Study on Self-Localization Techniques for Intelligent Vehicles

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Abstract - *Self localization is a serious and challenging issue to be considered and solved in intelligent Vehicles (IV's) system. These systems use self-localization to achieve Advanced Driver Assistance System (ADAS) which widely used in autonomous driving. There are several traditional methods proposed to achieve self-localization up to sub-meter level. Such as Global Position System (GPS), Global Navigation Satellite System (GNSS), Inertial Navigation System (INS) etc. These are not suitable for high speed autonomous vehicles due to their accuracy level and cost. Hence there is need for robust, cheap, reliable and accurate localization method is inevitable. In this literature survey we would like to give broad category of State-of-the-Art localization methods for Intelligent Vehicles with their potentials and limitations.*

Key Words: Cooperative Localization, Intelligent vehicles, LiDAR, Advanced Driver Assistance System (ADAS).

1. INTRODUCTION

Autonomous driving and Intelligent Vehicle (IV) system empowers consumers and businesses to seize the benefit of new transportation era. Self-Localization of a vehicle is prerequisite for Intelligent Vehicle (IV) system because self-localization used to achieve Advanced Driver Assistance System (ADAS). Traditional self- Localization methods should be studied for high speed autonomous vehicles due to their accuracy level and cost. Therefore, Traditional self- Localization methods and State-of-the-art localization methods with their potentials and limitations are studied here. The analysis starts with discussing the methods which uses information gathered from on-board sensors. These methods satisfy the accuracy required for intelligent vehicles but suffer from high cost and low robustness. In order to localize an object maps plays important role. In general, there are two main categories of maps: (i) planar which refers to maps that rely on layers or planes on a Geographic Information System (GIS), e.g. High Definition (HD) maps, and (ii) point-cloud which refers to maps based on a set of data points in the GIS.

1.1 Cooperative Localization Techniques

The augmentation of off-board information obtained through V2V and V2I communication systems to the sensory information has shown the potential to improve the vehicle localization accuracy, robustness, and reliability in different driving and environmental conditions [15]. In such systems, vehicles can broadcast information about their states to other vehicles (V2V), including speed, heading, and location, as well as the information related to the environment while adverse weather conditions or obstacles can be acquired from infrastructure (V2I). The cooperative localization techniques use wireless communication devices, such as Wi-Fi, cellular and UWB radio communications where transmitted signals are used to estimate the range to the broadcaster. There are several approaches to estimate the distance or relative position to the broadcaster of a signal.

1.2 Sensor Based Localization Techniques

These techniques rely only on on-board vehicle sensors to find the global position of a vehicle in a specified coordinate system such as Earth-centered Inertial (ECI) coordinate system, Earth-centered Earth-fixed (ECEF) coordinate system, or the geographical coordinate system. For the brevity of the paper, the detailed definition of each coordinate system is referred to [16]. The main sensors considered in this section include GPS, IMU, cameras, radar, LiDAR, and ultrasonic sensors. The following sections provide details of the capabilities of each sensor including benefits and limitations as well as analysis of localization techniques using each sensor standalone or a combination of sensors.

1.2.a GPS/IMU Based Navigation Satellite Systems (GNSS) such as GPS, GLONASS, BeiDou, and Galileo rely on at least four satellites to estimate global position at a relatively low cost. GNSS and INS are used together in such a way that they can provide a set of possible positions for visual localization. Li et al. [4] use Global Positioning System (GPS, one kind of GNSS) data to determine a possible position range. In [5], the authors also first use GPS data to match with digital map. Then they catch images to detect lanes, traffic signs and match with the map. This localization accuracy achieves sub-meter level. Similarly, Gu et al.[6] achieved vechicle localization in urban areas through combining of GNSS data, image, LiDAR and 3d map. Both lateral positioning error and speed error are evaluated in this study.

1.2.b LiDAR Based Techniques It is noted that Radar maps are susceptible to errors in the case of changes in the pre-existing map due to their limited capabilities in collecting environmental data. Therefore, to increase localization accuracy and robustness, more accurate maps with denser point clouds are required. LiDAR technology can collect significantly more data than Radar sensors, therefore potentially offer higher accuracy compared to the Radar based techniques. Gu et al. [6] achieved vehicle localization in urban areas through combining of GNSS data, image, LIDAR and 3D map. Both lat- eral positioning error and speed error are evaluated in this study.

1.2.c Radar Based Techniques A Radio detection and ranging (Radar) sensor is a ranging sensor which utilizes radio waves. Radar functions by emitting periodic radio waves which can bounce off obstacles back to the receiver and distance to target is measured from the time of arrival of radio waves. Each radio wave provides a single range measurement which gives the distance to the obstacle that reflected it back to the receiver. Radars also have relatively low power consumption, for example the Delphi Short Range Radars use only 0.9W and offer up to 64 range measurements at 20Hz with a field of view of ±75° and a range of 80m [7]. Hojun et al [8] use in-vehicle sensors to collect vehicle speed and yaw rate. Both of these two data play an important role in vehicle position computation. Gu et al. [9] mix 3D-GNSS with Inertial Measurement Unit (IMU) and also together with speedometer and this new sensor to enhance the localization accuracy. As discussed above, speedometers improved localization accuracy significantly and simplify the localization process drastically.

1.2.d Ultrasonic Based Techniques Localization methods have attempted to use alternative low cost sensors such as ultrasonic sensors. For instance, the authors in [10] proposed the use of ultrasonic sensors integrated with a set of sensors including a digital magnetic compass, a gyroscope and two encoders for ultrasonic based SLAM techniques. Ultrasonic sensors can scan the environment by utilizing a mechanical wave of oscillating pressure which can propagate through air or other materials.

1.2.e Camera Based Techniques As a method of replacing GPS with an alternative on-board sensor, the authors in [11] proposed a low-cost localisation method utilizing only cameras, where the images obtained from the cameras were down-sampled to a resolution of 800 x 600 pixels to reduce computation time. This vision-based localization approach combines a topological map and a point-cloud map to provide a SLAM type technique. A topological model to enhance the localization accuracy [12]. This study also follows a two-step approach. First, one previous localization results is used to set up a topological model and then this model selects a set of possible positions from visual map. GNSS can be replaced by using this model. In the second step, both holistic feature match- ing and local feature matching are combined, which outputs the computation result of the closest data collection node.

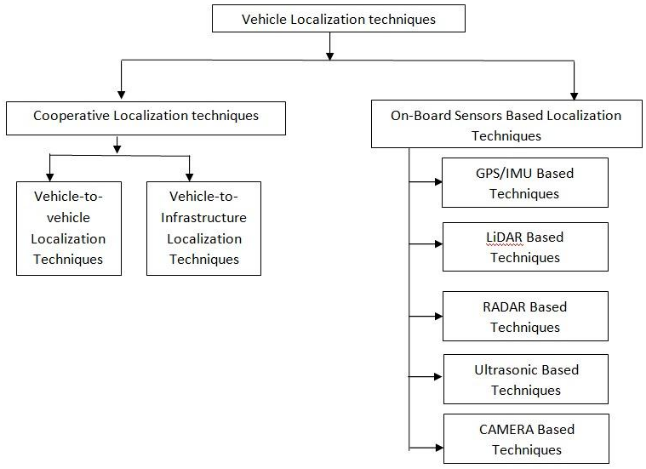

Fig -1: Taxonomy of Localization Techniques

Based on above classification we would like to present some of the studies carried out by different authors for efficient self-localization for intelligent vehicles. We also provide merits and de-merits of along with insights of the papers for future guidance.

[1] F. Zhang et al. proposed "A Sensor Fusion Approach for Localization with Cumulative Error Elimination" that describes a robust approach which improves the precision of vehicle localization in complex urban environments by fusing data from GPS, gyroscope and velocity sensors. In this method, KALMAN filter is used to estimate the position of the vehicle. This method integrates the information from the GPS and IMU. To test the approach, the authors used a GPS/IMU system which provides GPS data, heading angle, and velocity of the vehicle at 10Hz. The proposed method was successful in increasing the accuracy beyond standalone GPS or IMU capabilities; however cumulative errors were still present in the system. Over a driving distance of 408m, the system accumulated root mean square (RMS) errors of 7.2m, compared to that of 22.3m and 13.2m of IMU odometer and GPS, respectively. Therefore, while this technique was successful in mitigating some of the weaknesses of the standalone GPS and IMU methods, the magnitude of the localization errors means that the system would be inadequate for autonomous vehicle systems. The results show the potential of fusing data from multiple sensors to improve the accuracy and robustness beyond what each sensor can achieve as standalone. It provides a sensor fusion framework to estimate the position of the vehicle, and also gives a mathematical solution to eliminate the cumulative error stems from the relative pose measurements (provided by the gyroscope and velocity sensors). But pose measurement is not precise; hence efficient pose measurement for automatic driving is needed.

[2] C. Li et al. "Vision-based Precision Vehicle Localization In Urban Environments," this presents a vision-based localization method for autonomous Vehicles in urban environment. The localization process consists of two stages: coarse localization using topological map and fine localization using metric map. The topological map represented by the holistic image feature provides coarse location, whereas localization from metric map is relatively slow, but more accurate. The method using only the metric map can obtain the precise localization. But the efficiency and correct ratio of localization relatively are unsatisfied.

[3] I. Parra et al. "Robust visual odometer for vehicle localization in urban environments," proposed a low-cost localization method utilizing only cameras, where the images obtained from the cameras were down-sampled to a resolution of 800 x 600 pixels to reduce computation time. This vision-based localization approach combines a topological map and a point-cloud map to provide a SLAM type technique. The localization, first, estimates a rough position through dividing the images into grids and extracting the orientation histograms of each cell. Then, a fine localization was done using the map consisting of landmarks in the environment. The proposed two-stage localization method not only increases the accuracy of the localization but also reduces the computation requirements for the fine localization. Using the proposed method, mean positioning errors of 75cm were achieved. However, the system is sensitive to changes in illumination conditions or angle of observation which may cause the system to fail.

[4] S. Kamijo et al. "Autonomous Vehicle Technologies: Localization and Mapping," suggested using GPS/IMU for global positioning, whilst using the camera to recognize lane markers for lateral positioning. Using this approach, mean positioning errors of 0.73m were achieved. But this approach Susceptible to illumination and observation angle.

[5] J. Suhr, et al. "Sensor Fusion-Based Low-Cost Vehicle Localization System for Complex Urban Environments," paper proposes a sensor fusion-based low-cost vehicle localization system. The proposed system fuses a global positioning system (GPS), an inertial measurement unit (IMU), a wheel speed sensor, a single front camera, and a digital map via the particle filter. This system is advantageous over previous methods from the perspective of mass production. First, it only utilizes low-cost sensors. Second, it requires a low-volume digital map where road markings are expressed by a minimum number of points. Third, it consumes a small computational cost and has been implemented in a low-cost real-time embedded system. Fourth, it requests the perception sensor module to transmit a small amount of Information to the vehicle localization module. Last, it was quantitatively evaluated in a large-scale database. The lane and SRM detection currently runs on a PC (3.40GHz Intel Core i7-2600 CPU with 8G RAM) because this procedure is assumed to be implemented as a part of the multi-functional front camera module in the case of mass production. Over two experiments, this approach obtained mean lateral errors of 0.49m and 0.58m and mean longitudinal errors of 0.95m and 1.43m for the first and second experiments, respectively. The authors noted that the method has larger longitudinal errors than lateral errors because lanes and road markers were used for lateral localization, whereas longitudinal localization only uses road markers.

[6] N. Mattern and G. Wanielik, "Vehicle Localization in Urban Environments using Feature Maps and Aerial Images," proposed two different approaches for localizing vehicles based on combination of on-board vehicle camera and aerial images along with IMU/GPS signals. The first method utilizes feature maps based on aerial imaging containing information about landmarks, lane markings, curbs, and the road geometry. Imaging from the camera equipped on the vehicle was then used to localize the vehicle within the feature map. The second approach uses aerial images which are then processed to remove unnecessary information so that information only about local edges (e.g. the edges of features such as roads) is retained. The experimental results showed that, for the first method, 80% of position estimates had both lateral and longitudinal errors less than 1m, while the second method only achieved 60% of position estimates within this range. Moreover, the second method had peak errors of 3.5m and 7m which would cause the vehicle to choose the wrong lane. The authors mentioned that future improvements to these techniques could be achieved by further processing of the aerial or camera imaging. Overall, these two methods are still inadequate for autonomous vehicle localization due to the magnitude of errors present.

[7] D. Vivet, et al. , "Mobile Ground-Based Radar Sensor for Localization and Mapping: An Evaluation of two Approaches," proposed localization system using a Radar the authors evaluated the data obtained from a 360° field of view FCMW microwave Radar sensor through two different SLAM methods to localize a vehicle. The first method is a trajectory-oriented SLAM technique while the other one analyses the distortion caused by rotating Radar at high speed to obtain the trajectory of the vehicle and map the environment. For a vehicle traveling at the speed of 30km/h, the methods resulted in mean position errors of 10m and 12m for the first and second techniques, respectively, thereby indicating the technique will be unsuitable for autonomous vehicles

[8] E. Ward and J. Folkesson, "Vehicle localization with low cost radar sensors," A Radio detection and ranging (Radar) sensor is a ranging sensor which utilizes radio waves. Radar functions by emitting periodic radio waves which can bounce off obstacles back to the receiver and distance to target is measured from the time of arrival of radio waves. Delphi Short Range Radars use only 0.16W and offer up to 64 range measurements at 20Hz with a field of

view of ±75° and a range of 80m. Even lower power requirements can be achieved by Frequency Modulation Continuous Wave (FMCW) based Radars, which use continuous Radar signals rather than the periodic ones used in traditional Pulse Based Radar systems. For example, the K2pi microwave Radars based on FMCW can offer a 360° field of view and a range up to 100m, with power requirements as low as 0.1W, however the accuracy is typically lower than that of pulse-based radar systems. Method explored the use of pulse-based Short Range Radar (SRR) due to its low cost and good accuracy, where the Radar sensor acquires up to 64 detections, each at 20Hz. Also, information of speed and yaw rate were used from signals of a GPS/IMU system. The results showed RMS errors of 7.3cm laterally and 37.7cm longitudinally worst case errors of 27.8cm laterally and 115.1cm longitudinally.

[9] M. Cornick, et al. "Localizing Ground Penetrating RADAR: A Step Toward Robust Autonomous Ground Vehicle Localization," To improve the accuracies of Radar-based techniques, a novel approach of utilizing ground penetrating Radar technology for localization was proposed in. This method scans the subsurface features and the in homogeneity of the subterranean geology to create a map. These features are unique and static enough that localization for autonomous vehicles could be completed utilizing subterranean feature maps. Testing was done using a vehicle equipped with GPS/IMU system integrated with the Localizing Ground Penetrating Radar (LGPR) system with a ground penetrating depth of 2-3m, which was brought up to speeds of 100km/h in testing. The vehicles first created a subterranean feature map of the environment over the initial pass of the environment and then attempted to localize itself within this map. Results showed the capability to localize within positional RMS errors of 4cm, which is within limits for a vehicle to maintain its lane of traffic. But this method requires further study to understand its capabilities and limitations.

[10] Hata and D. Wolf, "Feature Detection for Vehicle Localization in Urban Environments Using Multilayer LIDAR," suggested using LiDAR to detect curbs and road markings to create a feature map of the environment and localize vehicles within the map. In the proposed approach, curbs were identified by acquiring LiDAR measurements in 32 concentric rings and analyzing the distance between the rings to identify curb-like features using filters. Also, road markings were identified by analyzing the LiDAR reflective intensity data and comparing it to expected values for road markings. These two features were then used to localize the vehicle within the feature map. The proposed approach resulted in lateral and longitudinal errors of less than 30cm which were considered satisfactory for autonomous driving in urban environments.

[11] J. Levinson, et al. "Map-Based Precision Vehicle Localization in Urban Environments," The authors proposed a solution integrating GPS, IMU, wheel odometer and LiDAR to generate high-resolution maps. The authors suggested eliminating map features that are unlikely to be static to create a 2D map of the road surface in the infrared spectrum. Therefore, obstacles such as moving cars are eliminated from the map. A SLAM-style relaxation filter was used to localize the vehicle within the created map at 200Hz. Using the proposed approach, errors as low as 10cm were obtained, although, in some occasions, such as when turning, errors reached as high as 30cm. The main weakness pointed out in the technique was its reliance on static maps, which meant that extreme changes to the road environments could cause the technique to fail.

[12] R. Wolcott and R. Eustice, "Visual Localization within LIDAR maps for automated urban driving," Devoleped addressing the high implementation cost of LiDAR techniques, investigated the use of camera-based localization within pre-existing LiDAR maps. In contrast to LiDAR, camera-based technology is less accurate and is susceptible to changes in illumination conditions or angle of observation but is significantly cheaper. Therefore, the authors suggested creating initial maps used for localization using LiDAR sensors and equipping autonomous vehicles with cameras to localise themselves within the LiDAR maps. This means that the highly accurate LiDAR maps are utilised, but autonomous vehicles could be significantly cheaper. This technique was shown to localise with longitudinal and lateral RMS errors of 19.1cm and 14.3cm, respectively, with data captured at 10Hz, which provides a similar order of magnitude errors to LiDAR techniques but at a significantly reduced cost, power, and processing requirements. Alternative methods of utilising laser technology whilst.

[13] L. Wei, C. Cappelle and Y. Ruichek, "Horizontal/Vertical LRFs and GIS Maps Aided Vehicle Localization in Urban Environment," utilizing laser technology whilst maintaining low implementation costs, is the use of single beam laser range finders (LRF), such as in , where A GPS system, gyroscope, two LRF systems and a 2D feature map, consisting of road and building shapes, were integrated. The two LRFs scanned the environment, with one scanning horizontally and one vertically to identify building facades and build a feature map based on this information. Comparing the pre-existing feature map to the local dynamic map resulted in mean positional errors of 3.098m, which is unsuitable for autonomous vehicle localization.

[14] S. Jung, J. Kim and S. Kim, "Simultaneous localization and mapping of a wheel-based autonomous vehicle with ultrasonic sensors," localization methods have attempted to use alternative low cost sensors such as ultrasonic sensors. For instance, the authors in proposed the use of ultrasonic sensors integrated with a set of sensors including a digital magnetic compass, a gyroscope and two encoders for ultrasonic based SLAM techniques. Ultrasonic sensors can scan the environment by utilizing a mechanical wave of oscillating pressure which can propagate through air

or other materials. Summary of the above all discussed protocols are given the table-1.

Technique (Reference)	Sensors	Accuracy	Advantages	Disadvantages
Pure GPS -	GPS	~10m	Low cost	Low accuracy Poor signal availability
GPS/IMU in ECEF Coordinates [1]	GPS & IMU	7.2m RMSE	Low cost IMU provides positioning during GPS signal blockage	Low accuracy Cumulative errors
Two-stage vision-based SLAM [2]	Camera	0.75m (Mean)	Low cost	Susceptible to illumination and observation angle
Stereovision odometry [3]	Camera	Up to 20.5m cumulative error over 166m distance	Low Cost	Low accuracy Cumulative errors
Vision-based localisation with lane detection [4]	Camera, GPS, IMU	0.73m (Mean)	Low cost	Susceptible to illumination and observation angle
Vision-based localisation with road marker detection [5]	Camera, GPS, IMU	0.58m, lat. 1.43m, l. (Mean)	Low cost	Susceptible to illumination and observation angle
Aerial Image-based localization [6]	Camera, GPS, IMU	80% within 1m	Low cost	High errors
Microwave-Radar SLAM [7]	Microwave Radar	10.5m (Mean)	Low power requirements Low cost	Low accuracy
Short Range Radar SLAM [8]	Radar, GPS, IMU	0.07m, lat. 0.38m, long. (RMSE)	Low power requirements Low cost High accuracy	Low robustness to dynamic environments
Localising Ground Penetrating Radar [9]	LGPR, GPS, IMU	0.04m (RMSE)	Very high accuracy Robust to weather and illumination conditions	Lack of testing Sensitivity (e.g. to frost heave, thaw settlement) uncertain
LiDAR SLAM [10], [11]	LiDAR, GPS, IMU	0.017m, lat. 0.033m, long. (RMSE)	High accuracy Robust to changes in environment	High cost High power & processing requirements Sensitive to weather conditions
Camera localisation within LiDAR map [12]	Camera, IMU	0.14m, lat. 0.19m, long. (RMSE)	High accuracy Low cost	Requires environments to be mapped using a dedicated LiDAR vehicle Robustness
LRF based localisation [13]	GPS, IMU, LRF	3.098m (Mean)	Low cost	High errors
Ultrasonic SLAM [14]	Ultrasonic	(Not given)	Low power requirements Low cost	Low accuracy Long processing time

Table -1: Summary of localization techniques

3. CONCLUSIONS

It was shown that, from the performance point of view, the LiDAR techniques show the greatest promise for the localization of autonomous applications; however, the high power and processing requirements and its high cost render it unfeasible from cost-efficiency and commercialization point of view. Therefore, further optimization of LiDAR technology or alternative approaches such as localizing ground penetrating Radar or vision-based localization within LiDAR maps could offer a path towards commercially feasible systems. Hence topological model along with LiDAR is an effective model to improve the localization accuracy.

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