

# ACCURATE ANGULAR MOTION AND ACCELERATION DETECTION FOR AN IN MOTION OBJECT BASED ON TRIPLE-AXIS DEVIATION CORRECTION

Ashwini T S<sup>1</sup>, Deepu R<sup>2</sup>

<sup>1</sup>Mtech. Student, Department of Computer Science and Engineering, Maharaja Institute of Technology, Mysore, Karnataka, India

<sup>2</sup>Head of Department, Computer Science and Engineering - Maharaja Institute of Technology, Mysore, Karnataka, India

\*\*\*

**Abstract** - Knowledge of the *instantaneous vehicle speed levels are desirable and a deciding factor to many crucial vehicular applications. Here the utilization of smart phone accelerometer and optionally the GPS triangulation is done to estimate the vehicle velocity, especially when only GPS localization is unavailable or inaccurate in urban settings. The estimation of the vehicle velocity can be accurately detected by aggregating the accelerometer's readings over time and find the acceleration errors which can lead to large drops and deviations between the estimated speed and the actual velocity of the vehicle in motion. Also the variances in the acceleration errors which can be very small over a large time period can be rectified at some points, known as reference points. This is where the true vehicle speed can be estimated. Due to this observation, here is a proposal for an accurate vehicle velocity estimation system, which detects the natural driving parameters in urban settings including making turns at different angles, stopping of the vehicle, and passing through uneven road surfaces. This can be used to derive reference point data and further eliminate the speed estimation errors caused by the accelerometer attunement delay error.*

**Key Words:** Vehicle Speed Detection, Angular Velocity, Parameterised Estimation, Acceleration Detection, Android, GPS, Accelerometer, OBD-II.

## 1. INTRODUCTION

The smartphone-based vehicular detection application has become widely popular in order to analyze and assess the increasingly complex urban traffic movement patterns and facilitate intelligent driving experiences which include vehicle triangulation, enhanced driver safety protocols, stability focused driving behavior analysis and AI powered transportation systems.

Among these applications, the vehicle velocity is an essential parameter. Accurate vehicle velocity estimation can make vehicle-speed data dependent applications more reliable. Generally, the speed of a vehicle can be obtained from the GPS locations analysis and the change rate between points A and B, where A and B are 2 random location coordinates. However, GPS embedded in smart-phones often suffers from the urban canyon-like structure, which could

result in low availability of GSM networks and thus lead to low accuracy.

In addition, the low update rate of GPS, it is not able to keep up with the frequent change of the vehicle speed in urban driving scenarios. Moreover, continuously using GPS drains the battery life rapidly.

Thus, it is hard to obtain accurate vehicle speed relying purely on GPS for applications requiring on-demand, on-spot and high-precision speed estimates.

Besides vehicle speed estimation based on GPS, there is an alternative path to achieving the same results by using the OBD-II interface. Although the speed obtained from OBD-II is nominally accurate, this approach relies on an OBD-II adapter which is an additional component.

Utilizing the cellular GSM network signal changes on smart-phones to perform vehicle speed tracing, it is shown that a promising mechanism using the smart-phone on the vehicle can facilitate vehicle speed estimation.

### 1.1 EXISTING SYSTEM

The current method used to derive speed of a moving vehicle is the Derivative Dynamic Time Warping (DDTW) algorithm, which introduces large overhead on collecting offline traces and prevents large-scale deployment of the system. Also, the speed estimation accuracy of DDTW suffers from the coarse-grained signal information which is not as accurate as required.

Usually there are two vehicle speed estimation mechanisms employed on the main roadways to detect velocity currently :

One of which is employing the loop detectors, and the other is using traffic cameras. These solutions all rely on pre-deployed infrastructures that incur installation cost.

The traffic camera could be installed in urban environments, but it suffers due to low accuracy, and bad weather conditions and has a high maintenance cost which deters its widespread usage for the purpose of speed detection at every turn which is not feasible.

## 1.2 PROPOSED SYSTEM

Considering a detection approach, using the smart phone sensors to sense natural driving parameters, to derive the vehicle velocity without requiring any additional hardware is not new but is not extremely accurate.

The basic concept is to obtain the vehicle's speed 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. The proposal is to perform an accurate vehicle speed estimation by sensing natural driving conditions using smart phone sensors.

By studying the impact of the acceleration error on the speed estimation results obtained from the integral of the phone's accelerometer readings.

Exploiting the 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 affects the accuracy of vehicle speed estimation, an accurate end result is obtained.

By developing a vehicle speed estimation system, that utilizes the information gained from the reference points data to measure and eliminate the occurrence of acceleration errors and achieves high accuracy at speed estimation of a vehicle in motion.

## 2. RELATED WORK

Jesse Levinson, Sebastian Thrun [1], have recognized that autonomous vehicle navigation in dynamic urban environments requires localization accuracy exceeding that available from GPS-based inertial guidance systems. It has been shown previously that GPS, IMU, and LIDAR data can be used to generate a high-resolution infrared remittance ground map that can be subsequently used for localization, having proposed an extension to this approach that yields substantial improvements over previous work in vehicle localization, including higher precision, the ability to learn and improve maps over time, and increased robustness to environment changes and dynamic obstacles. Specifically, to model the environment, instead of as a spatial grid of fixed infrared remittance values, as a probabilistic grid whereby every cell is represented as its own Gaussian distribution over remittance values. Subsequently, Bayesian inference is able to preferentially weight parts of the map most likely to be stationary and of consistent angular reflectivity, thereby reducing uncertainty and catastrophic errors. Furthermore, by using offline SLAM to align multiple passes of the same environment, possibly separated in time by days or even months, it is possible to build an increasingly robust understanding of the world that can be then exploited for localization.

Frederic Chausse et.al [2], have recognized in their work that all the data access routes are uncertain and even momentarily unavailable (GPS in urban areas for example). A data fusion process is necessary for sensors data to compensate one each other. Here to combine GPS absolute localization with data computed by a vision system giving the position and orientation of the vehicle on the road. This local information is transformed into a global reference using a map of the environment. The localization parameters are estimated using a particles filter making it possible to manage multimodal estimations (the vehicle can be on the left lane or on the right one for example). The best standard deviation reached is 4.8 m along the road axis and 8cm along the axis normal to the road.

Yan Wang et.al [3], have proposed a system that utilizes smartphone sensing of vehicle dynamics to determine driver phone use, which can facilitate many traffic safety applications. Our system uses embedded sensors in smartphones, i.e., accelerometers and gyroscopes, to capture differences in centripetal acceleration due to vehicle dynamics. These differences combined with angular speed can determine whether the phone is on the left or right side of the vehicle.

Derick A. Johnson et.al [4], have proposed a system which classifies driving style into two categories: "typical" (non-aggressive) and aggressive. Understanding and recognizing driving events that fall into these categories can aid in vehicle safety systems. Potentially aggressive driving behavior is currently a leading cause of traffic fatalities in the United States. More often than not, drivers are unaware that they commit potentially-aggressive actions daily. To increase awareness and promote driver safety, a system that uses Dynamic Time Warping (DTW) and smartphone based sensor-fusion (accelerometer, gyroscope, magnetometer, GPS, video) to detect, recognize and record these actions without external processing.

Todd N. Schoepflin [5], has proposed a system with a new three-stage algorithm to calibrate roadside traffic management cameras and track vehicles to create a traffic speed sensor. The algorithm first estimates the camera position relative to the roadway using the motion and edges of the vehicles. Given the camera position, the algorithm then calibrates the camera by estimating the lane boundaries and the vanishing point of the lines along the roadway. The algorithm transforms the image coordinates from the vehicle tracker into real-world coordinates using our simplified camera model.

Lei Kang and Suman Banerjee [6], have proposed a system where several innovative techniques are used to improve the overall accuracy and usability of smartphone sensors. First, the machine learning techniques are used to detect smartphone's relative orientation changes caused by human interactions. Second, the design of a slope-aware alignment algorithm to improve alignment accuracy. Third,

tracking the linear acceleration of the vehicle to address acceleration over/under estimation problems. Fourth, evaluating the trade-offs between GPS and inertial sensors, and fuse inertial sensors with GPS to improve the overall accuracy and usability.

Mattia Bruschetta et.al [7], have proposed a system to extend the use of the tool to nonprofessional drivers. Quality of the motion control strategies in generating both realistic and feasible inputs to the driver is therefore, more than ever, a crucial aspect. The motion strategies are implemented in the so-called motion cueing algorithms (MCAs). A recently proposed effective approach to MCA is based on model predictive control (MPC), as it is well suited to solve constrained optimal control problems and to take advantage of models of the human sensing system. However, the predictive aspect of the algorithm has not been exploited yet, due to the hard real-time requirement when using long prediction windows. Here is a real-time implementation of an MPC-based MCA with predictive feature is presented, endowed with an on-line switching policy to a non-predictive algorithm when the expected driver behavior is considered unreliable. The motion action based on the actual driver behavior and the expected one are considered in the same procedure, thus fully exploiting the availability of a perceptive model. An *optimal tuning* procedure is also proposed, based on a multi-objective optimization, where both performance improvement due to the prediction exploitation, and robustness to varying driver behaviour are considered. Finally, a characterization of the driver skill level is proposed and validated in an experimental environment for the specific case of the vertical DOF.

Cheng Bo et.al [8], have proposed a system to address a critical task of dynamically detecting the simultaneous behavior of driving and texting using smartphone as the sensor. Here the proposed design, and implement of TEXIVE achieves the goal of detecting texting operations during driving utilizing irregularities and rich micro-movements of users. Without relying on any external infrastructures and additional devices, and no need to bring any modification to vehicles, TEXIVE is able to successfully detect dangerous operations with good sensitivity, specificity and accuracy by leveraging the inertial sensors integrated in regular smartphones.

Zhichen Wu et.al [9], have proposed system for conditions where vehicle road-level localization cannot satisfy people's need for convenience and safety driving, lane-level localization becomes a corner stone in Intelligent Transportation System. Existing work on tracking vehicles on lane-level mostly depends on pre-deployed infrastructures and additional hardware, utilizing the smartphone sensing of driving conditions for vehicle lane-level localization on highways. Upon analysis of the driving traces collected from real driving environments, it is found that each type of lane change has its unique pattern on the vehicle's lateral acceleration. Based on this observation, is is

proposed that a Lane-Level Localization (*L3*) system, which can perform real-time vehicle localization on lane-level only using smartphones when vehicles are driving on highways be utilized. This system first uses embedded sensors in smartphones to capture the patterns of lane change behaviors. Then a Gaussian Distribution is employed to track vehicles on lane-level with tolerance of false detection. Extensive experiments demonstrate that *L3* is accurate and robust in real driving environments. The experimental results show that, on average, *L3* achieves accuracy of 91.49% on lane change detection and 86.94% on lane-level localization.

Gaoxiang Zhang et.al [10], have recognized that driving navigation is challenging in enclosed areas, e.g., urban canyon areas, due to loss of GPS signals, or poor availability of landmarks. Many leader-follower navigation systems are independent of GPS signals or landmarks: a leader device pre-collects sensory signals of landmarks along a pathway to build a reference trace; and the follower device compares the signals at his current location against the ones in the reference trace to get navigated. However, such navigation systems are subject to the volatility of the sensory data, e.g., image landmarks or WiFi signals may change over time. This requires labor intensive updates of sensory signals along the pathway. Trail-Tracker, a leader-follower driving navigation system that is free of the volatility of these sensory data. Specifically, Trail-Tracker creates the trajectory segments by fusing the visual and inertial data captured by smartphone sensors, and it compares one's trajectory segment against the leader's for navigation, instead of directly comparing the series of volatile sensory data recorded in their devices. Trail-Tracker is infrastructure-free and robust to the change of environment.

### 3. SYSTEM IMPLEMENTATION

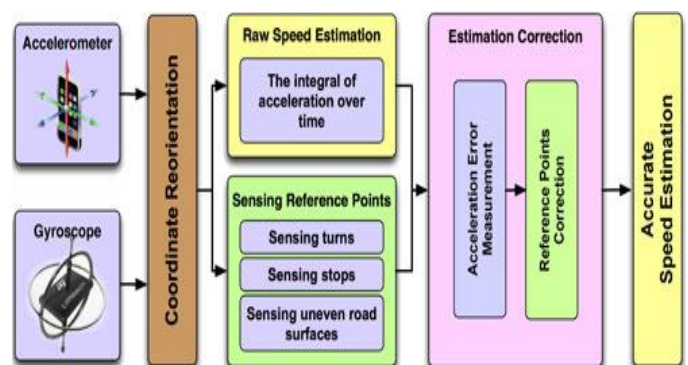


Fig - 1: System Architecture of the Speed Detection System.

As can be seen from Fig 1, the system architecture clearly mentions the link between the gyroscope and the accelerometer. The co-ordinate reorientation is a time consuming step and one of the reasons for the delay in the attunement of the accelerometer as the value feedback loop has to repeat 1000s of times per minute to constantly track the dynamics of the vehicular motion.

The integral acceleration over time provides us with the first order of data to be aggregated also known as raw speed estimation. The second order of data to be aggregated is a combination of reference points. The total aggregation of all these correlated datasets leads us to the final module of the system.

The final module of the system is based on two models of measurement and re-measurement i.e. acceleration and relative reference points on the tri-axis of the gyroscope.

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, the accelerometer senses the natural driving parameters to identify the reference points, which it then uses to cause improvements upon the information of the reference points to measure the acceleration error and further eliminate the accumulative error.

This system identifies three kinds of references points, making turns, stopping, and passing through uneven road surfaces, by sensing natural driving conditions.

**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.

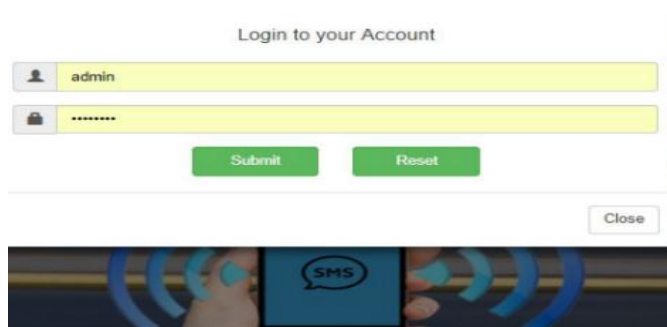
**Stopping Conditions for a Vehicle:** A vehicle stops frequently in urban environments because of stop signs, red traffic lights or heavy traffic. When a vehicle stops, the vehicle speed is determined to be zero and the change in Axis is also nil.

List

From: 27-12-2017 To: 27-12-2017

Name	Phone Num	Vehicle num	Latitude	Longitude	Date	Time
Yogesh	1234567890	KA13 EC2412	12.300591666666666	76.051609999999999	2017-12-27	06:29:56
Yogesh	1234567890	KA13 EC2412	12.300593333333332	76.05167	2017-12-27	06:30:01

**Fig -2:** A server logs the phone number, name and other details sent via the GPS.

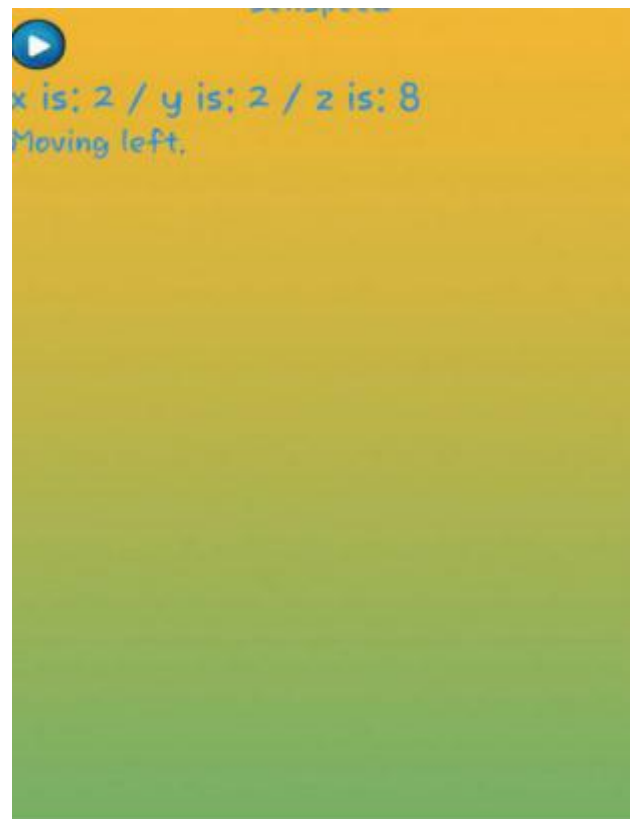


**Fig -3:** Server Login Page to the Data Logging System.

**Passing through uneven road surfaces:** Speed breakers, potholes, and other severe road surfaces are common on urban roads. The spikes and dips in the accelerometer’s readings from smart phones can be utilized to infer the vehicle movement.

**Detection of Reference Points:** To correct speed estimation from the integral of the accelerometer’s readings, the acceleration error should first be measured. The system senses natural driving parameters to determine the reference points including making turns, stopping and passing over uneven road surfaces.

**Detection of Turns:** When a vehicle makes a turn, it experiences a centripetal force, related to the velocity, also angular speed and turning radius are related. Thus, by the utilization of the accelerometer and the gyroscope it can be deduced that the tangential speed of a vehicle is directly affected by the negative X and Z- Axis tilt experienced, such as for a car is turning right, as is shown in Fig. 6



**Fig -4:** Detection of the turn of the vehicle based on the sensor readings.

**Detection of Stops:** Vehicle speed depreciates to zero when a vehicle halts completely, and to obtain the exact velocity at a stop reference point. Based on the observation, the data pattern of the acceleration on the vehicle’s z-axis for stop is remarkably different from that of moving. Fig. 7 plots the readings from the accelerometer’s z-axis when the vehicle is moving and stops. From Fig. 2, it can be seen that the jitters

of the acceleration on z-axis have almost vanished and the standard deviation of the acceleration on the z-axis remains low when the vehicle halts. Thus, the standard deviation of the acceleration on z-axis can be used to detect stop points which are a type of primary reference point. The standard deviation of the acceleration collected by smart phone is calculated in a window designed to display the values.

Sensing of uneven road surfaces, and obstructions such as speed breakers, potholes are common in urban environments. When a car is passing over uneven road surfaces, the accelerometer's readings from smart phones can also be utilized to infer the vehicle speed. Fig. 7 shows the accelerations on the car's z-axis, when a car is passing over a speed breaker on a turn.

It can be seen that no matter under online or offline environment, the system could accurately detect and reference the points and estimate the vehicle's speed exactly with the sampling rate adaptation in view.

Compared with the highest sampling frequency of 201 Hz, the average sampling frequency of the system is found to have reduced to 48 Hz.

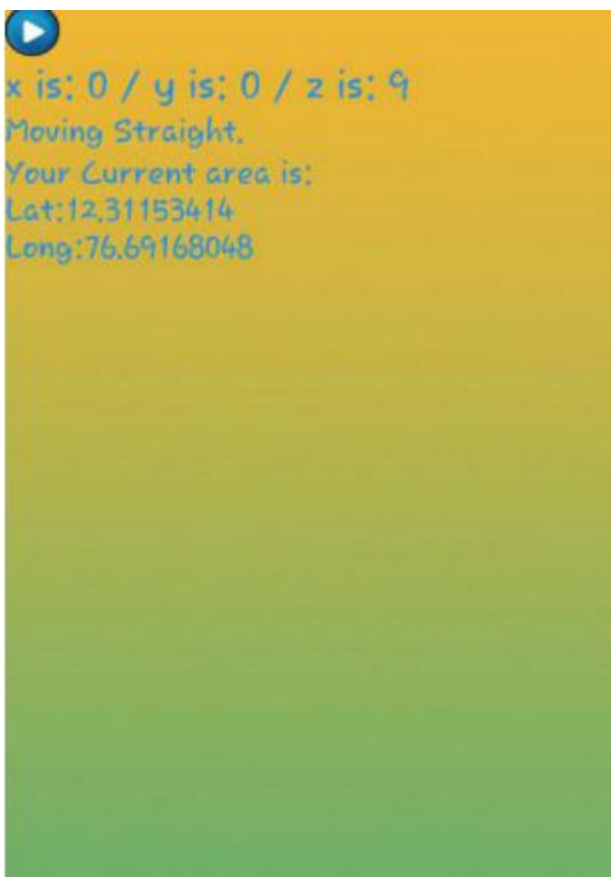


Fig -5: Straight movement of the vehicle based of X-axis being equal to 0.

The front wheels will hit the breaker, and then the rear wheels shall follow. In Fig. 7, the first peak is produced when the front wheel has passed over the breaker and the second peak is produced by the rear wheels passing over the breaker. The impact of sensor sampling rate are used in order to evaluate the sampling rate adaptation method used by the system.



Fig -6: Turning right, detection of movement in the vehicle based of X-axis being negative.



Fig -7: The circular movement detection when a car makes a turn via angular speed and acceleration.

However, the speed estimation accuracy remains nearly unchanged, which changes from 1.50 km/h to 1.80 km/h with the use of the offline algorithmic implementation and from 2.1 to 2.2 km/h with online algorithmic implementation. Thus, the sampling rate adaptation method could significantly reduce sampling rate without the degradation of the speed accuracy estimate.

#### 4. CONCLUSION

The solution to the issue of performing an accurate vehicle velocity estimation in urban a setting to allow and support pervasive vehicular applications is found to be accurate and quick. The use of smart phone sensors to sense natural driving values and conditions to achieve high degree of accuracy in estimating the speed is found to be precise. The vehicle speed estimation system is used to identify three useful reference points, i.e. making turns, vehicle stopping, and passage of the vehicle through uneven road surfaces successfully.

#### REFERENCES

- [1] J. Levinson and S. Thrun, –Robust vehicle localization in urban environments using probabilistic maps,|| in Proc. IEEE Int. Conf. Robot. Autom., 2010, pp. 4372–4378. M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.
- [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. K. Elissa
- [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] D. Johnson and M. Trivedi, –Driving style recognition using a smartphone as a sensor platform,|| in Proc. IEEE Int. Conf. Intell. Transportation Syst., 2011, pp. 1609–1615.
- [5] T. N. Schoepflin and D. J. Dailey, –Dynamic camera calibration of roadside traffic management cameras for vehicle speed estimation,|| IEEE Trans. Intell. Transportation Syst., vol. 4, no. 2, pp. 90–98, Jun. 2003.
- [6] Lei Kang and Suman Banerjee, University of Wisconsin-Madison, Practical Driving Analytics with Smartphone Sensors, 2017 IEEE Vehicular Networking Conference (VNC)
- [7] Mattia Bruschetta , Carlo Cenedese, Alessandro Beghi , and Fabio Maran, A Motion Cueing Algorithm With Look-Ahead and Driver Characterization: Application to Vertical Car Dynamics, IEEE TRANSACTIONS ON HUMAN-MACHINE SYSTEMS, VOL. 48, NO. 1, FEBRUARY 2018

- [8] Cheng Bo, Xuesi Jian, Taeho Jung, Junze Han, Xiang-Yang Li, Fellow, IEEE, Xufei Mao, Member, IEEE, and Yu Wang, Member, IEEE, Detecting Driver’s Smartphone Usage via Non-intrusively Sensing Driving Dynamics, IEEE Internet of Things Journal, 2015
- [9] Zhichen Wu, Jianda Li, Jiadi Yu, Yanmin Zhu, Guangtao Xue and Minglu Li Department of Computer Science and Engineering, Shanghai Jiao Tong University, Shanghai, P.R. China, L3: Sensing Driving Conditions for Vehicle Lane-Level Localization on Highways, IEEE INFOCOM 2016 - The 35th Annual IEEE International Conference on Computer Communications
- [10] Gaoxiang Zhang, Kaigui Bian, Lingyang Song Peking University, Trail-Tracker: Driving Navigation in Enclosed Areas by Smartphone Visual-inertial Sensing, 2017 IEEE

#### BIOGRAPHIES



Ashwini T S is a Masters Degree Final Year Student in Computer Science from Maharaja Institute Of Technology, Mysore.



Dr. Deepu R is the Head of Department of Computer Science and Engineering at Maharaja Institute of Technology, Mysore, with over 18 years of experience in academia and research with a specialization in digital image processing and is currently guiding 7 Ph.D. candidates.