Autonomous Vehicle Technologies : Localization and Mapping

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Abstract　Vehicle self-localization is an important and challenging issue in current driving assistance and autonomous driving research activities. This paper mainly investigates two kinds of methods for vehicle self-localization: active sensor based and passive sensor based. Active sensor based localization was firstly proposed for robot localization, and was introduced into autonomous driving recently. The Simultaneous Localization and Mapping (SLAM) techniques is the representative in active sensor based localization. The passive sensor based localization technologies are categorized and explained based on the type of sensors, Global Navigation Satellite System (GNSS), inertial sensors and cameras. In this paper, researches utilizing active sensors and passive sensors for autonomous vehicles are reviewed extensively. Finally, our challenges on self-localization in urban canyon by the system integration of passive sensors is introduced. GNSS error has been improved for the purpose of the self-localization in urban canyon. The performance of the proposed method would suggest possible solution autonomous vehicles which makes use of passive sensors more.

Key words　Autonomous vehicle, Localization, LIDAR, GNSS, Vision sensor, Digital map

1. Introduction

Autonomous driving technologies are expected to significantly improve driving safety and convenience by alleviating the burden of a driver. Currently, they are implemented as a form of an advanced driver assistance system to partially aid drivers. It is also anticipated that, in the near future, fully autonomous cars will emerge as the key component of intelligent transportation systems, replacing human drivers. The announcement of Google's self-driving cars in May 2014 was an encouraging step towards commercializing autonomous vehicles in the near future[1]. Major automotive manufacturers have also announced plans to market autonomous vehicles in the next decade[2,3].

Autonomous driving technology made an obvious progress, owing to the Defense Advanced Research Project Agency (DARPA) Grand Challenge held in 2007, which evaluated autonomous navigation technologies for urban environments. Most of the successful

competitors, concentrated on environment perception, precision localization, and navigation, in order to execute various urban driving skills including, lane changes, U-turns, parking, and merging into moving traffic [4]~[7]. Fig. 1 shows the Stanford's autonomous research vehicle used in DARPA 2007, which was equipped with multiple
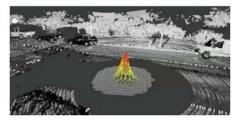

(a)

(b)

Fig. 1 Stanford's autonomous research vehicle and the demonstration of sensing and localization of the vehicle.　(a) Junior: Stanford's autonomous research vehicle[8]. (b) A 2-dimensional color histogram showing the posterior belief about our vehicle's location; the current Velodyne scan is also shown by gray color texture[8].

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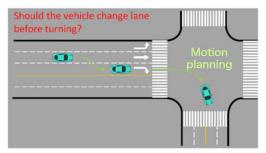
Fig. 2 Motion planning for the right turning case.

active sensors to conduct sensing and localization. Obviously, the environment perception is an essential function in autonomous driving, which can avoid the occurrence of collision. The precision localization is also significant, especially for the urban environment. Because the vehicle will be operated on the constructed urban road, the action of autonomous vehicle has to obey the traffic rules like human driver. For example, in the turning case, which is demonstrated in Fig. 2, the vehicle has to change to the right lane to achieve the right turning action. This decision is made based on the knowledge about the positioning, which is supposed to be lane-level. Moreover, this decision of the lane changing also needs the information from the digital map, including the semantic description of traffic rules.

Based on the type of sensors used, the localization methods can be categorized into: active sensor based and passive sensor based. The passive sensor collects data, including light, radiation, heat or signals in the surrounding environment, such as camera and GNSS receiver. While, the active sensor includes transmitters that send out a signal, a light wavelength or electrons to be bounced off the target, with data gathered by the sensor upon their reflection. The most popular active sensor for localization is Light Detection and Ranging (LIDAR) sensor. When we take a look into the intelligent vehicle literatures, it is easy to find many successful approaches that make use of active sensors, such as 2D LIDAR and Velodyne. Good examples of these are (4) to (7), which described practical approaches used in DARPA, performed the first tests of these ideas in real conditions. Then the application of active sensor, especially Velodyne, became a popular research topic, which was intensively published in the annual flag international conference, IEEE International Conference on Intelligent Transportation Systems (ITSC) and IEEE Intelligent Vehicles Symposium (IV) [8] ~ [15]. The reason for the favor of the active sensor is that this sensor can simplify the underlying distance estimation and while producing remarkably good results. Such simplification is achieved by acquiring dense clouds of 3D points with a laser.

However, developing localization approaches based on active sensors might be an important drawback with a view to their future introduction in driverless cars. This kind of sensors are very expensive nowadays, reaching in some cases a cost higher than the vehicle. Even assuming a drastic decrease of the cost of these sensors, they still present a critical problem regarding their excessively high energy consumption. These facts indicate

the necessity of considering lower-cost alternatives, as the ones provided by passive sensor, such as camera[16]. This paper will discuss about the possibility of using passive sensor for vehicle self-localization in urban environment.

But it does means the totally negative opinion about the active sensor. The collision avoidance function definitely needs the active sensor. Moreover, the more accurate drivability map we have, the less error is introduced into localization and motion planning. The application of active sensors for map generation is also preferable.

This paper analyzes the different roles of active sensors and passive sensors for vehicle localization in section 2 and section 3, respectively. Moreover, the section 2 also introduces the map construction from the data acquired from active sensors. Section 4 demonstrates an example of passive sensor based vehicle self-localization system. Finally, this paper concludes with the inspired discussion about the vehicle self-localization.

2. Localization and Mapping with Active Sensor

Simultaneous Localization and Mapping (SLAM) techniques are able to construct or update a map of an unknown environment while simultaneously keep track of an agent's location within it. SLAM has become a key component in robotic navigation, which has seen significant progress in the last two decades. Following the achievements, SLAM appears in autonomous driving as a technique of vehicle self-localization and mapping. Most applications of active sensors are bound with SLAM techniques. Therefore, this section mainly focuses on the active sensor based SLAM, and explains the application of active sensor from, localization and mapping, two aspects.

2.1 Localization in SLAM

2.1.1 SLAM algorithm

The intensive survey of the SLAM algorithm could be found in (17) to (19). A large variety of different estimation techniques have been proposed to address the SLAM problem. The first milestone of SLAM was presented by Smith and Cheeseman [20], [21], which proposed to use the Extended Kalman filter (EKF) for solving the problem of SLAM. As shown in Fig. 3, a mobile robot moves through an unknown environment and takes relative observations of landmarks, the estimates of these landmarks m_j are all necessarily correlated with each other because of the common error in estimated vehicle location x_k. A consistent full solution to the combined localization and mapping problem would require a joint state of EKF. The joint state is composed of the vehicle pose and every landmark position $\{x_k\ m_j\}$, to be updated following each landmark observation $z_{k, j}$.

Unfortunately, EKF covariance matrices are quadratic in the
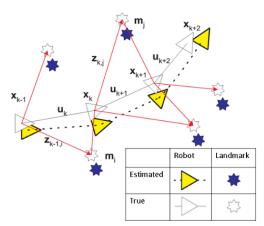
Fig. 3 Demonstration of SLAM problem[17].

number of the landmarks, and updating them requires time quadratic in the number of landmarks. FastSLAM, introduced by Montemerlo et al.[22], [23], with its basis in recursive Monte Carlo sampling, or particle filtering. Here, the probability distribution is on the trajectory $x_{0:k}$ rather than the single pose x_k because, when conditioned on the trajectory, the map landmarks become independent[17]. This is a key property of FastSLAM, and the reason for its speed. Thus, the map is represented as a set of independent landmarks, with linear complexity, rather than a joint map covariance with quadratic complexity.

2.1.2 Curb based Localization

Curb detection is an important capability for autonomous ground vehicles in urban environments. It is particularly useful for path planning and safe navigation. Another important task that can benefit from curb detection is localization.

There are several approaches for identifying curbs using 2D LIDARs in literatures[24], [25]. Qin et al. mounted a single tilted 2D LIDAR in the front of vehicle to detect the curb [25]. Because of the height difference between road shoulder and road surface, the jump can be observed in the ranging data of LIDAR. Based on this idea, the direction and distance of curb relative to the vehicle can be decided, and then the curb is used as a static reference for vehicle localization in next come time. This research group conducted an autonomous system demonstration in July 2011 using curb-only road features based localization, which is shown in Fig. 4. The experiment results showed that the lateral position of vehicle was accurate. However, the longitudinal variance changed remarkably along the drive. It is very interesting to note that when the vehicle was approaching the intersections and turnings, the longitudinal positioning error are decreased significantly by the longitudinal information of the curb features at intersection.

As 2D LIDARs do not obtain dense point clouds at once, a limited number of points can be detected as curbs in each frame. On the other hand, 3D LIDAR sensor (e.g. multilayer LIDAR) can suppress the lack of data. In (4) and (14), curb like obstacles can be detected by analyzing the ring compression of a multilayer LIDAR
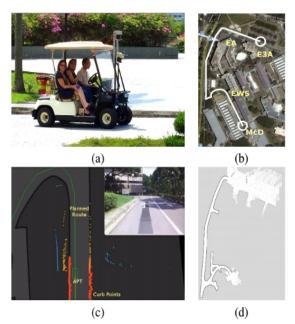

Fig. 4 Autonomous system demonstration. (a) Vehicle in operation, (b) Pickup-Dropoff points, (c) Snapshot of curb localization estimate, (d) curb map augmented by planar patches [25].
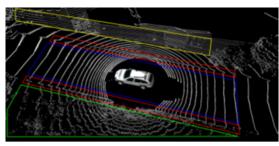

Fig. 5 Laser ring compression level is related to the surface slope. In this frame obstacles can be roughly distinguished as walls (yellow field), grass (green field), road (blue field) and curbs (red field). They are estimated using the ring compression data [14].

as shown in Fig 5. However, when obstacles as pedestrians and cars are present in the street, the object will possibly be detected as curbs. The regression filter was introduced to estimate the curb shape and to remove points that do not follow the road model [14]. The experiment showed that the longitudinal error was the major responsible for the localization error (mean 1.49 meters), despite of a relatively low lateral error of approximately 0.52 meter [14].

2.1.3 Road Mark based Localization

Some LIDAR sensors return infrared reflective intensity information. Hata et al. extended the curb detection based localization, and proposed to extract all road marks on road surface based on the LIDAR intensity for localization [15]. The road mark detector was developed based on the intensity histogram thresholding. The thresholding result is shown in Fig. 6. The localization results showed that both lateral error and longitudinal error are reduced by the integration of road marks and curb compared to curb only. But the mean of longitudinal error is still
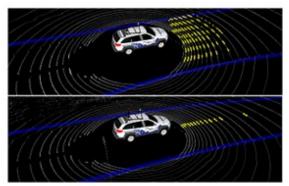
Fig. 6 Road marking detection through histogram thresholding. Blue lines are the road bounds estimated by curb detector and yellow points correspond to the detected road marking (Top: crosswalk; Bottom: double line) [15].
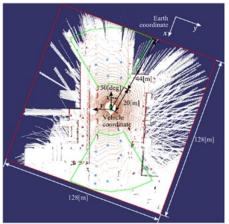

Fig. 7 A valid area of the local map (red square: a grid map area, green contours: feature map areas) [11].

larger than 1 meter [15].

2.1.4 Land marks and building based Localization

Besides the designed traffic features on road area, the objects along the road side were also adopted for localization. Choi et al. proposed a hybrid map-based SLAM [11]. This paper described the environment by using a grid map and a feature map together. The feature model selected thin and tall objects like street lamps or trees as landmarks. The grid map included the geometric information of surrounding buildings, as shown in Fig. 7. The feature-based SLAM approach showed generally the worst performance. It produced huge errors especially where no landmark measurement was found. The grid-based SLAM approach showed better results than the previous one. The hybrid map-based SLAM achieved the best performance. Moreover, the error accumulation was observed in the experiment result, which can be consider as the inherent weakness of SLAM.

2.2 Map Construction using SLAM

EKF-SLAM and particle filter based SLAM are more popular for the online localization. The graph-based formulation of the SLAM problem has been proposed by Lu and Milios in 1997 [26].

Consequently, graph-based SLAM methods have undergone a renaissance and currently belong to the state-of-the-art techniques with respect to speed and accuracy [27]. GraphSLAM extracts a set of soft constraints from the data, which are represented by a sparse graph. Motion constraints link any two consecutive robot poses, and measurement constraints link poses to land marks. GraphSLAM obtains the map and the robot path by resolving these constraints into a globally consistent estimate. The solution of the GraphSLAM can be considered as a least squares problem [28]. In the large-scale mapping problems, it was found that GraphSLAM can handle large number of features, and even incorporate GPS information into the mapping process [28].

Levinson et al. integrated GPS, IMU, wheel odometry, and LIDAR data acquired by an instrumented vehicle, to generate high-resolution 2D road surface maps using GraphSLAM method [29]. In order to generate pure road surface map, dynamic objects should be excluded and cause the hole effect. Thus, data collection should be conducted at multiple times. However, if the location of multiple measurements are set by GPS alone, ghosting occurs. After using GraphSLAM, the hole is filled and the ghost image is removed. In [29], the online-localization was conducted by using the learned map. In a variety of urban roads, the vehicle was able to localize in real-time relative to the previously created maps with errors of less than 0.1 meter, far exceeding the accuracy with GPS alone. Moreover, the proposed map based localization succeeded in GPS-denied environments, such as in tunnels and bridge [29].

Besides the 2D road surface map, the 3D environment models beyond the road surface was proposed as well, which could improve the reliability and accuracy, especially on unusually featureless roads. Stanford group built a 3D point cloud map for real urban environment [30]. With this 3D map, vehicle were able to drive autonomously in several urban environments that were previously too challenging. As one example, the vehicle participated in an autonomous vehicle demonstration in downtown Manhattan in which several blocks of 11th Avenue were closed to regular traffic. The vehicle operated fully autonomously and successfully stayed in the center of its lane, never hitting a curb or other obstacle.

Obviously, the localization with pre-prepared map is preferable recently, because of the accurate pre-prepared map can reduce the error accumulation in SLAM. Following this trend, many groups already developed their own 3D map for the research of autonomous driving. The Fig. 8 shows several examples, including Stanford, the University of Freiburg and Toyota Technological Institute.
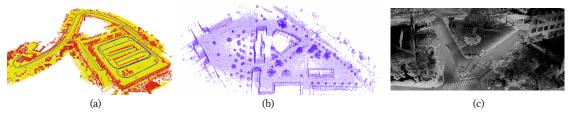
Fig. 8 (a) A 3D map of the Stanford parking garage acquired with an instrumented car. This map has been subsequently used to realize an autonomous parking behavior[27]. (b) Point cloud map acquired at the University of Freiburg (dataset is available at http://ais.informatik.uni-freiburg.de/projects/datasets/fr360/). (c) Mobile Mapping System (MMS) point cloud map at Toyota Technological Institute[12].

3. Localization with Passive Sensors

3.1 Global Navigation Satellite System (GNSS)

The Global Navigation Satellite System (GNSS) is a space-based satellite navigation system that freely provides location and time information to users. GPS, operated by the United States, was the representative positioning system. In the open sky field, the accuracy of GPS positioning is less than 0.1 meter [31]. But the land vehicle navigation system typically has to operate in the areas where GNSS signal is either blocked or reflected, such as the urban canyon. Currently, other satellite navigation systems such as GLObal NAvigation Satellite System (GLONASS) of Russia, Quasi-Zenith Satellite System (QZSS) of Japan, Galileo of Europe, BeiDou of China are now in operation or are about to start operation. The multiple GNSSs reduce the probability of outage happens and also improve the positioning accuracy for urban environment [32].

Currently, the most challenging problem in urban environment is that GNSS suffers from Non-Line-of-Sight (NLOS) and multipath effect. The various technologies of GNSS were developed to mitigate the multipath and NLOS effects, which are mainly cataloged by three: antenna-based [33], [34], receiver-based [35], [36], and navigation-processor-based [37] ~ [39] techniques. Most of the multipath mitigation algorithms do not consider the effect of signal reflection as an aid to the position estimation. With the development of ranging technologies, the 3D building information became available to estimate the multipath and NLOS effects. Meguro et al. used an omnidirectional infrared (IR) camera, which was installed on the roof of vehicle, for estimating the area of sky and identifying NLOS signals [40]. As an extended idea of NLOS exclusion, Bauer et al. built a shadow map, which can represent the satellite reception conditions real time [41]. The NLOS measurement can be detected and excluded from the positioning solution [41]. Moreover, Obst et al. utilized a dynamic 3D map to exclude the potential multipath signal from the observation set for a vehicle-based loosely coupled GNSS/INS integration system [42].

3.2 Inertial Navigation System (INS)

Inertial Navigation System (INS) is a navigation aid that uses multiple on-board sensors, such as speedometer and gyro sensor, to continuously calculate via dead reckoning the position, orientation, and velocity of a moving object. The INS system can provide accurately relative vehicle position in short time, but its accuracy degrades with time [43]. To overcome the disadvantages associated with the standalone operation of GNSS and INS, the two systems are often integrated together so that their drawbacks are minimized. In the early studies of this integration field, the researches focused on evaluating the integration system performance under open sky fields [44], [45]. Recently, the qualification of the integration system was discussed and performed in more different environment. In order to overcome the multipath interference when the GPS signal is reflected by external agent, Milanes et al. proposed a dynamic integration system using a decision unit, which can choose the correct one from GPS and INS [46]. Godha et al. employed constraints to describe the behavior of a typical land vehicle in the GPS/INS integrated system, when a GPS outage occurred in urban areas [47]. Noureldin et al. improved the Micro-Electro-Mechanical Systems (MEMS)-based inertial sensor errors to enhance the positioning accuracy during GPS outage [48].

3.3 Vision based object detection

Besides the GNSS sensor and INS sensor, another passive sensor, camera, is widely used for autonomous driving. Most vision based technologies are aiming to detect the objects in front of the vehicle. Here we just focus on the technologies for static object detection, which can potentially be used for localization.

The most important information on road surface is lane marks. Vision based lane detection technology has received considerable attention since the mid-1980s [49] ~ [51]. Techniques used varied from monocular [52] ~ [54] to stereo vision [55]. The general lane detection firstly performs the Inverse Perspective Mapping (IPM), and then conducts Hough Transformation or Random Sample Consensus (RANSAC) based line detection [53]. Actually, the lane detection already achieved quite high accuracy under good light condition. But those developments mainly focused on keeping the vehicle on

Fig. 9 Example output of the integrated urban curb recognition system. (a) Input image and corresponding Semi-Global Matching disparity image. (b) Stixel World and freespace (green line), curb classifier search area (red horizontal line), the curb classifier Region of Interest (ROI) with the highest posterior probability (green box), recovered curb location (yellow line)[61].

the lane and avoiding collisions.

In addition, the distance from the ego-vehicle to stop line or crossing road is important for autonomous driving, because the vehicle needs to make a smooth deceleration and stop before stop line. Seo et al. proposed to detect the stop line based on the assumption that the stop line is perpendicular to the lane, and track the stop line using Kalman filter to reduce the false alarm detection [56]. Marita et al. detected the stop line and cross road from stereo camera, and using the depth information to do the localization at the intersection scenarios [57]. Moreover, the arrow mark recognition was also proposed for localization at intersection [58], [59].

Curb detection is usually conducted in stereo camera. Because of the height difference between the road surface and road shoulder, the curb is represented as an edge in the depth image. The most direct way of curb detection is to find the curb line from the depth map [60]. More sophisticated algorithm for curb detection was developed based on the texture and depth information together, which is shown in Fig. 9 [61]. Moreover, the traffic light detection and traffic sign detection [62], [63] could be an aid of localization, because these objects are static, and their positions are possible to be added into map.

Even though the technologies of the vision based detection are quite mature, there are some points need to be discussed when we applied those technologies for localization. For example, the lane detection could not determine absolute position of the vehicle. In addition, using the multiple lane detection method for absolute positioning is also difficult, because of the occlusion of other surrounding vehicles in urban environment. But stop line, curb

and traffic sign can provide absolute positioning information for localization. Moreover, we need distance information from camera to the interested object for localization, therefore, the stereo camera is preferable for localization.

4. Proposed Passive Sensor Integration for Localization in Urban Environment

Our research team developed a passive sensor based integration system, includes GNSS, inertial sensors and on-board camera, in order to realize the precise localization in urban environment. This section presents this system to show the feasibility of the passive sensor based localization system.

4.1 3D map aided GNSS positioning

GNSS positioning result is supposed to be the main source in the integration algorithm. Therefore, the reduction of the error of the GNSS positioning result needs to be considered before integration. In order to reduce the effect of the multipath and NLOS while avoiding the distortion of Horizontal Dilution of Precision (HDOP), our research team developed a candidate distribution based positioning method using 3D building map and ray-tracing [64]~[66]. In this method, the 3D building map is constructed by using the 2-dimension building outline data and the height information of the building.

Firstly, this positioning method distributes a number of positioning candidates. Secondly, the ray tracing is employed to calculate the simulated pseudorange from each candidate point. In the case of the NLOS, the calculation of the reflection delay is straightforward, which is the signal reflection path minus the NLOS path. In comparison to the NLOS case, the multipath effect on pseudorange is more ambiguous, which is shown in the right image of Fig. 10. This research assumes the multipath effect is about 6dB weaker than the LOS signal, and the commercial receiver applies the strobe correlator [67] with 0.2 chip spacing based on the experience. This principle is used to simulate the pseudorange delay caused by multiple path.

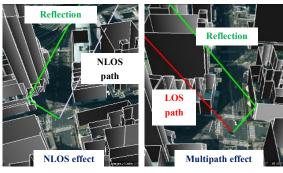After satellite condition validation, the satellites that satisfied

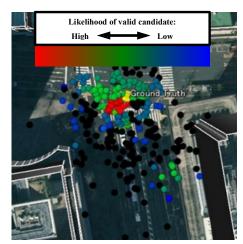Fig. 10 Visualization of NLOS and multipath effect.

Fig. 11 The demonstration of the probability of the particles.

consistency requirements are selected to calculate the pseudorange similarity between received pseudorange and simulated pseudorange. One example of the probability of the particles is shown in Fig. 11. The particles, which are near to the ground truth position, have high weighting, and others have low weighting. Finally, the weighted average of the positions of all the valid candidates is the final rectified position.
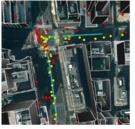
The developed 3D map based GPS positioning method was firstly applied for the pedestrian localization [64] ~ [66]. After that, the GLONASS and QZSS were introduced to the 3D building map based positioning method for pedestrian application [68] ~ [70]. Moreover, we successfully defined a positioning accuracy based on the distribution of the candidates and their pseudorange similarity. Table 1 summarizes the performance of the developed 3D building model based GNSS positioning method with difference configurations for pedestrian test.
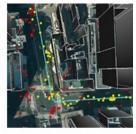
In over all, the proposed 3D map based GPS positioning method drastically reduces the positioning error compared to the conventional method. In additional, with the help of GLONASS and QZSS the proposed positioning method are improved in terms of positioning accuracy and availability. The error mean of the proposed 3D map method is 4.42 meters. In addition, authors proposed to denote the confidence level of the positioning result by the percentage of the valid candidate of all candidates outside the building. This idea is similar to the User Range Accuracy (URA) of the conventional GPS is to indicate its level of positioning service. Thus, the confidence level is named as URA_{3Dmap} in the paper. The proposed positioning accuracy URA_{3Dmap} further improves the

positioning results. The error mean of selected points is 3.78 meters. Although the availability of the selected points of the proposed 3D map method is about only 70 %, it should be enough if a filtering or smoothing technique is applied.
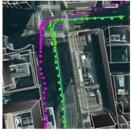
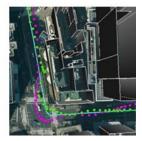## 4.2 Integration of 3D map aided GNSS positioning and INS

Even though the proposed 3D map GNSS method can reduce the positioning error dramatically, it is difficult to satisfy the requirement of vehicle self-localization. INS has an advantage in short time for the description of vehicle motion. Therefore, we proposed to integrate on-board inertial sensors with the 3D map based GNSS positioning method to achieve higher accuracy [71], [72]. In this research, the GPS based positioning result and local movement of vehicle were integrated in a Kalman filter framework. The vehicle speed measurement was obtained from the Controller Area Network (CAN) bus of car. The heading direction of the ego vehicle was derived from Inertial Measure Unit (IMU) was placed close to the center of the vehicle. If the outage of GPS occurred, the integration system relied on the prediction by means of inertial

(a)

(b)

Fig. 12 Visualization of positioning results, the ground truth is represented by the cyan line.　　(a) Results of the LS GPS method (red point) and proposed 3D map based GPS method (yellow point). (b) Results of the LS GPS based integration (purple point) and the 3D map GPS based integration (green point).

Table 1: The performance of the proposed 3D method using multiple data.

	RTKLIB SPP			3D map method			3D map method ($URA_{3Dmap} \leq 3$)		
	Mean (m)	Std (m)	Avail.	Mean (m)	Std (m)	Avail.	Mean (m)	Std (m)	Avail.
GPS only	27.20	36.35	69.24%	5.26	5.71	75.88%	3.30	2.40	49.52%
GPS+GLONASS	25.46	32.60	80.05%	4.81	4.21	87.65%	3.91	3.04	60.06%
GPS+GLONASS+QZSS	20.48	29.68	82.16%	4.42	3.63	92.36%	3.78	2.85	69.38%

sensors. Moreover, if the vehicle stop, the vehicle position was maintained as the position at last sampling time.

In order to demonstrate the effectiveness of the proposed integration method, we performed right turning and left turning experiments in urban canyon. The Least Square (LS) method was chosen as baseline method for comparison. The positioning results are visualized in Fig. 12. The results indicate our proposed 3D map based GPS method (yellow point in Fig. 12 (a)) is more reliable than the LS GPS method (red point in Fig. 12 (a)). Moreover, the integration with inertial sensors (green point in Fig. 12 (b)) can reduce positioning error compared to 3D map based GPS only. The quantitative analysis denotes that the integration of 3D map based GPS and INS achieved 1.8 meters error mean for vehicle self-localization. Moreover, we found about 50 % of the positioning results have the error less than half lane width.

4.3 Integration of 3D map aided GNSS positioning, INS and Vision based lane detection

Besides the GNSS and INS, passive sensor based sensing were also employed for localization, as we discussed in section 3. We proposed to integrate 2D map and vision-based lane detection with GNSS/INS positioning system, which is expected to determine the occupied lane of the host vehicle [73]. The lane detection algorithm used in this research was developed based on Aly's work [53].

The first step in the lane detection was to generate a top view of the road image based on the inverse perspective projection (IPM). Then Hough Transform and RANSAC were used to find two lines in the area of two lane width. After the lines were detected, the particle filter was employed for line tracking. Finally, the distances from the vehicle center to the two detected lines were the output of the lane detection. Thus, there are three main sources for positioning, GNSS, INS and lane detection. We proposes to use the particle filtering for multiple cues integration. INS describes motion of vehicle via the velocity and the heading direction. The motion of the vehicle is used for particle propagation in the integration algorithm. GNSS gives global localization measurement, which can estimate probability of particles. Lane detection function percepts the relative distance from the center of vehicle to left white line and right white line. This distance is additional measurement to refine the probability of particles.
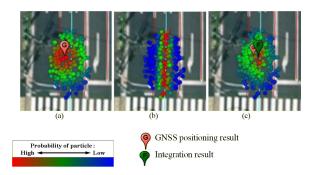

Fig. 13. Demonstration of probability evaluation for particles.
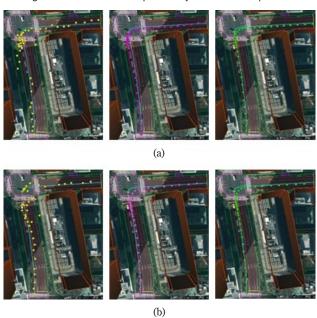

Fig. 14 Visualization of results: GNSS result (yellow dot), GNSS/INS integration result (purple dot), and GNSS/INS/lane detection integration result (green dot).   (a) First right turning experiment. (b) Second right turning experiment.

The Fig. 13 (a) shows the GNSS result and the probability of the particles calculated by only using GNSS measurement. The Fig. 13 (b) shows the probability of the particles calculated by only using the lane detection measurement. Because the vehicle drives along the center of lane, so the particles near to the lane center have higher probability. However, the lane detection just provides the relatively lateral position. It cannot reflect the probability difference along the longitudinal direction. Joint probability of GNSS and lane detection for all particles are denoted in Fig. 13 (c). Compared to Fig. 13 (a), the high weighting particles appear around of the center of lane, but not around of GNSS positioning result.

Table 2 The performance of the proposed vehicle self-localization system with different configurations: GNSS, GNSS/INS integration, GNSS/INS/Lane detection integration.

Ex.	Evaluation Way	GNSS	GNSS/ INS	GNSS/INS/ Lane detection
1st	Positioning Error mean (meter)	3.44	1.79	0.73
	Correct lane rate	43.2%	59.1%	93.2%
2nd	Positioning Error mean (meter)	2.41	1.29	0.71
	Correct lane rate	55.0%	82.5%	95.0%

Fig. 14 shows the positioning results of two experiments. The light blue line is the ground truth route. Yellow dot indicates the 3D map based GNSS positioning result, the purple dot and green dot denote the GNSS/INS integration result and GNSS/INS/lane detection integration result, respectively. Table 2 shows the quantitative comparison of these three methods. The employed the 3D map based GNSS methods shows extremely good performance in the urban positioning result is about 3 meters. About 50% epochs are located at correct lane. Even though this technique cannot be applied for vehicle localization directly, its good performance provides a basis for the integration. After the integration with INS, the positioning error mean is reduced to about 1.5 meters and correct lane rate is increased. The fifth column of Table 2 indicates the integration of GNSS/INS/lane detection can achieve sub-meter accuracy and more than 93% correct lane rate.

5. Conclusions

This paper investigates two kinds of methods for vehicle self-localization: active sensor based and passive sensor based. Active sensor based simultaneous localization and mapping (SLAM) techniques was firstly proposed for robot localization, and was introduced into vehicle self-localization. The recent progress of SLAM indicated that the road marks, curbs, land marks, even building structures could be helpful for vehicle localization in urban environment. Moreover, because localization with pre-prepared map was preferable, the off-line SLAM started to be studied for the generation of road map. The passive sensors are categorized into, GNSS, inertial sensor and camera. The paper survey shows it is difficult to achieve acceptable performance using only one type of passive sensor. Therefore, we were aiming to improve the GNSS positioning method, proposed a 3D map based GNSS method and further integrated GNSS, INS and vision based lane detection together to pursue high accuracy. The performance of the integration system showed the potential of the passive sensor for the precise localization in urban environment.

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