2014 IEEE International Conference on Systems, Man, and Cybernetics
October 5-8, 2014, San Diego, CA, USA

# Estimating True Speed of Moving Vehicle using Smartphone-based GPS Measurement

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*Abstract*— **The Global Positioning System (GPS) receivers are now an integral part of smartphones. However, phone based GPS measurements display much less accuracy as compared to professional grade receivers. On the other hand, the deep penetration of smartphones in consumer market offers opportunity for customizing new solutions. One such possible application is targeted towards identifying risky driving profile for the purpose of customizing auto-insurance premium. For this to be successful, one needs to estimate the true vehicle speed. In this paper, we have presented a method to estimate the true speed of a moving vehicle derived solely from GPS measurements. In this case the accelerometer sensors are not used in conjunction with GPS measurement. The results are compared with OBD2 speed measurement. The proposed method computes a better estimate of vehicle speed, where correctness is measured relative to OBD2 measurement.**

***Keywords—OBD2; GPS; Moving Vehicle, Speed Correction***

## I. INTRODUCTION

Driving to work has become an important part of our life and this brings in the increased risk of accidents. Many researches are being performed in order to analyze the driving behavior with respect to the accident risk involved. Driving type is classified into two major categories: non-aggressive (typical) and aggressive [1]. Aggressive driving is the subject of study as it has highest correlation with accidents [2]. It includes excessive speeding, sudden hard breaks and lane changes. All these events can be derived by measuring the speed of the car itself.

Currently with the availability of low-cost, advanced embedded systems and communication infrastructure, it has become simpler to monitor the cyber-physical system (CPS) in real time and analyze the acquired data in order to decipher the underlying physical process. It is now possible even to analyze the acquired data (at runtime) on the device. There are prior works on road condition monitoring and driving behavior analysis by use of accelerometer [3-4]. Toledo [3] provides the detailed usage of in-vehicle data recorder (IVDR) and calculates the risk indices which are weighted mean of high risk maneuvers (hard-bump, sharp cornering and speed-limit violation). The sensors used for these analysis are primarily 3-axes accelerometer and GPS. With the progress in telematics development, it is possible to compute different driving patterns using OBD2 (on-board diagnostic system). Smartphones [4] can also be used to capture and process such data and subsequently send the captured/processed data over communication network to cloud storage or dedicated data bases. Further analysis can be done on server side to evaluate the driving behavior. Smartphone based sensing for identifying aggressive driving behavior is also given in [5-6]. Scoring method for driving behavior is statistically developed and represented in [7-8]. It is known that the GPS based measurements can suffer from serious measurement errors under specific conditions like urban canyon situations. Therefore a number of works, over a period of time have tried to address this issue. One representative work is described in [9] where the application of Kalman filters for map-matching is discussed. The extent of smartphone penetration in consumer market offers opportunity for customizing new solutions. One such possible application is targeted towards identifying risky driving profile for the purpose of customizing auto-insurance premium. The said application will be considered successful, if it can estimate the true vehicle speed; particularly the sudden changes in speed. Ideally, OBD2 based speed measurement (in-vehicle recorder) is able to detect the risky profiles in run-time and in a reliable manner. However, the costs involved in such implementation, for every vehicle-driver combine has not permitted the commercial success of the application {as yet}. Nowadays, the insurers are considering using the driver's own smartphone as the hardware platform. In a smartphone platform, we can use GPS, accelerometers and gyroscope for capturing driving behavior. But, for reliable use of inertial sensors, the phone location needs to be fixed with respect to the moving vehicle. GPS based measurement is not dependent on the phone's orientation changes and thus (theoretically at-least) can be used to measure driving behavior.

In this paper we have addressed the problem of finding true speed of a moving vehicle using GPS measurements through the smartphone owned by driver/passenger in the vehicle. Mobile phone GPS is recreational GPS. Recreational and professional GPS units have different purposes [10]. As described in the said whitepaper [10], a recreational GPS unit suffers from greater 'Dilution of Precision'. For such, HDOP (Horizontal Dilution of Precision) of 6-12 is very common and often HDOP exceeds 20m. For a recreational GPS in autonomous mode is 10-meter accuracy is typical [11]. Often, the GPS speed is internally filtered in the receiver. In case of sharp acceleration/ deceleration or one of the events followed by the other, GPS speed is not an accurate measure of true speed of the vehicle. It takes some time to reflect speed changes hence misses sudden changes in speed. To overcome this sluggish nature of GPS speed measurement, authors present an adaptive method to derive true estimate of vehicle speed from GPS measurements only. This is done by introducing two types of moving averages filter with normalized weight coefficients. The presented approach gives an accurate profile of vehicle speed in a journey.

For purpose of comparison, OBD2 speed is taken as benchmark for true vehicle speed. Bluetooth based OBD2 device is installed in the vehicle, which collects vehicle speed at 1sec interval and transmits it a mobile phone. An application residing in the phone continues to log the OBD measurement as well as GPS measurement at 1Hz sampling rate.

In the subsequent sections, we present the theoretical approach for the error correction along with the results.

## II. VELOCITY CORRECTION APPROACH

GPS data for moving vehicle contains timestamp, HDOP (also known as Horizontal Accuracy), latitude, longitude and GPS measured speed. The GPS receiver inside a smartphone takes the measurements and these data are then sent to two different modules: 'Speed and HDOP' data to selection filter sub-section and 'location and speed' to configuration settings block. One element of the proposed method is the cascaded filter section for the purpose of significantly reducing the measurement errors in GPS based speed measurement. Such errors are inherent to the architecture of the low cost & recreational GPS based navigational sensors incorporated in present day mobile phones. Moreover, GPS speed measurement is sluggish to sudden changes in vehicle speed; particularly those events where the vehicle brakes and accelerates substantially over a short duration like 2-3 seconds time (called hereafter corner events). The simple adaptation method proposed in this paper is able to capture such corner events. The method incorporates the following steps (described in fig. 1):

i. Sensing the GPS positional coordinates GPS speed, time stamp and horizontal accuracy (of GPS measurement) for the moving vehicle. This measurement is done using GPS of mobile phones, owned by the driver or passenger of the moving vehicle.

ii. Pass the data through a data selection filter, which filters out erroneous GPS reading.(GPS with horizontal accuracy >16 m)

iii. Output of the selection filter is then passed to SDA (slope dependent averaging) filter.

iv. Output of the SDA filter is passed to two types of digital filters (with finite impulse response), in parallel.

v. The output of these filters are then passed through a composition filter which combines the weighted inputs to obtain a better estimate of the true vehicle speed.

The input to the filter bank is GPS measured speed where the speed is denoted as $v_i$ in m/s at time instances of $t_i$ for i = 0, 1, .. etc. In the presented method, the computation begins only after the first three samples (GPS measurements) are obtained.

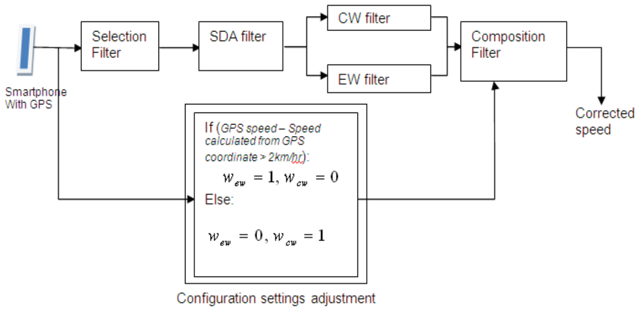


Fig. 1. Schematic diagram of proposed speed correction method

### A. *Selection filter*

When a data point is found to have HDOP (or Horizontal Accuracy) > 16 m, we discard the data as erroneous and replace the same with a speed value that is an average of the previous & next valid speed measurements. (Valid measurement means where HA (Horizontal Accuracy) < 16m).

### B. *Slope Dependent Averaging (SDA) filter*

GPS speed triplet measurements(3 consecutive speed samples) occasionally display extremely rare driving signatures (like braking exceeding 8km/h in 1sec followed immediately by acceleration of nearly same range). SDA filters out these potentially erroneous measurements. Let $v_0$, $v_1$, $v_2$ be the consecutive speeds recorded at time instances of $t_0$, $t_1$, $t_2$ respectively. Then the measurement points are defined as ($v_i$, $t_i$) for i=0 to 2. Let us define $\bar{v}_0$ as SDA corrected speed corresponding to $v_0$.

(a) Calculate θ by using following equation

$$\theta = \pi - \mathrm{abs}(\tan^{-1}(\frac{v_2 - v_1}{t_2 - t_1}) - \tan^{-1}(\frac{v_1 - \bar{v}_0}{t_1 - t_0})) \quad (1)$$

(b) If ($\theta < \pi/4$), we calculate the weights as

$$w_0 = w_2 = (\frac{1-w_1}{2}) \text{ where, } w_1 = 0 \quad (2\alpha)$$

Else, the consecutive weights are calculated as

$$w_0 = w_2 = {}^{(1-w_1)}\!/_{2} \text{ , where } w_1 = 1 \quad 2(\beta)$$

(c) Then, the corrected velocity corresponding to input $v_2$ is

$$\bar{v}_2 = w_1\bar{v}_1 + w_2 v_2 + w_3 v_3 \quad (3)$$

### C. *Error Correction Filters*

The output of SDA is then fed to the error correction filters. We implement two types of "Moving Averages Filter" where the weight coefficients are obtained through Chebyshev polynomials of $2^{nd}$ kind. Use of Chebyshev approximation reduces large error points [12]. Both the filters have finite impulse response. Let us assume that x[i] be the input to the digital filters and y[i] be the corrected speed at the output of these filters, then the general representation of the moving average digital filters (FIR filter) is given as

$$w_0 x(i) + w_1 x(i-1) + w_2 x(i-2) = y'(i) = \bar{\bar{y}}(m) \tag{4}$$

Equation (4) signifies that the 'i'-th index at the input is mapped to 'm'-th index at the corrected output. For both of these filters, the weights are obtained by using Chebyshev polynomials of the 2nd kind i.e. $U_i(x)$, where x = 1.24 (order 2 filter). The value of x=1.24 is a typical signature of the offset error in OBD2 versus GPS speed measurements for many passenger cars (those which are tested); this signature is obtained through regression analysis of the measured GPS speed data (i =0,1,2) with OBD2 measured speed. [Note: Typically, the manufacturers overestimate the speed calculation and this calculation is dependent on the tire size. If the tire is worn out or changed, the original calibration is invalidated]. These weights are then normalized to get the weights used in the FIR filters. For x = 1.24, the normalized weight coefficients are 0.596774/0.2873/0.11158. The two filter implementations, though using the same coefficient values, differ in their impulse response. The two filter implementations are described as below:

(I) Centre (CW) filter

The impulse response is given as

$$h[n] = 0.2873\delta[n+1] + 0.59677\delta[n] + 0.11158\delta[n-1] \tag{5}$$

The corrected speed is calculated as:

$$\bar{\bar{v}}_0 = w_{-1}\bar{v}_{-1} + w_0\bar{v}_0 + w_1\bar{v}_1 \text{ (in Km/h)} \tag{6}$$

Here, the speed value for $v_0$ is corrected after completing the measurement of next sample $v_{-1}$. We can say "current observation is used to estimate correct values for past events".

(II) Edge (EW) filter

The impulse response is given as

$$h[n] = 0.59677\delta[n] + 0.2873\delta[n-1] + 0.11158\delta[n-2] \tag{7}$$

The corrected speed is calculated as:

$$\bar{\bar{v}}_0 = w_0\bar{v}_0 + w_1\bar{v}_1 + w_2\bar{v}_2 \text{ (in Km/h)} \tag{8}$$

We can say "current as well as past measurements are used to estimate correct values for current event"

### D. *Composition filter*

Let us denote the output from CW and EW filter denoted by $v_{CW}(m)$ & $v_{EW}(m)$, (where m-th index is explained earlier). Let $\hat{v}(m)$ be the final corrected speed; then it is computed as follows:

$$\hat{v}(m) = w_{cw} v_{CW}(m) + w_{ew} v_{EW}(m) \tag{9}$$

In (9), $w_{cw}$ and $w_{ew}$ are the relative weight coefficients based on the adaptation need. Thus,

$$w_{cw} + w_{ew} = 1 \text{ , where } w_{ew} w_{ew} \geq 0 \tag{10}$$

Hence, the estimated true speeds (corresponding to the measured speed inputs $v_0, v_1, v_3$) are $\hat{v}_0, \hat{v}_1, \hat{v}_2$ . The composition filter plays the most significant role in speed estimation. It is shown in the results section that primarily Centre (CW) filter gives a much better estimation of true speed as compared to EW filter. However, CW filter (as well as EW filter) is sluggish in nature (being averaging filter); thus it is unable to capture the corner points. To mitigate this issue, we adapt the method by verifying the GPS speed measurement with the temporal variation of GPS position. For corner events, it is seen that the speed derived from GPS position change (distance travelled) shows a better approximation to real speed change. Thus, whenever the system measures a major discrepancy between the two speeds (both GPS measurements), we alter the final weight coefficients namely $w_{cw}$ and $w_{ew}$. Such adaptation (done inside configuration settings adjustment block) leads us to better and quicker estimation of true speed.

## III. EXPERIMENTAL SET-UP

Fig. 2. Photograph of the experimental set-up displaying Bluetooth OBD2 device and Tab as data logger

The work presented in this paper is drawn on repeated experimentation. Our experimental set up is shown in fig. 2. It consists of:

a) Kiwi Bluetooth which is a plug and play automotive tool that connects through the onboard diagnostic port (OBD2 / CAN) in cars [13].

b) Torque Pro Android App which is used to log the OBD2 speed along with GPS measurements [14].

c) Android smartphones

The above experimental set up is activated once the vehicle starts moving and the data set, that is used for validation represents same one hour (approximately) route from home to office.

## IV. RESULTS

The presented approach for estimating true speed from GPS based direct speed measurement has been tested extensively. Some sample results are presented in this section.

The impulse response for the two FIR filters namely Centre (CW) and Edge (EW) have been presented in equations (5) and (7), respectively. The frequency responses for the two filters are shown in fig. 3. The frequency response for Edge filter confirms the inverse Chebyshev nature, where we observe monotonic pass band and ripples in stop band. The same is not true for Centre, since the relative positions of the weight coefficients are altered. Moreover, the Edge filter has narrower pass band as compared to Centre.

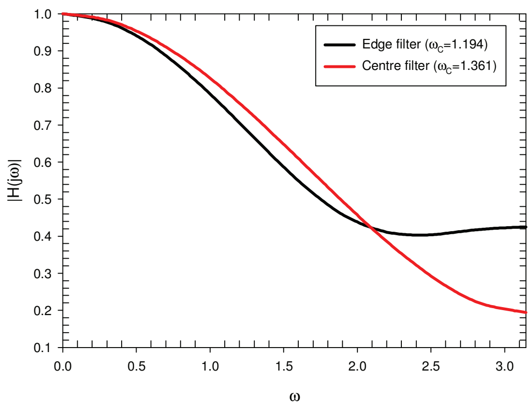


Fig. 3. Frequency response of the two FIR filters.

Fig. 4 displays both OBD2 measured speed and GPS measured speed over cycles of deceleration and acceleration.

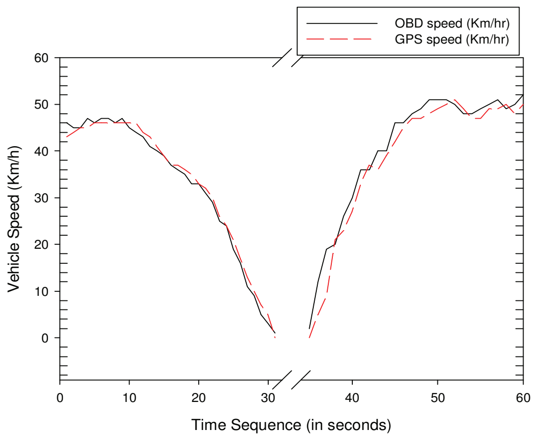


Fig. 4. OBD2 measured speed is compared with GPS speed measurement

It is seen from figure 4 that GPS speed is lower to OBD2 by approximately 2-4Km/h for accelerating as well as steadily moving vehicle. However, when the vehicle rapidly decelerates, GPS measurement is little more optimistic as compared to OBD2. Similar trends are shown through repeated measurements.

In many real life applications, it is envisaged that smartphone based GPS measurement is the only source of information. Keeping that in mind, we apply the error correction filters on the GPS speed measurement as shown in figure 5.

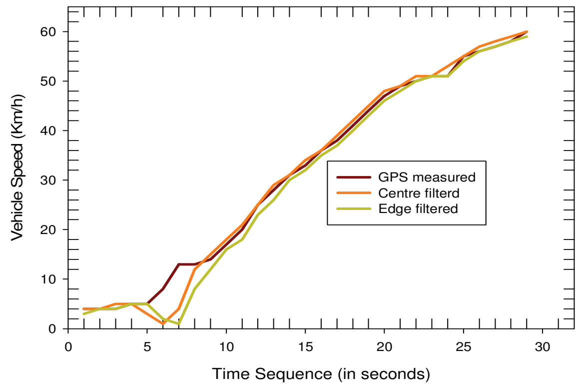


Fig. 5. GPS measured speed is corrected using the two FIR filter types

In figure 5, we compare the measured GPS speed (km/h) with the two corrected speed values namely Centre & Edge (described as above). It shows that the CW correction offers an overestimated speed (as compared to GPS) and EW offers an underestimated speed.

For smooth movements of vehicle (speed linearly increasing or decreasing), the CW correction gives a closer match to OBD2 speed; except for corners. Figure 6 shows a particular example, where at a particular instance of time (time sequence no. 7), the vehicle reduces speed momentarily, then accelerates again.

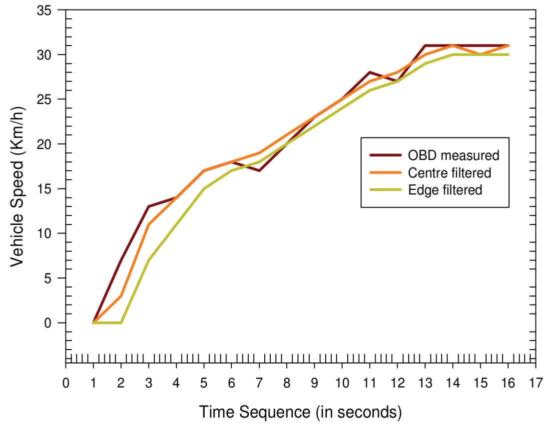


Fig. 6. OBD2 measured speed is compared with the two corrected speeds

Both CW & EW correction speeds are unable to capture the change, but we can use both (adaptively) to get closer to reality. The method is outlined in the next result as shown in figure 7.

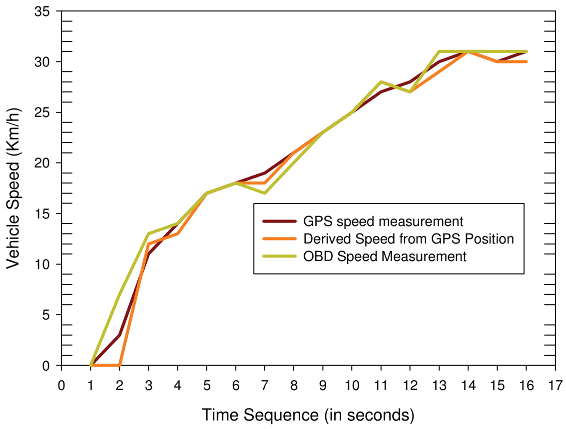


Fig. 7: OBD2 speed is compared with GPS speed measurements as well as speed computed from position

We mentioned that during the measurement cycle, a parallel computation continues, where the GPS measured speed is compared with speed deduced from GPS measured location (Lat/Long coordinates). This is shown in figure 7. It is seen that at the time sequence no. 7, the OBD2 speed first reduced, then increased. The GPS speed measurement could not capture the sudden and short duration change. On the other hand, the speed deduced from GPS positions (i.e., distance travelled in 1 second) is able to capture the trend.

Whenever the GPS measured speed is greater than the derived speed by more than 2km/h, a FLAG is raised. This FLAG makes $w_{ew} = 1$ & $w_{cw} = 0$ in the composition filter (*See* eqs. 9 & 10). This is shown in figure 8. Ideally, the output should always be CW, but during the time when the above condition is met, the output switches to EW, thereby giving a closer approximation to reality as measured using OBD2 speed.

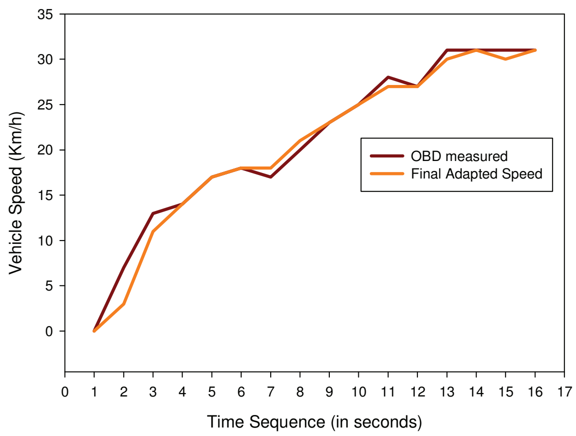


Fig. 8: OBD2 speed is compared with final computed speed from GPS measurements

Finally, we show a sample result when the vehicle is decelerating. Fig. 9 displays a comparison of OBD2 speed with both CW & EW speeds. In this case, CW is underestimated to OBD2 speed whereas EW is overestimated. A weighted average of EW & CW gives closer approximation to OBD2 measured speed.

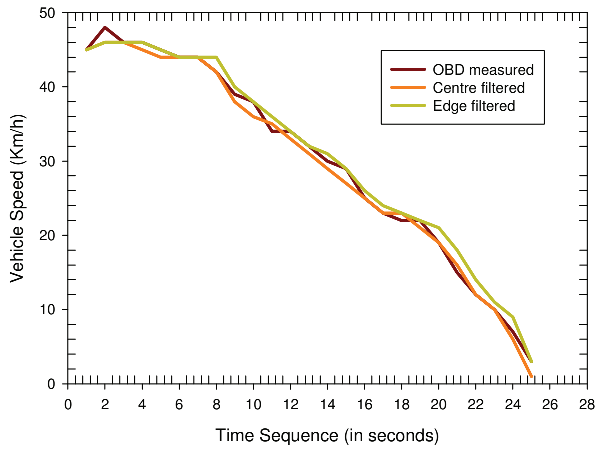


Fig. 9: OBD2 speed vs corrected speeds for deceleration.

The figures presented above are based on real data collected using smartphone and plots shows comparison of raw GPS, OBD2 speed and corrected speed by using proposed method. Above mentioned method can be implemented inside smartphone for runtime analytics purpose.

## V. CONCLUSION

Smartphone based speed estimation for a moving vehicle find application in usage-based auto-insurance. Normally, the insurers derive the driving risk based on the estimation of aggressiveness in driving. For example, the insurer is interested to know how many hard brakes and accelerations are committed in one trip. An accurate and reliable smartphone based detection of such events requires accurate speed estimation; particularly the sharp changes in vehicle state needs to be captured well. In this paper, we present a method of adaptively correcting the GPS speed measurement, in order to estimate the true speed of the moving vehicle. The proposed algorithm has been implemented in Android-based phone and regular testing is ongoing.

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