

# SenSpeed: Estimation of Vehical speed in urban Areas

Rajashekhara H S<sup>1</sup>, Shashirekha H<sup>2</sup>

<sup>1</sup> Student, Dept. of Computer Science & Engineering VTU, Regional Centre, Mysuru, Karnataka, India <sup>2</sup> Assistant Professor, VTU, Regional Centre, Mysuru Karnataka. India \_\_\_\_\_\*\*\*\_\_\_\_\_

**Abstract** - Theoretical—Acquiring moment vehicle speed is alluring and a foundation to numerous vital vehicular applications. This paper uses cell phone sensors to gauge the vehicle speed, particularly when GPS is inaccessible or off base in urban conditions. Specifically, we assess the vehicle speed by incorporating the accelerometer's readings after some time and discover the increasing speed mistakes can prompt extensive deviations between the evaluated speed and the genuine one. Facilitate examination demonstrates that the progressions of speeding up mistakes are little after some time which can be redressed at a few focuses, called reference focuses, where the genuine vehicle speed can beevaluated. Perceiving this perception, we propose an exact vehicle speed estimation framework, SenSpeed, which detects common driving conditions in urban situations including making turns, ceasing, and going through uneven street surfaces, to infer reference focuses and additionally kills the speed estimation deviations created by increasing speed blunders. Broad investigations exhibit that SenSpeed is exact and powerful in genuine driving conditions. By and large, the continuous speed estimation mistake on neighborhood street is 2:1km=h, and the disconnected speed estimation mistake is as low as 1:21 km/h. While the normal mistake of GPS is 5:0 and 4:5 km/h, separately.

Key Words: senspeed, smartphone, driving condition, urban area, speed.

## **1. INTRODUCTION**

The cell phone based vehicular applications progress toward becoming more famous to dissect the inexorably complex urban movement streams and encourage more astute driving encounters including vehicle restriction upgrading driving wellbeing driving conduct examination and building insightful transportation frameworks Among these applications, the vehicle speed is a fundamental input. Exact vehicle speed estimation could make those vehicle-speed subordinate applications more dependable under complex movement frameworks in urban conditions.

By and large, the speed of a vehicle can be acquired fromGPS. In any case, GPS implanted in cell phones regularly experiences the urban gully condition [9], which could bring about low accessibility and exactness. Furthermore, the low

refresh rate of GPS is not ready to stay aware of the continuous change of the vehicle speed in urban driving conditions. Also, consistently utilizing GPS depletes the telephone battery rapidly. In this way, it is difficult to get precise vehicle speed depending on GPS for applications requiring ongoing or high-precision speed estimations. Other than vehicle speed estimation in view of time which can be revised on the off chance that we can determine the speed blunders sooner or later focuses. In view of this basic yet valuable discovering, we build up a vehicle speed estimation framework, Sen-Speed, which uses cell phone sensors (accelerometer what's more, whirligig) to detect the down to earth driving conditions, which can be abused to wipe out the increasing speed blunders what's more, gauge vehicle speed precisely.

Specifically, our framework, SenSpeed, recognizes exceptional reference focuses from the normal driving conditions to construe the vehicle's speed at each reference point grounded on various highlights displayed by these reference focuses. Such reference focuses incorporate making turns, ceasing (at an activity light or stop sign or because of street movement) and going through uneven street surfaces (e.g., hindrances or potholes). In light of the speed gathered from the reference focuses, SenSpeed measures the quickening blunder between every two neighboring reference focuses and wipes out such blunders to accomplish high-precision speed estimation. The principle preferred standpoint of SenSpeed is that it faculties the special elements in common driving conditions through basic cell phone sensors to encourage vehicle speed estimation. Besides, SenSpeed is anything but difficult to execute and computational practical on standard cell phone stages. Our broad investigations in both Shanghai, China and New York City, USA approve the exactness and the achievability of utilizing our framework in genuine driving conditions. We highlight our fundamental commitments as takes after.We propose to perform exact vehicle speed estimation by detecting normal driving conditions utilizing cell phone sensors. We concentrate the effect of the quickening blunder on the speed estimation comes about gotten from the fundamental of the telephone's accelerometer readings. We misuse three sorts of reference focuses detected from regular driving situations to deduce the vehicle speed at each reference point, which could be used to lessen the speeding up mistake that influence the exactness of vehicle speed estimation. We build up a vehicle

speed estimation framework, Sen- Speed, which uses the data acquired from the reference focuses to quantify and kill the increasing speed blunder and accomplishes high precision speed estimation. We direct broad examinations in two urban areas, Shanghai, China and Manhattan in New York City, USA. The outcomes demonstrate that, in delegate urban conditions, SenSpeed can gauge the vehicle speed progressively with a normal mistake of 2:12 km/h, while accomplishing 1:21 km/h amid the disconnected estimation.

## 2. BASIC IDEA

We initially depict how to get the vehicle speed from cell phone sensors. The vehicle's quickening can be acquired from the accelerometer sensor in the cell phone at the point when a telephone is lined up with the vehicle. Assume the accelerometer's y-pivot is along the moving bearing of the vehicle as appeared in Fig. 1. We could then screen the vehicle increasing speed by recovering readings from the accelerometer's y-hub. The vehicle speed can then be figured from the basic of the increasing speed information after some time: In spite of the fact that the essential thought of utilizing cell phone sensors to gauge vehicle speed is straightforward, it is trying to accomplish high-exactness speed estimations. The most self-evident issue is that the commotion from sensor readings cause genuine mistakes in the estimation comes about. Such sensor readings are influenced by different clamor experienced while driving, for example, motor vibrations, repetitive sound. What's more, the estimation mistakes are aggregated when coordinating the accelerometer's readings after some time. To concentrate the effect of the aggregate mistake on the speed estimation's exactness, we lead explores about 1,200 kilometers driving at various urban areas with three distinctive cell phones (Galaxy Nexus by Samsung, Nexus4 by LG and iPhone4s by Apple) for more than two weeks. Fig. 2 demonstrates the aftereffects of a 12 minutes driving that think about the vital estimation of readings from the accelerometer's y-hub with the genuine vehicle speed gathered from an OBD-II connector. It can be seen from Fig. 2 that the indispensable outcomes (i.e., the purple bend) develops quickly after some time. This is since the collective mistakes cause extensive deviations between the speed estimation from the essential esteem and the genuine speed. Along these lines, keeping in mind the end goal to appraise the vehicle speed precisely, the aggregate mistake must be disposed of. One vital perception is that the dark bend of the distinction between the basic incentive from Eq. (2) and the genuine speed increments straightly after some time, which shows that the progressions after some time of the speeding up blunder are small. These outcomes are steady amid our tests at various urban areas with three distinctive cell phones. In this manner, on the off chance that we can infer methods to gauge the increasing speed mistake, the necessary estimation of the accelerometer's readings can be rectified to draw near to the genuine vehicle speed. Since the distinction bend between the indispen sableesteem and the genuine speed is an estimated straight capacity of time,

the quickening mistake is emphatically identified with the slant of the bend. In the event that we can get the genuine velocities at two time focuses along the distinction bend, the incline of the bend could then be figured and the increasing speed blunder could be inferred as needs be. Nonetheless, the distinction bend is not precisely straight, and slight changes of the incline (i.e., the increasing speed mistake) would influence the exactness of the speed estimation. To detect the slight changes after some time of the increasing speed mistakes, we ought to catch as numerous as conceivable time focuses, called reference focuses, where the genuine speed is known, then figure increasing speed blunders between every two neighboring focuses. After knowing these increasing speed blunders, the essential esteems can be rectified to get nearer to the genuine rates.

## **3. SYSTEM OVERVIEW**

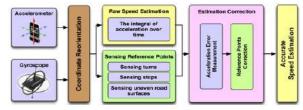


Fig. 3. System architecture

The vehicle speed can be evaluated by coordinating of increasing speed information after some time. In any case, the collective blunder from the one-sided increasing speeds causes vast deviations between the genuine speed and the assessed speed. Keeping in mind the end goal to understand an exact vehicle speed estimation, SenSpeed faculties the normal driving conditions to distinguish the reference focuses, then uses the data of the reference focuses to gauge the quickening blunder and further disposes of collective blunder.

Our framework recognizes three sorts of references focuses, making turns, halting, and going through uneven street surfaces, by detecting common driving conditions in view of cell phone sensors. 1) making turns. A vehicle typically experiences a lot of turns in urban conditions. The vehicle speed can be surmised by a standard of the round development when a vehicle makes a turn. 2) ceasing. A vehicle stops much of the time in urban situations on account of stop signs, red movement lights or substantial activity. At the point when a vehicle stops, the vehicle speed is resolved to be zero. 3) passing through uneven street surfaces. Hindrances, potholes, and other serious street surfaces are basic on urban streets. The accelerometer's readings from cell phones can be used to surmise the vehicle speed, when an auto is disregarding uneven street surfaces.

The work process of SenSpeed is appeared in Fig. 3. Sen-Speed utilizes two sorts of sensors in cell phones, accelerometers also, gyrators, to gauge the vehicle speed.

The accelerometer is utilized to screen the vehicle increasing speed also, the gyrator is utilized to screen the vehicle rakish speed. Getting the readings from the accelerometer what's more, the whirligig, SenSpeed first performs Coordinate

Reorientation to adjust the telephone's organize framework to the vehicle's. From that point onward, the crude rates are acquired by computing the indispensable of the adjusted readings from the accelerometer in Raw Speed Estimation. In the interim, Sen- Speed detects reference focuses by breaking down the adjusted readings from the accelerometer and the whirligig in detecting reference focuses and gathers the vehicle speed at each reference point. Next, in speeding up blunder estimation, the increasing speed mistakes between every two contiguous reference focuses are figured and after that used to redress the crude speed estimations in reference focuses amendment.

At last, SenSpeed yields high-exactness speed estimations. So as to accomplish exact speed estimations, the

speeds at the two neighboring reference directs require toward be known. In any case, the speed at the following reference point is obscure on the continuous speed estimation, so the quickening blunder between two reference focuses can not be figured. Since we know the progressions of the speeding up mistake after some time are little, increasing speed blunder estimation utilizes the exponential moving normal to determine the current speeding up mistake from late histories. In this manner, SenSpeed can give constant speed estimation of vehicles.

## 4. EVALUATION

## 4.1 Prototype

We implement SenSpeed as an open source Android App and install it on smartphones: Galaxy Nexus (Manufactured by Samsung, Android 4.2, 1.2 GHz dual-core, 1 GB RAM, Maximum sampling rate of accelerometer and gyroscope: 100 Hz) and Nexus4 (Manufactured by LG, Android 4.2, 1.5 GHz quad-core, 2 GB RAM, Maximum sampling rate of accelerometer and gyroscope: 200 Hz). SenSpeed senses the natural driving conditions by using both accelerometers and gyroscopes. Meanwhile, the raw data of accelerometers' and gyroscopes' reading are stored on smartphones for offline data analysis. the areas that our traces covered in these two cities. In Shanghai, we evaluate our system on different road types including local roads and elevated roads, as well as different regions including the area within Inner Ring (financial districts and shopping centers) and the area outside Outer nRing (living districts). Similarly in Manhattan, two kinds of road types (local road and highway), as well as two regions (the financial district in Downtown and the living district in Uptown), are covered in our experiments. Furthermore, experiments are conducted in both peak time and off-peak time. In addition, three types of cars are involved in ourb experiments: Volkswagen Lavida and Passat are used in Shanghai, and Nissan Altima is used in Manhattan, New York City. We collect about 2,500 kilometers driving traces in Shanghai for over one month and 1,600 kilometers driving traces in Manhattan for over three weeks.

#### 4.2 Real Road Driving Environments

To evaluate the generality and robustness of SenSpeed, we conduct experiments in two typical urban environments: one is in Shanghai, China with Nexus4, and the other one is in New York City, USA with Galaxy Nexus. the areas that our traces covered in these two cities. In Shanghai, we evaluate our system on different road types including local roads and elevated roads, as well as different regions including the area within Inner Ring (financial districts and shopping centers) and the area outside Outer Ring (living districts). Similarly in Manhattan, two kinds of road types (local road and highway), as well as two regions (the financial district in Downtown and the living district in Uptown), are covered in our experiments. Furthermore, experiments are conducted in both peak time and off-peak time. In addition, three types of cars are involved in our experiments: Volkswagen Lavida and Passat are used in Shanghai, and Nissan Altima is used in Manhattan, New York City, We collect about 2,500 kilometers driving traces in Shanghai for over one month and 1,600 kilometers driving vtraces in Manhattan for over three weeks.

## 4.3 Impact of Sensor Sampling Rate

In order to evaluate the sampling rate adaptation method accuracy. Fig. 24 shows the CDF of the speed estimation errors using and without using the sampling rat adaptation. It can be seen that no matter under online or offline environment, SenSpeed could precisely sense reference points and estimate vehicle speed accurately with the sampling rate adaptation. Compared with the highest sampling frequency (200 Hz), the average sampling frequency of Sen-Speed is reduced to 47:7 Hz. However, the speed estimation accuracy remains nearly unchanged, which changes from 1:05 to 1:08 km/h with offline algorithm and from 2:1 to 2:17 km/h with online algorithm. Thus, the sampling rate adaptation method could significantly reduce sampling rate without the degradation of speed estimation accuracy. Next, we evaluate the impact of the sampling rate adaptation on power consumption by using Nexus4 with the maximum sampling rate is 200 Hz. We collect around 500 kilometers driving traces for over eight hours on local roads and elevated roads in Shanghai. It can be seen from Fig. 25a that GPS has a relative large power consumption, which is 213 mW on average. Besides, SenSpeed with full sampling rate consumes 56 and 58 mW with offline and online algorithm, respectively. Compared with that, SenSpeed with frequency adaptation only need power consumption of 13 mW, which is very power efficient. In order to consider both the speed estimation accuracy and power consumption, a

novel evaluation criterion, Estimation Efficiency, is proposed, i.e., EstimationEfficiency ¼ 1=ðEstimationError\_ PowerConsumptionP

#### **5 CONCLUSION**

In this paper, we address the issue of performing exact vehicle speed estimation in urban conditions to bolster unavoidable vehicular applications. We utilize cell phone sensors to detect normal driving conditions to accomplish high estimation precision. Specifically, we propose a vehicle speed estimation framework called SenSpeed to recognize three helpful reference focuses, including making turns, vehicle halting, and going through uneven street surfaces, to gauge and dispense with the blunders brought about by utilizing telephone's accelerometer straightforwardly readings for speed estimation.

The key knowledge is that regular driving conditions presentunique highlights and can be misused to empower exact continuous vehicle speed estimation. Our broad investigations driving in two distinct urban communities more than one month time period demonstrate that SenSpeed can assess the vehicle speed progressively with a low normal mistake of 2:12 km/h, while accomplishing 1:21 km/h amid the disconnected estimation.

### **ACKNOWLEDGMENTS**

A sincere thanks to Mrs shashshirekha H Assistant professor Department of CS&E VTU PG center Mysuru. Dr K thippeswamy Head of the department CS&E Vtu PG center Mysuru And to my friends

#### REFERENCES

[1] J V. Tyagi, S. Kalyanaraman, and R. Krishnapuram, "Vehicular traffic

density state estimation based on cumulative road acoustics," IEEE Trans. Intell. Transportation Syst., vol. 13, no. 3, pp. 1156–1166, Sep. 2012.

[2] F. Chausse, J. Laneurit, and R. Chapuis, "Vehicle localization on a

digital map using particles filtering," in Proc. Symp. Intell. Veh.,

2005, pp. 243-248.

[3] Y. Wang, J. Yang, H. Liu, Y. Chen, M. Gruteser, and R. P. Martin,

"Sensing vehicle dynamics for determining driver phone use," in

Proc. ACM 11th Annu. Int. Conf. Mobile Syst., Appl. Serv., 2013.

pp. 41-54.

[4] J. White, C. Thompson, H. Turner, B. Dougherty, and D. C. Schmidt, "Wreckwatch: Automatic traffic accident detection and

notification with smartphones," Mob. Netw. Appl., vol. 16, no. 3,

pp. 285-303, Jun. 2011.

[5] J. Paefgen, F. Kehr, Y. Zhai, and F. Michahelles, "Driving behavior

analysis with smartphones: Insights from a controlled field study," in Proc. ACM 11th Int. Conf. Mobile Ubiquitous Multimedia,

2012, pp. 36:1-36:8.

[6] G. Chandrasekaran, T. Vu, A. Varshavsky, M. Gruteser, R. Martin,

J. Yang, and Y. Chen, "Tracking vehicular speed variations by warping mobile phone signal strengths," in Proc. IEEE Int. Conf.

Pervasive Comput. Commun., 2011, pp. 213–221.

[7] G. Chandrasekaran, T. Vu, A. Varshavsky, M. Gruteser, R. Р

Martin, J. Yang, and Y. Chen, "Vehicular speed estimation using

received signal strength from mobile phones," in Proc. 12th ACM

Int. Conf. Ubiquitous Comput., 2010, pp. 237–240.

[8] B. Coifman, "Improved velocity estimation using single loop

detectors," Transportation Res. Part A: Policy Pract., vol. 35, no. 10,

pp. 863-880, 2001.

[9] B. Coifman, "Using dual loop speed traps to identify detector

errors," Transportation Res. Rec.: J. Transportation Res. Board.

vol. 1683, pp. 47–58, 1999.

[10] V. Cevher, R. Chellappa, and J. McClellan, "Vehicle speed estimation

using acoustic wave patterns," IEEE Trans. Sonignal Process., vol. 57, no. 1, pp. 30-47, Jan. 2009.

## **BIOGRAPHIES**



Rajashekhar H S Presently pursuing his second year M.Tech Degree in department of CS&E at Visvesvaraya Technological University, PG Centre, Mysuru 570029. He has completed his B.E in CSE branch at HMSIT Tumkur, Karnataka in the year 2013



Shashirekha Mrs. Η asisstant proffesor at VTU visvesvaraya technological universityat PG center Mysuru. she is doing her PhD, her areas of interests are Data mining, Data analytics, Machine learning, Deep learning, Neural networks

Т