the vibration stimulus and the acceleration variance along x- and y-axis to filter out non-pothole vibration stimuli. For example, the typical duration of door slamming is less than 0.2 second. For making turns and braking, the acceleration along x- and y-axis is obviously non-zero. Accordingly, we can exclude those unrelated vibration stimuli. In addition, a pothole is believed to be found when the acceleration in z-axis tends to decrease and the duration and the amplitude of such descending trend are larger than predefined thresholds.

4.4 Perceiving Pothole Profiles

Given the pre-processed acceleration data, P^3 can smartly perceive the pothole profile by integrating three following techniques

1) *Active vibration recovery*: To estimate the profile of a pothole, it is essential to recover the real vibrations of the probing wheel from the acceleration data collected by the smartphone. However, it is often the case that vehicles may have different speeds and values of attributes with respect to the mass of the vehicle, spring coefficients and damping factors of the suspension system, which makes such recovery very difficult with so many unknown factors.

   In general, the vibration process while a vehicle is crossing over a pothole can be divided into two parts, i.e., forcing vibration and underdamping vibration. As illustrated in Fig. 3, when the front wheel hits a pothole, the vehicle is forced to vibrate and forcing vibration part begins (demonstrated as the left red block in Fig. 3) until the wheel leaves the pothole. After that, the underdamping vibration part starts (shown as the right blue block) where the vehicle continues to vibrate at its natural damped frequency with the amplitude gradually decreasing to zero. Since the underdamping vibration happens when the vehicle is running on an even road surface, the value of y is therefore zero. So Equation (1) can be transformed as

$$\ddot{x} + \frac{c}{m}\dot{x} + \frac{k}{m}x = 0 \rightarrow \ddot{x} + 2n\dot{x} + p^2x = 0, \tag{3}$$

   where n denotes $\frac{c}{2m}$, and p denotes $\sqrt{\frac{k}{m}}$. In underdamping vibration where $n < p$, the result of in (3) is

$$x = Ae^{-nt}sin(\sqrt{p^2 - n^2t} + \alpha), \tag{4}$$

   where A and α are the initial amplitude and phase of the underdamping vibration, respectively. It can be seen from (4) that the periodicity T of the underdamping vibration is fixed, which is

$$T = \frac{2\pi}{\sqrt{p^2 - n^2}} \approx \frac{2\pi}{p} \rightarrow p = \frac{2\pi}{T}. \tag{5}$$

   As a result, the frequency of the underdamping vibration is p, which only depends on k and m. With the damper in the suspension system of the probing

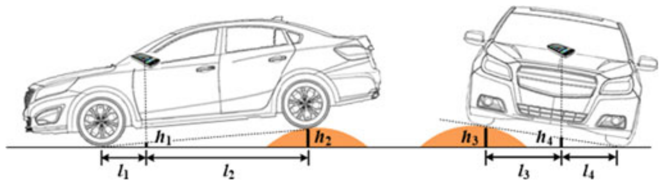


Fig. 4. Demonstration of smartphone placement.

wheel, the amplitude of the underdamping vibration attenuates at a fixed rate

$$\eta = \frac{A_i}{A_{i+1}} = \frac{Ae^{-nt}}{Ae^{-n(t+T)}} = e^{nT} \rightarrow n = \frac{ln(\eta)}{T}, \quad (6)$$

where A_i and A_{i+1} denote the amplitudes of two consecutive vibration waves, respectively and δ denotes $ln(\eta)$. As shown in the central subplot in Fig. 3, the periodicity T and the amplitude attenuation rate of the underdamping vibration can be easily obtained.

Together with (5) and (6), we can finally estimate the vertical shift distance of the wheel y during the forcing vibration from (2)

$$y = e^{-\frac{p\pi}{\delta}t} \int q(t)e^{\frac{p\pi}{\delta}t}\,\mathrm{d}t. \quad (7)$$

With this observation, P^3 first needs to extract the acceleration readings of underdamping vibrations; then it can actively learns the attributes of the vehicle and recovery the vibration of the probing wheel.

Nevertheless, the boundary between the forcing vibration part and the underdamping vibration part is not obvious. Note that the periodicity of the forcing vibration is decided by the shape of the pothole while that of the underdamping vibration is only related to the inherent attributes of the vehicle. With this fact, we first extract individual vibration waves by searching two consecutive local minimums on the z-axis acceleration signal and then compare the periods of two consecutive vibration waves. If both of the periods are equal or very close, the underdamping vibration is identified and the corresponding vibration waves are regarded as the beginning of the underdamping vibration. With the identified underdamping vibration (as illustrated in the central subplot of Fig. 3), and p, δ can be calculated as $\frac{2\pi}{T}$ and $ln\frac{A_i}{A_{i+1}}$. Finally, we can recover the vertical shift distance of the probing wheel y by solving (7) with those learned parameters.

2) *Depth estimation*: With the recovered vibrations of the probing wheel, it is easy to roughly estimate the depth of the pothole. Nevertheless, as the smartphone is not placed right above the probing wheel which is experiencing the pothole, the estimated depth may not be accurate. To deal with this problem, P^3 corrects the error according to a linear model between the estimated depth of the pothole and the placement of the smartphone.

Specifically, because the smartphone is placed on the instrument panel of the vehicle which is far from the probing wheel (i.e., the rear wheel in Fig. 4), the vertical shift distance of the probing wheel inferred by the smartphone (e.g., h_1 in the left subplot) is biased from the real value (e.g., h_2 in the left subplot). For example, in the case of Fig. 4, the relation between h_1 and h_2 can be represented as $\frac{h_1}{h_2} = \frac{l_1}{l_1+l_2}$. The particular values of l_1 and l_2 can be obtained by looking up a table given the brand and type of the vehicle. In addition, when the smartphone is put in the center of the instrument panel, there is also a displacement from the probing wheel, as demonstrated in the right subplot of Fig. 4. Therefore, the corresponding relation between the inferred vertical offset distance h_4 and the real value h_3 is $\frac{h_4}{h_3} = \frac{l_4}{l_4+l_3} = \frac{1}{2}$. Knowing the bias relationship, we can correct those depth estimation errors by linearly scaling the inferred depth. The bottom subplot of Fig. 3, illustrates the estimated vertical shift distance of the probing wheel as time series, where the colored block represents the inferred pothole.

3) *Length estimation*: In addition to the depth, the length of the pothole can also be estimated by multiplying the traversing speed of the vehicle with the duration for the probing wheel from entering to leaving the pothole.

To obtain the instant speed of the vehicle, however, is very challenging as the speed measured by GPS is not that accurate. In P^3, we adopt the method proposed in prior work [6]. The rationale behind this scheme is that the vibrations caused by the front wheel and the rear wheel are similar. By calculating auto-correlation on the vertical acceleration signal and checking the auto-correlation spike, we can locate two similar vibration segments and the corresponding lag (i.e., the delay) caused by the front and rear wheels when hitting the same pothole. Consequently, the instant speed can be calculated by dividing the wheelbase by the lag. The information of the wheelbase of the vehicle can be obtained by looking up the table as mentioned above.

With the estimated time series of the estimated vertical shift distance of the probing wheel, the duration for the probing wheel from entering to leaving the pothole can be easily obtained, illustrated as win the bottom subplot of Fig. 3.

5 Practical Issues

We first discuss the accuracy improvement technique by aggregating individual perceptions, then we discuss several potential design issues when applying P^3 in practice in this section.

5.1 Individual Perception Aggregation

In fact, the profile perceptions of a pothole from individuals may not be that accurate because these results could be influenced by various factors such as different smartphones used, different vehicle speeds, noise and other abnormal vibrations of vehicles. For example, Fig. 5 plots the depth estimate error rate as a function of vehicle speed and smartphone sampling rate. It can be seen that different vehicle

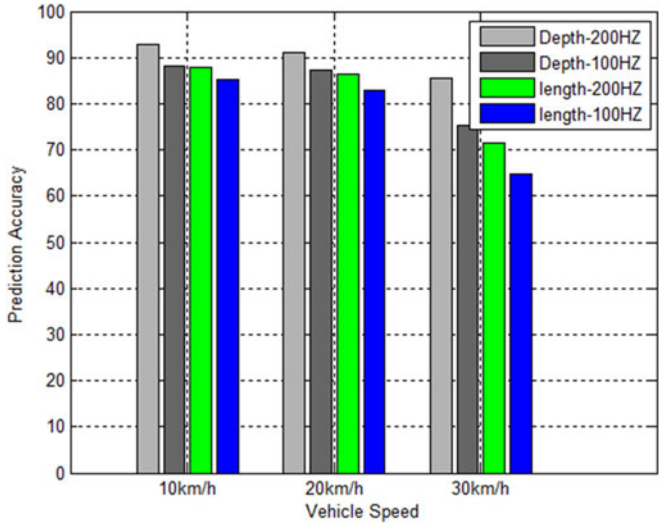


Fig. 5. Depth prediction accuracy affected by both speed smartphone sampling rate.

speeds and sampling rates would lead to different estimation accuracy. Furthermore, vehicles may traverse different part of a pothole (e.g., the edge of the pothole or the central part of the pothole), making different views about the same pothole.

In P^3, a data center is set up for two reasons. First, all individual perceptions are collected in order to obtain the road-surface-condition information in a metropolitan scale. A perception is a five-tuple (location, depth, width, speed, sampling rate), where location is the longitude and the latitude of the pothole obtained with the on-board GPS receiver, depth and width are the profile estimates about the pothole, speed is the vehicle speed, and sampling rate is the sampling rate of the on-board smartphone. Second, perceptions about the same pothole are inaccurate and should be aggregated to get more accurate estimates.

Before aggregation, perceptions about the edge of a pothole should be discarded as we are mainly concerned about the maximum depth and span of the pothole. To this end, we utilize a K-means algorithm to cluster all perceptions of the same pothole according to the depth field. The K-means algorithm is a simple yet effective technique to cluster feature vectors into a predefined k number of groups [12]. The selection of appropriate value of k is crucial and is an open research problem [3]. We use a heuristic, called gap statistic [14], involves comparing the change in intra-cluster dissimilarity W_k for given data and that for a reference null distribution [19]. Gap statistic provides a statistical method to find the elbow of intra-cluster dissimilarity W_k as the values of k varies. Using gap statistic, the optimal value of k can be chosen. Finally, we choose the group with at least k perceptions and the maximum average depth for aggregation.

For aggregation, we study the correlation between the estimation accuracy and the vehicle speed and the sampling rate of the on-board smartphone. We have the observation that the estimation can be very accurate with a low vehicle speed and a high sampling rate as illustrated by Fig. 5. Based on this observation, those individual perceptions obtained at a low vehicle speed or with a high sampling rate smartphone will be assigned with a higher degree of confidence. We get the aggregated result by taking the weighted average of all individual perceptions. As a result, the aggregated depth and width will be used to describe the "worst-case" of the pothole.

5.2 Other Practical Issues

Influence of Vehicle Speed and Phone Sampling Rate. When a vehicle hits a pothole at a very high speed, it is possible that the intensity of the shock exceeds the of the suspension system, which may makes the smartphone jump off the surface of the instrument panel or causes the magnitude of the vertical acceleration goes beyond the measuring range of the smartphone. Furthermore, when the vehicle moves at a high speed (for example, at $80\ \mathrm{km/h}$), due to the limited sampling rate of the smartphone (e.g., around 200 Hz), the number of available samples about the pothole becomes quite limited. As a result, the estimated profile of the pothole might be inaccurate. To migrate the influence of high vehicle speeds and low phone sampling rates to the estimation accuracy, P^3 can select those individual perceptions obtained with low vehicle speeds for aggregation. In an urban driving environment, we believe that at any time at any where there exist the speed-limited samples which are suitable for our scheme and computation.

In specific, with a crowdsourcing application involving plenty vehicles, it is possible that we can obtain pothole profiles perceived by those low-speed vehicles. In addition, as the hardware of modern smartphones improves and more advanced accelerometers with faster sampling rates are embedded in smartphones, the highest vehicle speed of our approach can be increased.

Effective Sensory Data and Probing Wheel Selection. In P^3, one essential condition is for both of the front and the rear wheels to cross over the same pothole, as required in estimating the instant speed of the vehicle. However, it is possible that both of the wheels or one of them may miss the pothole. In order to deal with this case, P^3 only conducts pothole profile perception with effective sensory data and leave other trace unused. With the large number of participants, all potholes will be eventually recovered. With effective sensory data, the pothole can be estimated based on the vibration information collected by either the front wheel or the rear one. In P^3, we select the rear wheel as the probing wheel. The main reason is that it is easier to extract the underdamping vibration of the rear wheel as that of the front wheel often overlaps with the forcing vibration of the rear wheel when the vehicle speed is relatively high. Recall that P^3 utilizes underdamping vibrations to actively learn the inherent attributes of the vehicle and further estimates the pothole. Using rear wheels as probing wheels can lead to better estimation accuracy.

Smartphone Placement and Reorientation. In P^3, the smartphone is required to put at the center of the instrument panel of the vehicle. This allows the smartphone to correct estimation errors caused by the displacement of the smartphone and the probing wheel according to the linear model mentioned in above section. However, it is possible to loosen this requirement as long as the smartphone can recognize its relative location within the vehicle. As far as the estimation accuracy is concerned, the best position to put the smartphone is on the package tray of the vehicle right

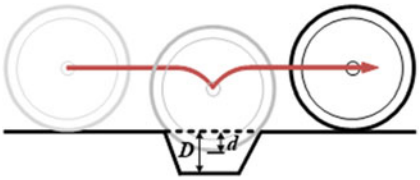


Fig. 6. Demonstration of effective depth.

above the rear wheels. The main consideration of putting the phone on the instrument panel is for the ease of use for the driver. In addition, P^3 cannot derive meaningful pothole profiles unless the coordinate system of the smartphone is aligned with that of the vehicle. Since the pose of the phone could be arbitrary, we need to align the two coordinate systems. We adopt the solution proposed in [6] where a rotation matrix is used to do the coordinate system transformation.

The True and the Perceived Depth of Potholes. In the case where the length and depth of a pothole is less than the diameter and larger than the radius of the probing wheel, respectively, P^3 cannot perceive the real depth of the pothole (e.g., denoted as D in Fig. 6) but a perceived depth of the pothole (e.g., denoted as d in Fig. 6). Although the actual depth of potholes is desired, knowing the perceived depth can also provide invaluable assessment about the damage of the road surface.

Obtaining the Wheelbase Information. In P^3, additional attributes of vehicles such as the wheelbase information and the distance relationship between the instrument panel and the rear wheels are required but cannot be actively learnt by the smartphone. One possible solution to this issue is to let drivers manually provide such information as inputs to P^3. One better solution which migrates the labor work of driver is to let drivers select the brand and the type of their vehicles. Then the corresponding attributes can be obtained by looking up a pre-built table.

The Road Slope. There are doubts about the impact of road slope to the detection accuracy. We tackled the case in previous work [6]. It shows that the road slope factor can be well filtered in the sensing framework thus the road slope can cause no impact on the detection and profiling phase. As long as we get the vibrations vertical to the road surface (no matter it is level or on a slope) the P^3 can work. The key point is how to obtain vibrations vertical to the road surface even when the road is on a slope. To this end, we can adapt the technique proposed in our previous work [6], which reorients the coordinate system of the attached smartphone so that the coordinate system of the smartphone can align with that of the vehicle.

6 Prototype System

We implement P^3 as an Android application and install it on a Galaxy Nexus 3 (made by Samsung, Android 4.2, 1.2 GHz dual-core, 1 GB RAM, maximum sampling rate of the embedded accelerometer: 100 Hz). We use a workstation of HP Z230 (manufactured by HP, Windows 8, Intel Core i7, 3.2 GHz, 8 GB RAM) to serve as the data center server for aggregation in our prototype system.

We conducted field experiments on our campus to validate the feasibility of the P^3 design. Specifically, we first make a pothole on our campus (as shown in the upper right subplot of Fig. 7) with the length and depth of about 50 and

Fig. 7. Field study with the implementation of the prototype system.

5 cm, respectively. We use a four-door sedan (i.e., a Volkswagen Passat B5) and place the smartphone at the center of the top cover of the instrument panel as shown in the upper left subplot of Fig. 7. We drive the car and let the right side of wheels to cross over the pothole at a speed of 10 and $30\ \mathrm{km/h}$, respectively, for 10 times and estimate the depth and length of the pothole according to the design of P^3.

Based on the above field experiments, it can be seen that P^3 can effectively learn the related attributes of the car and estimate the length and depth of the pothole without too much human intervention as expected. Nevertheless, we also have learnt two following lessons. First, P^3 can achieve good estimation accuracy when the car is moving at a low speed. When the vehicle speed exceeds $30\ \mathrm{km/h}$, the derived results can severely deviate from the ground truth, as what we have discussed in above section. Second, linear aggregation based on vehicle speeds can improve the estimation accuracy. For example, the estimated length and depth of the pothole in the field experiment is 56 and $5.2\ \mathrm{cm}$. We will further investigate the performance of P^3 in various settings in the performance evaluation section.

7 Performance Evaluation

7.1 Methodology

To evaluate the performance of P^3, besides of the Galaxy Nexus 3 smartphone and the Volkswagen Passat B5, we also involve a new smartphone of the Google Nexus 4 (made by LG, Android 4.2, 1.5 GHz quad-core, 2 GB RAM, maximum sampling rate of accelerometer: 200 Hz), a Volkswagen Lavida and two SUVs (a Honda CR-V and a Volkswagen Tiguan) in our experiments. Moreover, we consider different vehicle speeds, different phone placement (i.e., at the center and the right end of the top cover of the instrument panel as shown in the left subplot of Fig. 7) and different sides of wheels (i.e., the left-side and the right-side). We identify 23 different potholes in the downtown area(see Fig. 8) of a metropolis and obtain a trace of over 2,760 segments of vibration data collected with different configuration of vehicle type, vehicle speed, phone placement and side of wheels from June 4th to July 2nd for analysis.

For the ground truth purpose, we plot the distribution of the real 23 potholes of the downtown road in Fig. 9. We see

Fig. 8. Those 23 potholes on the Google map and the example potholes.

that the length and depth of these potholes are among quite large ranges. The depth ranges from 2 to $10\ \mathrm{cm}$ while the length between 30 to $120\ \mathrm{cm}$.

We evaluate the performance of P^3 using the estimation error rate (denoted as) metric defined as follows:

$$\varepsilon = \left|\frac{d_{estimate} - d_{real}}{d_{real}}\right|,$$

where $d_{estimate}$ denotes the estimated length or depth of a pothole where as d_{real} denotes the ground truth of the length or depth of that pothole. In the following sections, we investigate the impact of various factors (i.e., vehicle speed, phone sampling rate, smartphone placement and different potholes) to the performance of P^3 and present the details.

7.2 Impact of Vehicle Speeds and Phone Sampling Rates

As we have learnt from our prototype implementation, vehicle speeds as well as the phone sampling rates are essential to the performance of P^3. In this experiment, we examine the impact of vehicle speeds and phone sampling rates. Specifically, we vary the vehicle speed ranging from 10 to $30\ \mathrm{km/h}$ with an interval of $10\ \mathrm{km/h}$ and drive both vehicles over all 23 potholes with both smartphones placed at the center of the instrument panel and right-side wheels hitting potholes. For each speed and each pothole, we drive five times and estimate the profile of all potholes.

Fig. 5 plots the depth estimation error rate as a function of different vehicle speeds. It can be seen that, in general, low vehicle speeds can achieve good depth estimation. For example, the average estimation error rate for Passat B5 is around 9 and 12 percent with G4 (200 Hz) at the speed of 10 and $20\ \mathrm{km/h}$, respectively. Second, the higher sampling rate will lead to more accuracy of pothole perception. For example, the performance of P^3 with G4 outperforms that with G3 at all speeds. Last, using a vehicle with a better suspension system will achieve better estimations. For example, the CR-V has less estimation error rates comparing with Passat B5. In summary, we have the conclusion that good suspension systems of vehicles and high sampling rates of smartphones can help improve the estimation accuracy and extend the applicable speed condition of P^3.

Fig. 10 plots the length estimation error rate as a function of vehicle speeds. We have similar observations except that

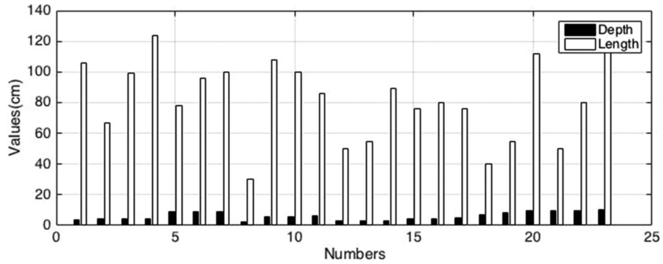
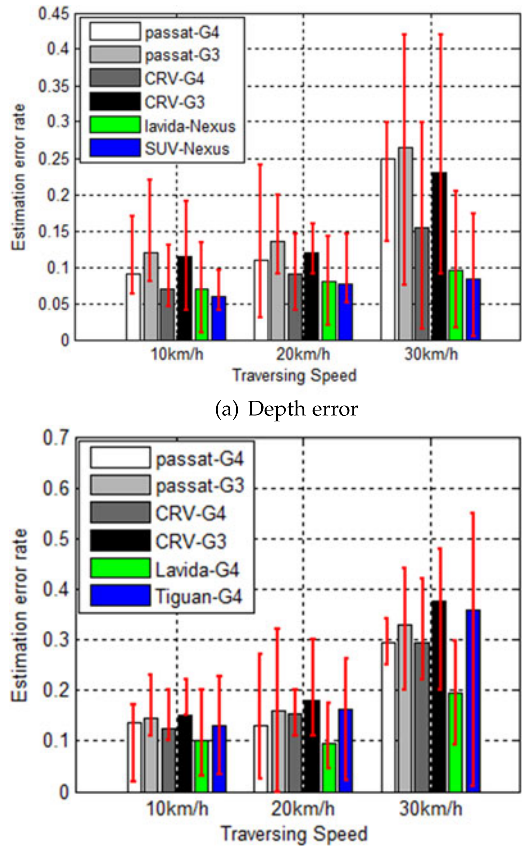


Fig. 9. Distribution of depth and length of 23 detected potholes.

the length estimation error rate is slightly larger than the depth estimation error rate and the difference between different vehicles is minor. Recall that, in P^3, the instant speed of the probing wheel is estimated as the average speed during the time period from the moment when the front wheel hits a pothole to that when the rear wheel does. This may lead to inaccurate speed estimation and further cause the length estimation errors, which are independent of vehicles.

7.3 Impact of Phone Placement and Side Wheel

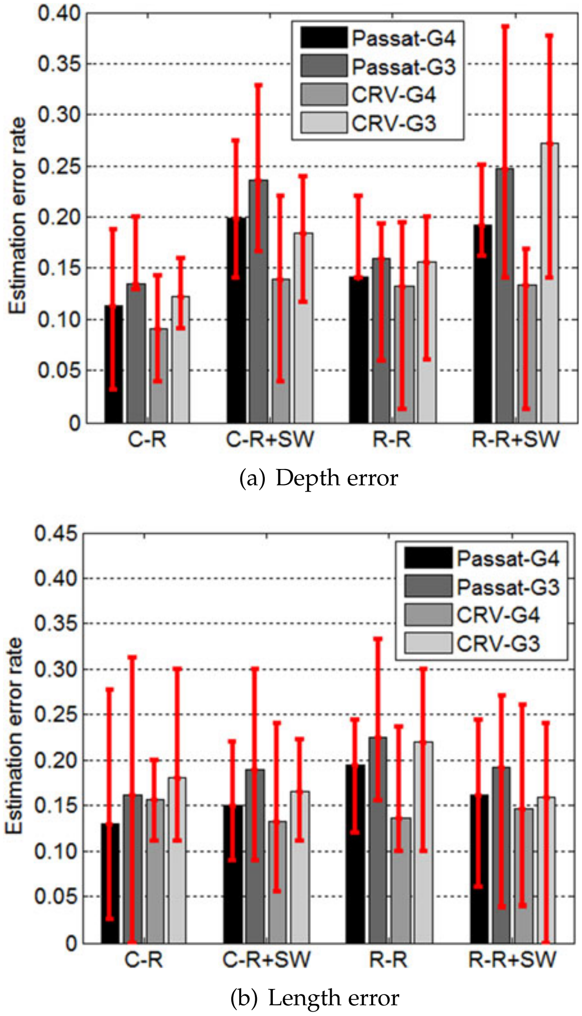
As it is possible that vibrations of the wheel on the other side of the probing wheel (called the side wheel) may affect the pothole perception, we examine the eight potholes out of 23 potholes which have uneven road surface nearby. When crossing over these three potholes, it is possible to cause violent side wheel vibrations in addition to the major vibrations caused by the probing wheel at the same time. In this experiment, we examine the impact of phone placement and the side wheel.



(a) Depth error

(b) Length error

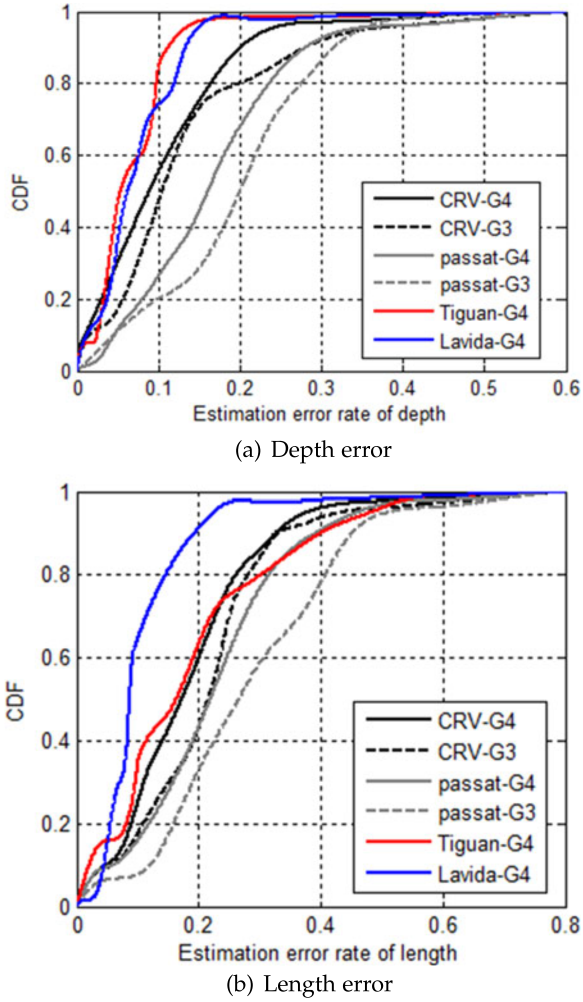
Fig. 10. Depth and length error at different speed.



(a) Depth error

(b) Length error

Fig. 11. Depth and length error with different placements.



(a) Depth error

(b) Length error

Fig. 12. CDF of depth and length estimation errors.

Specifically, we vary the placement of both smartphones at the center (we denote this case as “C-”, standing for “Center phone placement”) and the right corner (we denote this case as “R-”, standing for “Right phone placement”) of the instrument panels of both vehicles. For each of those potholes, we first drive both vehicles to let right-side wheels hit the pothole in both directions. In one of the direction, there is no side wheel vibrations (we denote this case as “R”, standing for “Right-side probing wheels”) while, in the other direction, we let the side wheel go through the uneven road surface (we denote this case as “R+SW”, standing for “Right-side probing wheels plus Side Wheel vibrations on the left”). Therefore, by combining the phone placement and the side wheel vibrations, we have four cases, i.e., C-R, C-R+SW, R-R and R-R+SW, in total. For each of those cases, we drive at the speed of $20\ \mathrm{km/h}$ for five times and estimate the profile of all potholes.

Fig. 11a plots the depth estimate error rate as a function of phone placement and with/without side wheel vibrations. It can be seen that the estimation error rate with center phone placement is the more stable and accurate than with right placement. The reason is that it is hard to place the phone right above the right wheels, in which case we cannot obtain the accurate scaling factor in the linear error correction model described above. It can also be seen that the side wheel vibrations will increase the estimation error rate. The reason is that the side wheel vibrations are usually asynchronous with the vibrations of the probing wheel. Those asynchronous vibrations would interfere with each other and therefore affects the estimation accuracy.

Fig. 11b plots the length estimation error rate for all cases. It is interesting to see that the side wheel vibrations has little influence on the length estimation. As explained in above experiment, the inaccuracy of length estimation mainly lies in the estimation errors of the instant speed and the forcing vibration duration caused by a pothole, which are both independent of the effect of side wheel vibrations.

We also try the left-side four cases, i.e., C-L, C-L+SW, L-L and L-L+SW, and get similar results, which are omitted from this paper due to the page limitation.

7.4 Overall Performance

As we have learned from above experiments, to examine the best performance of P^3, we select those vibration data from the trace when both smartphones are placed at the center of the instrument panel and both vehicles move at the speed less than $30\ \mathrm{km/h}$. We estimate the profile of all 23 potholes based on the selected data and plot the cumulative distribution functions (CDFs) of the depth and length estimation error rate in Fig. 12, respectively. From these plots, it can be seen that the Tiguan with a better suspension system and the G4 smartphone with a higher sampling rate of 200 Hz can always achieve lower estimation errors. For example, with the Tiguan and the G4 smartphone, 90 percent of the depth have an error rate less than 10 percent. With the Lavida with a G4 smartphone 90 percent of the length can have an error rate less than 20 percent.

Furthermore, we aggregate of all the pothole perception data by using the linear error correction models described in Section 5.1. The overall aggregated depth and length estimation error rates over all potholes decrease from 15 and 19 percent to 13 and 16 percent, respectively. It shows that the pothole perceptions with normal vehicles and smartphones can also provide useful information for P^3 to improve global pothole estimation. In the future, we plan to enlarge the pothole profiling platform to the metropolitan scale in crowdsourcing way, to enable the solution of precise metropolitan-scale pothole sensing and profiling.

8 Conclusion and Future Work

In this paper, we have studied the problem of pothole profile perception at a metropolitan scale. We have proposed an innovative scheme P^3, which is light-weighted and can be implemented on smartphones. The beauty of P^3 is that it can smartly learn the necessary attributes of various vehicles and estimate the profile of a dangerous pothole without too much human intervention. Moreover, P^3 is rather robust to various conditions such as poor light, bad weather and distinct vehicle types. Leveraging the large population of smartphones, P^3 can achieve excellent coverage and improve individual estimation by aggregating trustworthy local estimates obtained at low vehicle speeds and high sampling rates. We have conducted extensive field experiments and results show that P^3 can achieve low depth and length estimation error rate at 13 and 16 percent, respectively.

In the future, we will further improve P^3 in the following directions. First, we will implement a crowdsourcing platform to collect more individual perceptions of metropolitan scale potholes. Second, we will look into the profound aggregation methods. Third, we will further study how to perceive the complete profile of a pothole instead of the worst case. Finally, we will further study more sophisticated vibration models other than the one-DOF model to infer more accurate pothole profiles. Besides, we will study how to obtain the accurate location information of potholes for better aggregation without the need of GPS.

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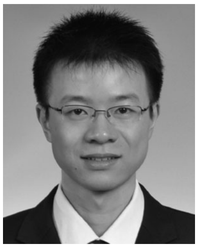

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