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Acceleration Discovery of vehicle in Natural Driving condition

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Abstract— ***An accelerometer is a device that measures* proper acceleration*. Properacceleration,beingthe* acceleration *(or* rate of change *of* velocity*) of a body in its own instantaneous* rest frame*,is not the same as coordinate acceleration, being the acceleration in a fixed* coordinate system*. For example, an accelerometer at rest on the surface of the Earth will measure an acceleration due to Earth's gravity, straight upwards (by definition) of g ≈ 9.81 m/s2. By contrast, accelerometers in* free fall *(falling toward the center of the Earth at a rate of about 9.81 m/s2) will measure zero.In general, accelerometer-based position and velocity estimates from low-cost sensors (hundreds of US dollars instead of tens of thousands) are very poor and are simply unusable. This isn't because the accelerometers themselves are poor, but because the orientation of the sensor must be known with a high degree of accuracy so that gravity measurements can be distinguished from the physical acceleration of the sensor. Even small errors in the orientation estimate will produce extremely high errors in the measured acceleration, which translate into even larger errors in the velocity and position estimates.***

IndexTerms
—**Vehicles, Acceleration, Estimation, Sensors, Accelerometers, Roa ds, Global Positioning System**

I. INTRODUCTION

Android applications are composed of one or more application components (activities, services, content providers, and broadcast receivers).Each component performs a different role in the overall application behavior, and each one can be activated individually (even by other applications).The manifest file must declare all components in the application and should also declare all application requirements, such as the minimum version of Android required and any hardware configurations required.Non-code application resources (images, strings, layout files, etc.) should include alternatives for different device configurations (such as different strings for different languages).The smart phone-based vehicular applications become more and more popular to analyze the increasingly complex urban traffic flows and facilitate more intelligent driving experiences including vehicle localization[1][2], enhancing driving safety[3][4], driving behavior analysis[5][6] and building intelligent transportation systems[7][8]. Among these applications, the vehicle speed is an essential input. Accurate vehicle speed estimation could make those vehicle-speed dependent applications more reliable under complex traffic systems in urban environments. Generally, the speed of a vehicle can be obtained from GPS. However, GPS embedded in smartphones often suffers from the urban canyon environment [9], which would cause low availability and accuracy. Besides, the low update rate of GPS is not able to keep up with the frequent change of the vehicle speed in urban driving environments. Additionally, continuously using GPS drains the phone battery quickly. Thus, it is hard to obtain accurate vehicle speed relying on GPS for applications requiring real-time or high accuracy speed estimations. Besides vehicle speed estimation based on GPS, there are a couple of alternatives by using either the OBD-II interface [3] or smartphone's cell tower signals [10][11]. Although the speed obtained from OBD-II is quite accurate, this approach relies on an additional OBDII adapter. Using cell tower signal changes on smartphones to perform vehicle speed tracking, [10][11] show a promising direction that the smart phone on the vehicle can be employed to facilitate vehicle speed estimation.

However, the existing studies utilizing Derivative Dynamic Time Warping (DDTW) algorithm that introduces large overhead on collecting offline trace and prevents large-scale deployment. Also, the speed estimation accuracy of DDTW suffers from the coarse-grained signal information.

Moving along this direction, in this paper we consider a sensing approach, which uses smart phone sensors to sense natural driving conditions, to derive the vehicle speed without requiring any additional hardware. The basic idea is to obtain the vehicle's speed estimation by integrating the phone's accelerometer readings along the vehicle's moving direction over time. While the idea of integrating the acceleration values over time seems simple, a number of challenges arise in practice. First, the accelerometer readings are noisy and affected by various driving environments. Second, the speed estimation should be real-time and accurate. Finally, the solution should be lightweight and computational feasible on smartphones.

We first show the vehicle speed estimation using the integral of accelerometer's readings through real road driving

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experiments in two different cities. We find that directly performing integration over acceleration results in large deviations from the true speed of the vehicle. The interesting observation is that the error between the integral value and true speed increases almost linearly over time, and is independent of different phone types. This indicates that the changes of the acceleration error are very small over time which can be corrected if we can derive the speed errors at some time points. Based on this simple yet useful finding, we develop a vehicle speed estimation system, SenSpeed, which utilizes smart phone sensors (accelerometer and gyroscope) to sense the practical driving conditions, which can be exploited to eliminate the acceleration errors and estimate vehicle speed accurately.

In particular, our system, SenSpeed, identifies unique reference points from the natural driving conditions to infer the vehicle's speed at each reference point grounded on different features presented by these reference points. Such reference points include making turns, stopping (at a traffic light or stop sign or due to road traffic) and passing through uneven road surfaces (e.g., speed bumps or potholes). Based on the speed inferred from the reference points, SenSpeed measures the acceleration error between each two adjacent reference points and eliminates such errors to achieve high-accuracy speed estimation. The main advantage of SenSpeed is that it senses the unique features in natural driving conditions through simple smart phone sensors to facilitate vehicle speed estimation. Furthermore, SenSpeed is easy to implement and computational feasible on standard smart phone platforms. Our extensive experiments in both Shanghai, China and New York City, USA validate the accuracy and the feasibility of using our system in real driving environments.

EXISTING SYSTEM:

The existing studies utilizing Derivative Dynamic Time Warping (DDTW) algorithm introduces large overhead on collecting offline trace and prevents large-scale deployment. Also, the speed estimation accuracy of DDTWsuffers from the coarse-grained signal information.In the existing work, there are two vehicle speed estimation mechanisms deployed on highways or main roads. One is employing the loop detectors, and the other is using traffic cameras. These solutions all rely on predeployed infrastructures that incur installation cost. The traffic camera could be installed in urban environments, but it suffers low accuracy, bad weather conditions and high maintenance cost.

DISADVANTAGES OF EXISTING SYSTEM:

GPS embedded in smartphones often suffers from the urban canyon environment, which could result in low availability and accuracy. In addition, the low update rate of GPS is not able to keep up with the frequent change of the vehicle speed in urban driving environments. Moreover, continuously using GPS drains the phone battery quickly. Thus, it is hard to obtain accurate vehicle speed relying on GPS for applications requiring real-time or high-accuracy speed estimations.The accelerometer readings are noisy and affected by various driving environments. The speed estimation is not real-time and accurate. The solution is not lightweight and computational not feasible on smartphones.

PROPOSED SYSTEM:

In this paper we consider a sensing approach, which uses smart phone sensors to sense natural driving conditions, to derive the vehicle speed without requiring any additional hardware. The basic idea is to obtain the vehicle's speed estimation by integrating the phone's accelerometer readings along the vehicle's moving direction over time. While the idea of integrating the acceleration values over time seems simple, a number of challenges arise in practice. We propose to perform accurate vehicle speed estimation by sensing natural driving conditions using smart phone sensors.We study the impact of the acceleration error on the speed estimation results obtained from the integral of the phone's accelerometer readings.We exploit three kinds of reference points sensed from natural driving scenarios to infer the vehicle speed at each reference point, which could be utilized to reduce the acceleration error that affect the accuracy of vehicle speed estimation.We develop a vehicle speed estimation system, Sen-Speed, which utilizes the information obtained from the reference points to measure and eliminate the acceleration error and achieves high accuracy speed estimation.

ADVANTAGES OF PROPOSED SYSTEM:

Our system, SenSpeed, identifies unique reference points from the natural driving conditions to infer the vehicle's speed at each reference point grounded on different features presented by these reference points. Such reference points include making turns, stopping (at a traffic light or stop sign or due to road traffic) and passing through uneven road surfaces (e.g., speed bumps or potholes). Based on the speed inferred from the reference points, SenSpeed measures the acceleration error between each two adjacent reference points and eliminates such errors to achieve high-accuracy speed estimation. The main advantage of SenSpeed is that it senses the unique features in natural driving conditions through simple smart phone sensors to facilitate vehicle speed estimation. Furthermore, SenSpeed is easy to implement and computational feasible on standard smart phone platforms.

II. Related Work

In this section, we review the existing work on vehicle speed estimation, which can be categorized as follows. Estimation using pre-deployed infrastructures: In the existing work, there are two vehicle speed estimation mechanisms deployed on highways or main roads. One is employing the loop detectors[12][13], and the other is using traffic cameras[8]. These solutions all rely on pre-deployed infrastructures that incur installation cost. The traffic camera could be installed in urban environments, but it suffers low accuracy, bad weather conditions and high maintenance cost.

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Estimation using additional devices: OBD-II adapter [3] is a popular interface to provide the vehicle speed in real-time. Acoustic wave sensors [14] [15] are utilized to estimate the vehicle speed in open environments. Furthermore, traffic magnetic sensors are also employed to capture the vehicle speed[16]. These approaches need to install additional hardware to perform speed estimation.

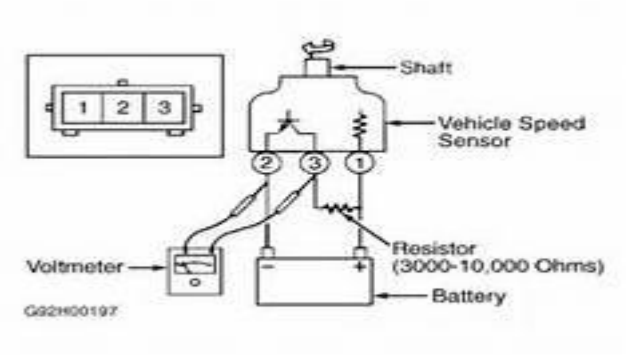

Fig. 1. Illustration of the vehicle's coordinate system and the smartphone's coordinate system.

Estimation using phones: To eliminate the need of predeployed infrastructures and additional hardware, recent studies concentrate on using cell phones to measure the vehicle speed. In particular, [17][18] use GPS or sub-sampled GPS to drive the vehicle speed. Although GPS is a simple way to obtain vehicle speed, the urban canyon environment and the low update frequency of GPS make it difficult to accurately capture the frequent changing vehicle speed in urban environments. And continuously using GPS causes quicker battery drainage on smartphones. Knowing the drawbacks of using GPS, [11] [10] estimate the vehicle speed by warping mobile phone signal strengths and use the handovers between base stations to measure the vehicle speed. These solutions need to build a signal database which may incur high labor cost and cannot achieve high estimation accuracy.

Obtaining the vehicle speed becomes more and more important in supporting large amounts of vehicular applications. Our work is different from the previous studies in that we explore a smart phone-enabled sensing approach based on natural driving conditions without the need of GPS or additional hardware.

III. MATH

We first describe how to obtain the vehicle speed from smart phone sensors. The vehicle's acceleration can be obtained from the accelerometer sensor in the smart phone when a phone is aligned with the vehicle. Suppose the accelerometer's y-axis is along the moving direction of the vehicle as shown in Fig.1.

We could then monitor the vehicle acceleration by retrieving readings from the accelerometer's y-axis. The vehicle speed can then be calculated from the integral of the acceleration data over time:

$S\,peed(T) = S\,peed(0) + \int acc(t)\,dt$ --------(1)

where $S\,peed(T)$ is the vehicle speed at time T and $acc(t)$ is the vehicle acceleration function of each time instant t.

Instead of producing a continuous function $acc(t)$, the accelerometer in practice takes a series of the vehicle acceleration samples at a certain sampling rate. Thus the vehicle speed can be transformed as

$S\,peed(T) = S\,peed(0) + \int 1/k\,accy(i)$ -------- (2)

where k is the sample rate of the accelerometer and accy(i) is the ith sample, i.e. the ith received reading from the accelerometer's axis. Therefore, in order to obtain the vehicle speed, we take a series of the acceleration samples by monitoring the accelerometer continuously.

Although the basic idea of using smart phone sensors to estimate vehicle speed is simple, it is challenging to achieve high-accuracy speed estimations. The most obvious problem is that the noise from sensor readings cause serious errors in the estimation results. Such sensor readings are affected by various noise encountered while driving such as engine vibrations, white noise, etc. And the estimation errors are accumulated when integrating the accelerometer's readings over time.To study the impact of the accumulative error on the speed estimation's accuracy, we conduct experiments about 700 miles driving at different urban regions with three different smartphones (Galaxy Nexus by Samsung, Nexus4 by LG and iPhone4s by Apple) for over two weeks.

It can be seen that the integral results (i.e., the purple curve) grows rapidly over time. This is because the accumulative errors cause large deviations between the speed estimation from the integral value and the true speed. Therefore, in order to estimate the vehicle speed accurately, the accumulative error must be eliminated. One important observation is that the black curve of the difference between the integral value from Equ.(2) and the true speed increases almost linearly over time, which indicates that the changes over time of the acceleration error are very small. These results are consistent during our experiments at different urban regions with three different smartphones. Thus, if we can derive techniques to measure the acceleration error, the integral value of the accelerometer's readings can be corrected to get close to the true vehicle speed. Since the difference curve between the integral value and the true speed is an approximate linear function of time, the acceleration error is strongly related to the slope of the curve. If we can obtain the true speeds at two time points along the difference curve, the slope of the curve could then be calculated and the acceleration error could be derived accordingly. However, the difference curve is not exactly linear, and slight changes of the slope (i.e., the acceleration error) would affect the accuracy of the speed estimation. To sense the slight changes over time of the acceleration errors, we should capture as many as possible time points, called reference points, where the true speed is known, then calculate acceleration errors between each two adjacent

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IV. Design of Speed

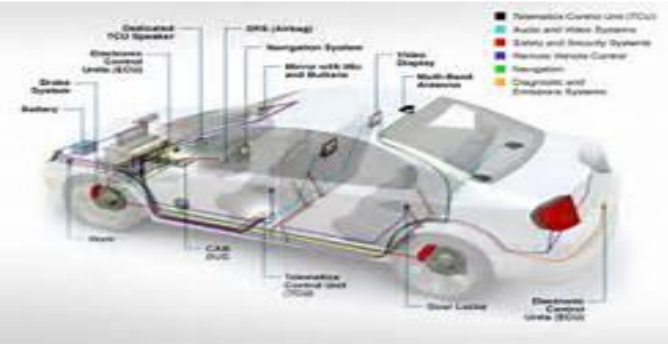

Fig. 2. System architecture.

In this section, we present the design of our proposed system, SenSpeed, which estimates vehicle speed accurately through sensing driving conditions in urban environments. SenSpeed does not depend on any pre-deployed infrastructure and additional hardware.

A. System Overview

The vehicle speed can be estimated by integrating of acceleration data over time. However, the accumulative error from the biased accelerations causes large deviations between the true speed and the estimated speed. In order to realize an accurate vehicle speed estimation, SenSpeed senses the natural driving conditions to identify the reference points, then uses the information of the reference points to measure the acceleration error and further eliminates accumulative error.

Our system identifies three kinds of references points, making turns, stopping, and passing through uneven road surfaces, by sensing natural driving conditions based on smart phone sensors.

1) making turns: A vehicle usually undergoes plenty of turns in urban environments. The vehicle speed can be inferred according to a principle of the circular movement when a vehicle makes a turn.

2) stopping: A vehicle stops frequently in urban environments because of stop signs, red traffic lights or heavy traffic. When a vehicle stops, the vehicle speed is determined to be zero.

3) passing through uneven road surfaces: Speed bumps, potholes, and other severe road surfaces are common on urban roads.

The accelerometer's readings from smartphones can be utilized to infer the vehicle speed, when a car is passing over uneven road surfaces. The work flow of SenSpeed is shown in Fig.2. SenSpeed uses two kinds of sensors in smartphones, accelerometers and gyroscopes, to estimate the vehicle speed. The accelerometer is used to monitor the vehicle acceleration and the gyroscope is used to monitor the vehicle angular speed. Getting the readings from the accelerometer and the gyroscope, SenSpeed first performs Coordinate Reorientation to align the phone's coordinate system with the vehicle's. After that, the raw speeds are obtained by calculating the integral of the aligned readings from the accelerometer in Raw Speed Estimation. Meanwhile, SenSpeed senses reference points by analyzing the aligned readings from the accelerometer and the gyroscope in Sensing Reference Points and infers the vehicle speed at each reference point. Next, in Acceleration Error Measurement,the acceleration errors between each two adjacent reference points are calculated and then used to correct the raw speed estimations in Reference Points Correction. Finally, SenSpeed outputs high-accuracy speed estimations. In order to achieve accurate speed estimations, the speeds at the two adjacent reference points need to be known. However, the speed at the next reference point is unknown on the real-time speed estimation, so the acceleration error between two reference points can not be calculated. Since we know the changes of the acceleration error over time are very small, Acceleration Error Measurement uses the exponential moving average to derive the current acceleration error from recent histories. Therefore, SenSpeed can provide real-time speed estimation of vehicles.

B. Sensing Reference Points

To correct speed estimation from the integral of the accelerometer's readings, the acceleration error should first be measured. If we know the speed at reference points, the acceleration error can be inferred. SenSpeed senses natural driving conditions to identify reference points including making turns, stopping and passing over uneven road surfaces.

1) Sensing Turns: When a vehicle makes a turn, it experiences a centripetal force, which is related to its speed, angular speed and turning radius. Thus, by utilizing the accelerometer and the gyroscope, we can derive the tangential speed of a vehicle. Suppose a car is turning right, as is shown in Fig.4, then $v = \omega R$, $a = \omega 2R$, and $\omega = \omega$, where a is the centripetal acceleration, ωis the angular speed of the car, R is the turning radius and ω is the angular speed that is related to the center of the orbit circle. Thus, we obtain

$v = a/\omega'$---------------(3)

Since the centripetal acceleration a and the angular speed ω can be obtained from the accelerometer and the gyroscope respectively, the speed can be calculated based on Equ.(3). Fig.5 plots the angular speed obtained from the gyroscope, the speed measurement from Equ.(3) and the speed from an OBD-II adapter when a vehicle makes a turn, i.e., at a turn reference point. It can be seen that the change of the angular speed is very clear at the turn reference point. If the readingsfrom the gyroscope exceeded a trained threshold, SenSpeed determines the vehicle is making a turn. In addition, the values of the speed measurement from Equ.(3) at the turn reference point are very close to the ground truth. Then, we analyze the speed measurement error at turn reference points. A series of experiments are conducted in real driving environments.

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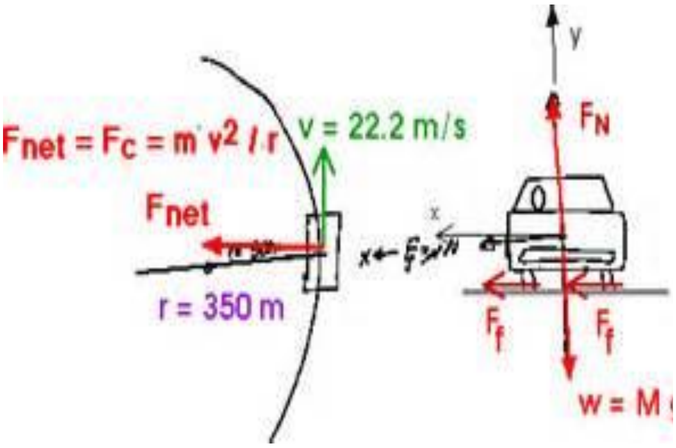

Fig. 3. Illustration of the circular movement when a car makes a turn.

2) Sensing Stops: The vehicle speed decreases to zero when a vehicle stops, so we can obtain the exact speed at a stop reference point. The vehicle stops. Thus, the standard deviation of the acceleration on z-axis can be used to detect stop reference points.

3) ***Sensing Uneven Road Surfaces:*** Speed bumps, potholes, and uneven road surfaces are common in urban environments. When a car is passing over uneven road surfaces, the accelerometer's readings from smartphones can also be utilized to infer the vehicle speed. we know the time interval T between these two peaks, as well as the wheelbase W of the vehicle, then the vehicle speed can be measured as

$$v = W/T .$$

Considering the similarity between these two peaks, we use the *auto-correlation* analysis to find T. Given an acceleration sequence on z-axis, $\{Acc\}$, auto-correlation of lag τ is:

$$R(\tau) = E[(Acc_i - \mu)(Acc_{i+\tau} - \mu)]\sigma 2 \text{ --------(4)}$$

where μ is the mean value of Acc and σ is the standard deviation. Fig.8 also shows the auto-correlation results of the accelerometer's readings on z-axis. Obviously, $R(\tau)$ is an even function, so $R(\tau) = R(-\tau)$. To get the T, we need to find the maximum peak value except the one at $\tau = 0$, and the horizontal distance from the maximum peak to $\tau = 0$ equals to T. And for the wheelbase, we can get it from vehicle's product specifications.It can be seen that 80% of measurement errors are lower than 1.7*mph* under the low speed (i.e., 0 − 30*mph*), 80% of measurement errors are lower than 2.2*mph* under the high speed (i.e., 60 − 90*mph*), and the average error is about 1.12*mph*. Also, we find that the vehicle speed affects the measurement accuracy, i.e., the accuracy slightly increases as the speed decreases. This is because that the accuracy is affected by the sampling rate. For example, suppose the vehicle speed is 20*mph*, the sampling rate of the accelerometer is 200*Hz* and the wheelbase is 3*m*, then the samples between the two wheels passing over a bump or pothole is *wheelbase speed*

$$\cdot f\, frequency \approx 56$$

samples. By contrast, when the vehicle speed is 80*mph*, the number of the samples decreases to 17*samples*. A smaller number of samples causes slightly worse accuracy. However, the average vehicle speed in urban area is relatively low (under 60*mph*). Thus the vehicle speed at uneven road surfaces can be accurately measured in real driving environments.

C. Eliminating Accumulative Errors

With the above sensed reference points, once a vehicle makes turns, stops or passes over uneven road surfaces, Sen-Speed is able to estimate the instant vehicle speed. In order to realize an accurate vehicle speed estimation, SenSpeed utilizes reference points to qualify the acceleration error and eliminate accumulative error.The vehicle starts with zero speed, and there are two reference points PA and PB (i.e., the vehicle passes the reference point A and B at time Ta and Tb respectively). Suppose the integral value of the accelerometer's reading. from zero to time t is S (t) and the measured speed at the reference point x is RPS x, the errors of the vehicle speed at the reference point a and b are S (Ta) = S (Ta) − RPS a and $S(Tb) = S(Tb) - RPS\ b$ respectively. Since the value of acceleration error is nearly a steady constant and strongly related to the slope of the $S(t)$ curve, the acceleration error between PA and PB can be calculated as:

$$\tilde{A} = S(Tb) - S(Ta)Tba \text{------------(5)}$$

where Tba is the interval time between the reference points A and B. $S(t)$ between A and B is:

$$S(t) = S(t) - S(Ta) - \tilde{A} \times (t - Ta) \text{--------(6)}$$

As a result, the mean estimation error after speed correction by using the reference points is 0.65*mph*. The above algorithm uses the information of two adjacent reference points to correct the speed estimations between these two points. Since we know that the acceleration error changes slightly over time, thus the current acceleration error can be derived from the recent reference points. In particular, we utilize the *exponential moving average* to estimate the current acceleration error by using the recent reference points. When the *ith* reference point is sensed, the current acceleration error $\tilde{A}\, i$ between the *ith* and $(i + 1)th$ reference point is updated through:

$$\tilde{A}i = \alpha \cdot \tilde{A}i{-}1 + (1 - \alpha) \times S(Ti) - S(Ti{-}1)/Ti{-}1 \text{-----(7)}$$

where α is the weight coefficient. The real-time speed estimation between the *ith* and the $(i{+}1)th$ reference point is corrected by:

$$S(t) = S(t) - S(Ti) - \tilde{A}i{+}1 \times (t - Ti) \text{------- (8)}$$

We also apply this online algorithm to the same data used in Fig.2, and present the corrected speed estimation in Fig.11. We observe that there are some small differences between the online estimation and the ground truth, which indicates the online algorithm has a comparable accuracy when compared with the offline algorithm. Although the differences exist,

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they are very small and the mean estimation error of the online speed estimation algorithm is 1.08mph.

V.IMPLEMENTATION

MODULES:

- Obtain the vehicle speed,Sensing Turns,Sensing Stops ,Sensing Uneven Road Surfaces,Sending data Alert SMS module.

MODULES DESCSRIPTION:

Obtain the vehicle speedWe first describe how to obtain the vehicle speed from smart phone sensors. The vehicle's acceleration can be obtained from the accelerometer sensor in the smart phone when a phone is aligned with the vehicle. Suppose the accelerometer's y-axis is along the moving direction of the vehicle. We could then monitor the vehicle acceleration by retrieving readings from the accelerometer's y-axis. The vehicle speed can then be calculated from the integral of the acceleration data over time.

Although the basic idea of using smart phone sensors to estimate vehicle speed is simple, it is challenging to achieve high-accuracy speed estimations. The most obvious problem is that the noise from sensor readings cause serious errors in the estimation results. Such sensor readings are affected by various noise encountered while driving such as engine vibrations, white noise, etc. And the estimation errors are accumulated when integrating the accelerometer's readings over time.

In this module, we present the design of our proposed system, SenSpeed, which estimates vehicle speed accurately through sensing driving conditions in urban environments. SenSpeed does not depend on any pre-deployed infrastructure and additional hardware.

Sensing Turns

The vehicle speed can be estimated by integrating of acceleration data over time. However, the accumulative error from the biased accelerations causes large deviations between the true speed and the estimated speed. In order to realize an accurate vehicle speed estimation, SenSpeed senses the natural driving conditions to identify the reference points, then uses the information of the reference points to measure the acceleration error and further eliminates accumulative error.

Our system identifies three kinds of references points, making turns, stopping, and passing through uneven road surfaces, by sensing natural driving conditions based on smart phone sensors.A vehicle usually undergoes plenty of turns in urban environments. The vehicle speed can be inferred according to a principle of the circular movement when a vehicle makes a turn. When a vehicle makes a turn, it experiences a centripetal force, which is related to its speed, angular speed and turning radius. Thus, by utilizing the accelerometer and the gyroscope, we can derive the tangential speed of a vehicle.

Sensing Stops

A vehicle stops frequently in urban environments because of stop signs, red traffic lights or heavy traffic. When a vehicle stops, the vehicle speed is determined to be zero. The vehicle speed decreases to zero when a vehicle stops, so we can obtain the exact speed at a stop reference point. Based on our observation, the data pattern of the acceleration on the vehicle's z-axis for stop is remarkably different from that of moving. It plots the readings from the accelerometer's z-axis when the vehicle is moving and stops. It can be seen that the jitter of the acceleration on z-axis is almost disappeared and the standard deviation of the acceleration on z-axis remains low while the vehicle stops. Thus, the standard deviation of the acceleration on z-axis can be used to detect stop reference points. The standard deviation of the acceleration collected by smart phone is calculated in a small sliding window

Sensing Uneven Road Surfaces

Speed bumps, potholes, and other severe road surfaces are common on urban roads. The accelerometer's readings from smartphones can be utilized to infer the vehicle speed, when a car is passing over uneven road surfaces. Speed bumps, potholes, and uneven road surfaces are common in urban environments. When a car is passing over uneven road surfaces, the accelerometer's readings from smartphones can also be utilized to infer the vehicle speed. It shows the accelerations on the car's z-axis, when a car is passing over a speed bump. The front wheels hit the bump first and then the rear wheels.

Sending data Alert SMS module

In this module, based on the variation of directions an alert messages is sent to the Owner (The number which is saved in app default, which can be changed) with a data say car number or any etc. The module, is triggered when it crosses the threshold limit of the Reference points. The mobile should have sufficient balance to send the SMS.

INPUT DESIGN

The input design is the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps are necessary to put transaction data in to a usable form for processing can be achieved by inspecting the computer to read data from a written or printed document or it can occur by having people keying the data directly into the system. The design of input focuses on controlling the amount of input required, controlling the errors, avoiding delay, avoiding extra steps and keeping the process simple. The input is designed in such a way so that it provides security and ease of use with retaining the privacy. Input Design considered the following things:

What data should be given as input?How the data should be arranged or coded?The dialog to guide the operating personnel in providing input.Methods for preparing input validations and steps to follow when error occur.

OUTPUT DESIGN

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A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

1. Designing computer output should proceed in an organized, well thought out manner; the right output must be developed while ensuring that each output element is designed so that people will find the system can use easily and effectively. When analysis design computer output, they should Identify the specific output that is needed to meet the requirements.

2. Select methods for presenting information.

3. Create document, report, or other formats that contain information produced by the system.

The output form of an information system should accomplish one or more of the following objectives.Convey information about past activities, current status or projections of the Future. Signal important events, opportunities, problems, or warnings. Trigger an action. Confirm an action.

In fig 4 it is showing the result of our present system where it is calculating the longitude and latitude values and when it reaches a maximum speed a automated message will be transferred to the registered mobile.

Fig 4: Showing the result of our present system.

V. CONCLUSION

In this paper, we address the problem of performing accurate vehicle speed estimation in urban environments.Most accelerometers are Micro-Electro-Mechanical Sensors (MEMS). The basic principle of operation behind the MEMS accelerometer is the displacement of a small proof mass etched into the silicon surface of the integrated circuit and suspended by small beams. Consistent with Newton's second law of motion (F = ma), as an acceleration is applied to the device, a force develops which displaces the mass. The support beams act as a spring, and the fluid (usually air) trapped inside the IC acts as a damper, resulting in a second order lumped physical system. This is the source of the limited operational bandwidth and non-uniform frequency response of accelerometers.

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