Speed-Breaker Early Warning System

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Abstract

There is evidence to support the claim that speed-breakers can cause accidents and injury. When a vehicle approaches a speed-breaker at a speed greater than some threshold velocity, the risk of accident or injury is substantial. Speed-breakers are inconspicuous in low visibility conditions, like at night, or when there is fog, rain or snow. This problem is particularly acute in developing countries where speed-breakers don't always accompany warning signs. We propose an early warning system that uses a smartphone based application to alert the driver in advance when the vehicle is approaching a speed-breaker. In addition, the application constantly monitors the smartphone accelerometer to detect previously unknown speed-breakers. The proposed detection algorithm is easy to implement because it does not require accelerometer reorientation. This is one of the main contributions of our work since previous approaches have used expensive computations to reorient the accelerometer. The algorithm was evaluated using 678 Km of drive data, which involved 22 different drivers, 5 different types of vehicles (bus, auto rickshaw, cycle rickshaw, motorcycle, and car), and 4 smartphones. The results are very promising and can be further improved by aggregating detection reports from multiple smartphones.

1 Introduction

Speed-breakers (speed humps/speed bumps/sleeping policeman) are traffic calming devices commonly installed to reduce speed related accidents [23]. Speed-breakers are designed to be driven over at a predetermined comfortable speed, while causing exceeding discomfort at higher speeds. The reduction in average vehicular speed significantly improves the safety of people in the neighboring areas. For example, a before and after study in Ghana found that speed humps reduced casualty crash frequencies by 37.5%, fatal crashes by 46% and pedestrian crashes by 72% [8]. This traffic calming technique is of special value in developing countries because "stop", "yield" and "speed limit" signs do not work due to shortage of traffic enforcement resources [1]. As a result, speed-breakers are ubiquitous in many developing countries, including India, Chile, Egypt, Ghana and Pakistan [12].

Even though there is evidence that speed-breakers reduce speed related accidents, they have also been known to cause accidents and injuries. When an automobile approaches a speed-breaker at a speed greater than a threshold velocity, the risk of accident or injury to the passengers becomes substantial [11]. For example, a motorcyclist who hit a speed hump in Isleworth in 2001 was ejected from the bike and suffered serious injuries (paralysis) [14]. In another incident, a 20 year old female was killed in Pune, India in 2012 after her motorbike went over a speed-breaker at a high speed [6]. Motorcycles and scooters are specially vulnerable because inconspicuous speed-breakers can throw them off balance [14]. Additionally, passengers of large vehicles like buses, trucks and tempos are also vulnerable to speed-breaker induced injuries. In [5], authors provided case details of patients who suffered back and neck injuries that occurred when their transport bus crossed a speed hump. In one case, a 49 year old female traveling on a double decker bus was jolted upwards when the bus traversed a speed hump, and on landing back fractured her third lumbar vertebra. In the two cases cited in [5], there was evidence that the buses were traveling at a speed greater than recommended for crossing speed humps. A recent study from Chile reported that 46 patients admitted in Hospital del Trabajador de Santiago over a eleven year period from 1997 to 2008 sustained spine fractures after passing over a speed hump [17]. Of these 46 patients, 44 were injured in a bus (42 were in the last row), whereas 2 were in a car. Yet another study from Turkey [3] reported five cases of speed-breaker induced spinal column injuries, and in four out of the five cases the ve-

hicles were traveling at a speed faster than recommended for crossing that speed-breaker. Crossing a speed bump at higher than recommended speed may also damage vehicles and the freight, increasing overall logistical costs. For example, it was shown that apples stored in bins get bruised during the passage of a truck over a speed bump, and a reduction in speed helps reduce fruit damage [24].

Speed-breakers are inconspicuous under special conditions, like when there is snow, fog, or rain; or at night when they are hard to see. This problem is particularly acute in developing countries where speed-breakers don't always accompany advanced warning signs. England's Department of Transport recommends that road humps must be located so that they are always preceded by a speed reducing feature [18]. Traffic lights are required to warn of the presence of road humps and there must be adequate lighting source in the surrounding area [18]. Such guidelines are often ignored in developing countries and as a result most speed-breakers do not have any markings or warning lights. Moreover, poorly trained workers often create speed-breakers that do not comply with standard dimensions [20]. Recently Bangalore police counted 4,536 non-compliant, illegal speed-breakers [20]. Illegal speed-breakers have been reported in cities all across India (e.g., [2]) and in countries like Pakistan [10], Malaysia [13] and Russia [22]. The dimensions of these illegal speed-breakers deviate significantly from what is considered safe by the government and transportation researchers worldwide [9, 11, 19]. Moreover, they are often installed in locations frequented by transport buses, increasing the risk of spinal column injuries. Hence, drivers in developing countries should be extra careful and slow down even more to avoid injuries from illegal and unmarked speed-breakers.

We propose a system named the Speed-breaker early WArning System (SWAS) that uses a smartphone based application to alert the driver in advance when the vehicle is approaching a speed-breaker. This gives the driver sufficient warning (and time) to slow down to a safe speed. SWAS can warn the driver even when there are no warning signs or lights on the road, or when the markings are inconspicuous due to low visibility conditions. The smartphone application downloads GPS coordinates of all speed-breakers in the vicinity from a SWAS server. It then starts monitoring the phone's instantaneous GPS location and warns the driver when the vehicle approaches a speed-breaker. Smartphone based application is a viable solution for the developing world because of the increasing availability of low cost (less than $100) Android based smartphones.

The main challenge lies in populating the SWAS database with speed-breaker locations. To accomplish this, the same smartphone application that provides speed-breaker warnings also detects new speed-breakers.

This application collects readings from the smartphone's 3 axis accelerometer and examines them for patterns that represent speed-breakers. When it infers a previously unknown speed-breaker, its location is shared with the SWAS server. When the SWAS server receives information about a new speed-breaker from multiple smartphones, it adds this speed-breaker and its location to the SWAS database.

We make two main contributions in this work. First, we propose a new algorithm for detecting speed-breakers given a time series of 3 axis accelerometer data. Second, we demonstrate that it is possible to extract information from the amplitude vector, obviating the need for accelerometer reorientation. This approach is simpler to implement in comparison with previously published methods that require inputs from other sensors like GPS [16] or magnetometer [4] for accelerometer reorientation. In addition, we evaluated our algorithm using a rich data set which includes various different types of vehicles, drivers and speed-breakers.

2   Related Work

A method for detecting vehicle braking and road bumps was proposed in [4]. They used machine learning techniques to detect road anomalies and braking events from accelerometer and magnetometer data. The method will not always work because magnetometer is not present in all phones, is susceptible to magnetic interference and increases battery consumption. In addition, the performance of this algorithm was not evaluated for various different types of speed-breakers, vehicles and drivers. A method for detecting speed bumps and braking events was also proposed in [16]. This work did not differentiate between potholes and speed-breakers, and labeled them both as speed bumps. Just like [4] requires magnetometer for reorientation, [16] requires GPS for reorientation, increasing overall complexity and battery consumption. Recently, mobile phone crowd-sourcing based pothole detection has also gained significant attention [7]. In this work [7], the mobile phone had to be placed a certain way on the dashboard to avoid reorientation complexity. Authors of [21] attempted to solve the pothole detection problem without taking into account accelerometer reorientation. In another work, authors of [15] proposed a fixed threshold based pothole detection algorithm that may not work with different types of phones or cars because of the difference in overall sensitivity to variations along vehicle's z-axis.
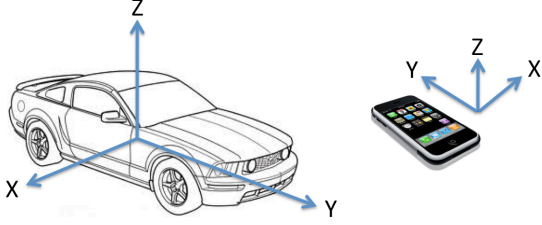
Figure 1: The three axes of a car and a smartphone. The Z-axis of the phone does not always align with the z-axis of the car, e.g., when the phone is in the driver's pant pocket.

3 Detection Methodology

If the sampling rate is fixed at R samples/sec, the SWAS application collects a total of $3 \times RT$ samples in a fixed time duration of T seconds ($1 \times RT$ samples from each of the 3 axes). Then, given a set of $3 \times RT$ samples, the application must decide whether or not there was a speed-breaker when these samples were collected. The value of T was fixed to 2 seconds based on the observation that it usually takes less than 2 seconds to cross a speed-breaker (assuming some fixed maximum velocity).

Smartphone's axes don't always align with the car's axes (see Figure 1) because passengers can place their smartphone in any location, e.g., pant pocket, purse, car seat, dashboard, etc. Since road anomalies like potholes and speed-breakers primarily manifest along the z-axis of the vehicle, previous works attempted to re-orient the phone's axes with that of the car using some other sensors [4, 16]. We have adopted a slightly different approach in this work, wherein, only the amplitude of the acceleration vector is sufficient to detect speed-breakers. Since the amplitude comprises of forces experienced along all three axes, it already has a component of forces experienced along the vehicle's z-axis. Hence, it should be possible to detect speed-breakers from time series of amplitude data.

As a first step, the $3 \times RT$ accelerometer readings are converted to the corresponding set of RT amplitude samples. If x_i, y_i and z_i are the values of the X, Y and Z axis accelerometer readings, then the amplitude is simply $a_i = \sqrt{x_i^2 + y_i^2 + z_i^2}$.

3.1 Feature Vector

Given a set of RT amplitude samples, the following features are used to detect speed-breakers.

1. Standard Deviation: It was observed that the amplitude of acceleration vector sways widely when
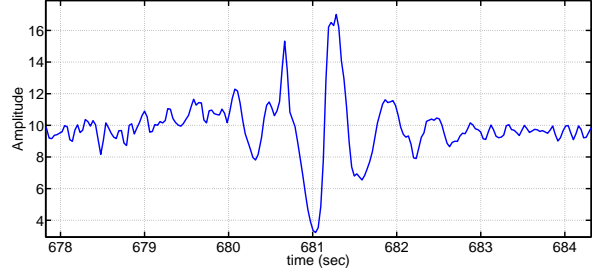

Figure 2: Type 1 speed-breaker occurred between time 680 sec and 682 sec. Consider a two second window starting at time 680 sec, then the feature vector is as follows {2.622, 6, 0.399, 3.5744, 5.0066}. Features are listed in the same order that they are defined in Section 3.1.

the vehicle crosses a speed-breaker. As a result the standard deviation of amplitude samples collected in a T second window is expected to be higher than usual during a speed-breaker (see Figures 2 and 3).

2. Number of Mean Crossings: Given a set of RT amplitude samples collected over a time period of T seconds, this feature counts the number of times that the amplitude signal crosses the mean of these RT amplitude samples. Since a speed-breaker causes the amplitude signal to sway widely, the number of mean crossings is expected to be lower during a speed-breaker.

3. Maximum Mean Crossing Interval: The time interval between two consecutive mean crossings is defined as the mean crossing interval. The maximum mean crossing interval during the sampling window of T seconds is expected to be longer when there is a speed-breaker.

4. Ratio of Standard Deviations of Current and Previous Window: Ratio of standard deviations of current and previous window is expected to be higher in the case of speed-breaker.

5. Ratio of Standard Deviations of Current and Next Window: Ratio of standard deviations of current and next window is expected to be higher in the case of speed-breaker.

3.2 Classification

We collected evaluation data using several different types of vehicles (i.e., car, motorcycle, bus, cycle-rickshaw, and auto rickshaw) driven by different people on various different roads in New Delhi, India. Given a time
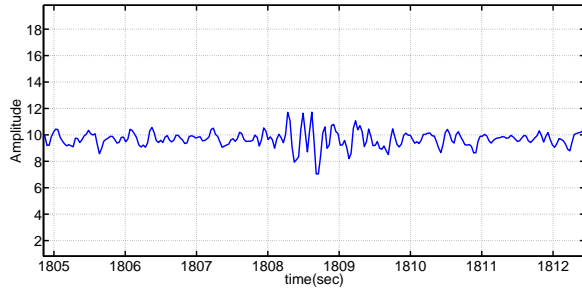
Figure 3: Time series of amplitude without any speed-breakers. Consider a two second window starting at time 1807 sec, then the feature vector is as follows {0.3404, 11, 0.245, 0.8812, 0.7729}. Features are listed in the same order that they are defined in Section 3.1.
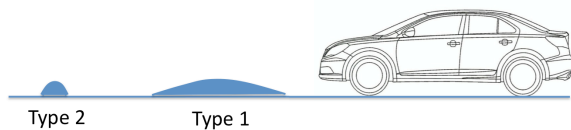

Figure 4: Two different types of speed-breakers common in New Delhi, India.

series of accelerometer data from a particular drive, we first extracted sample windows where the person conducting the measurements had visually observed and marked a speed-breaker. Feature vectors obtained from these windows formed the set labeled "speed-breaker". The set labeled "not a speed-breaker" was obtained by selecting windows of samples where the person collecting the measurements did not observe any speed-breakers. Sometimes, when the vehicle crossed a pot-hole, the resultant feature vector was manually identified and marked as "not a speed-breaker". The two labeled data sets were of the same size to avoid bias in classification. We used the support vector machine (SVM) for the classification because it is a discriminating, inherently non-linear (when kernel is applied) approach and there is no need to make assumption of data parameters (distribution parameters). Each of the five features were normalized by subtracting the mean and dividing by standard deviation.

4 Data Set

We wrote an Android application for recording accelerometer data along with user input. At least two phones were used in every drive, one for collecting accelerometer data (measurer), and the other for record-
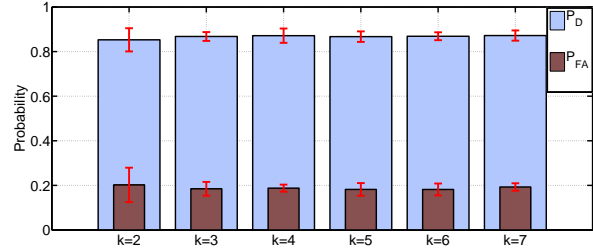

Figure 5: Probabilities of detection P_D and false alarms P_{FA} for different values of k in k-fold cross validation.

ing user input (marker). The measurer was placed in different locations during the different drives, e.g., pant pocket, dashboard, near the gearbox, near the rear car speakers, etc. Whenever we observed that the vehicle was passing over a speed-breaker, we pressed a button on the marker to record the ground truth. The two phones were time synchronized so that the ground truth markings in the marker could be correlated with the accelerometer readings in the measurer. The marker had two buttons for recording user input, namely, "Type 1 Speed-Breaker" and "Type 2 Speed-Breaker". Figure 4 depicts two types of speed-breakers that are common in New Delhi. Type 1 speed-breakers usually have a travel length of 3 to 6 feet and are 5 to 10 inches high, whereas Type 2 speed-breakers are 3 to 6 inches high with a length of 1 ft to 2 ft.

The evaluation data was collected in New Delhi, National Capital Region (NCR) and the total data set distance was 677.9 Km. Three measurers and one marker were used for some of the drives resulting in data set distance that was three times the actual travelled distance. The three data sets are still unique and interesting because measurers were of different make and were placed in different locations inside the vehicle. We used several different vehicles for the data collection, 219.5 Km in auto rickshaws (or three wheeler or tuk-tuk), 40.15 Km in cycle rickshaws (or bike taxi), 290.5 Km in cars, 53.6 Km in motorcycles and 74.1 Km in Bus. Whenever possible, one measurer was placed in front of the driver, e.g., on the dashboard (in case of a car) or in the front basket (in case of the cycle rickshaw), to replicate an important use case where the driver uses an integrated phone based navigation and speed-breaker warning system. A total of 22 different drivers (some very aggressive) were behind the wheel during our data collection.

5 Evaluation

First, k-fold cross validation was performed on the entire labeled data set from all types of vehicles. If the marker
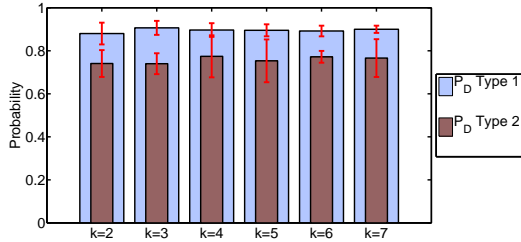
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Figure 6: Probability of detection P_D of Type 1 and Type 2 speed-breakers for different values of k in k-fold cross validation.
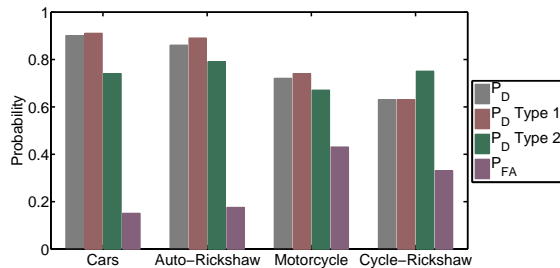

Figure 7: Probabilities of detection and false alarms when the classifier was trained using data from the same type of vehicle as the one under test.

recorded n speed-breakers during any particular drive, then $2n$ labeled feature vectors could be extracted from this drive, half of them labeled "not a speed-breaker". All labeled feature vectors from all the drives were then randomly distributed amongst k equal sized groups. The classifier was trained using $k-1$ groups and tested using the one remaining group. This process was repeated multiple times to obtain probabilities of detection and false alarms. Figures 5 and 6 show classifier performance as a function of k, and here it is evident that the classifier has good performance for all considered values of k. It is also clear from Figure 6 that Type 1 speed-breakers have a higher probability of detection than Type 2 speed-breakers. This may be because variations induced by Type 2 speed-breakers last for a shorter duration than those by Type 1 speed-breakers.

In another evaluation, we trained the classifier using labeled samples from the same type of vehicle as the drive under test. For example, data collected using a particular car was tested with a classifier that was trained using data only from (other) cars. This experiment was necessary to understand the effect of other vehicle training data on classification accuracy. The performance results for four different vehicle types are shown in the Figure 7. Data collected in buses was omitted because the number of speed-breakers observed during these drives

was statistically insignificant. Clearly, the classifier performs better on data from cars and auto-rickshaws than on data from motorcycle and cycle-rickshaws. The high false positive rate in the case of a motorcycle can be explained by the fact that the motorcyclist was changing gears and applying brakes using his feet, and the measurer phone was in his pant pocket. In the case of cycle rickshaws, we observed that the noise levels were very high in the accelerometer data, probably because of a poor suspension system.

6 Discussion

When the SWAS application running on a particular smartphone detects a previously unknown speed-breaker, it shares speed-breaker location with the SWAS server. The server doesn't immediately add this speed-breaker to the confirmed list, but instead waits for other smartphones to report the same. If multiple smartphones report the same speed-breaker, it can be added to the confirmed list. This step is necessary to ensure that false alarm locations aren't stored as speed-breakers, and drivers aren't alerted when they approach a location where someone else experienced a false alarm. If the probability of false alarms is 0.1, the probability that four different smartphones will falsely report the same location as a speed-breaker is 0.0001 (under certain independence assumptions). The server can further reduce the overall probability of false alarms by increasing the threshold for minimum number of sources that reinforce the same belief to an even higher value. Note that the overall probability of detection also decreases with a decreases in false alarm probability. The SWAS server can tradeoff the two probabilities by increasing or decreasing the threshold for number of sources that must report a speed-breaker before it is confirmed.

In addition to fine tuning the probabilities of false alarm and detection, the SWAS server can also reject speed-breaker reports from certain types of vehicles. Figure 7 shows that the detector performs best when the smartphone is in a car or auto-rickshaw. The false alarm rate is very high in case of motorcycle and the detection rate is very low in case of cycle-rickshaw. If the SWAS server (or application) is aware of the vehicle type, it can reject new speed-breaker reports when the vehicle type is motorcycle or cycle-rickshaw. Vehicle type is either inferred from things like acceleration, motor noise (microphone), and average velocity (GPS), or is explicitly input by the mobile user.

Once the database of speed-breaker locations has been built, applications other than early warning system can be enhanced with speed-breaker information. For example, it has been shown that a speed-breaker can delay an emergency vehicle by as much as 10 seconds per device

[14]. Present day navigation systems take into account things like driving distance, traffic congestion, time of day, etc., but not speed breaker location. These systems can be enhanced with information about location and estimated dimensions of speed-breakers. Ambulances can then be routed over paths that minimize the overall driving time, while taking into account all speed-breakers in the path.

The SWAS smartphone application should be optimized to reduce the overall battery consumption. The application's warning function continuously monitors instantaneous GPS location and generates an alert when the vehicle approaches a speed-breaker. The continuous GPS location lookup has an undesirable outcome of significantly increasing the overall battery consumption. As a solution, the application can maintain a vehicle velocity estimate, and after downloading the list of speed-breakers in the vicinity, it can calculate the time required to reach the nearest speed-breaker. The application can then switch off the GPS (to save battery) for some time period which is shorter than the time required to reach the nearest speed-breaker.

7 Conclusion

This work proposed an early warning system that can alert the driver in advance when the vehicle is approaching a speed-breaker. Since the proposed detection algorithm does not require accelerometer reorientation, this work demonstrates that variations along the vehicle's z-axis can be detected using very simple methods. It was shown that the probability of detection of type 1 speed-breakers is higher than the probability of detection of type 2 speed-breakers. It was also shown that the detector has good performance when smartphone is in a car or an auo-rickshaw, and not so good performance when it is in a motorcycle or cycle-rickshaw.

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