Real-time localization method for autonomous vehicle using 3D-LIDAR

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ABSTRACT: Precise and robust localization is a significant task for autonomous vehicles in complex scenarios. In this paper, a novel method is proposed to precisely locate the autonomous vehicle using a 3D-LIDAR sensor. The curb-based feature matching and intensity-based feature matching results are fused to obtain an accurate estimated position. A curb detection method is proposed to extract the curb position and an area probability searching method is proposed to match the intensity feature. Experimental results demonstrate the accuracy and robustness of the proposed method.

1 INTRODUCTION

Precise and robust localization is a significant task for autonomous vehicles in complex scenarios. Knowing the accurate position of an autonomous vehicle is necessary for decision making and path planning. Global Positioning System (GPS) receivers and Inertial Measurement Unit (IMU) were usually applied for localization systems in the past few decades. The position accuracy was not guaranteed due to insufficient number of visible satellites or multi-path reflections of the signal. Thus, researchers have proposed many map-based vehicle localization algorithms to improve the accuracy of vehicle position.

Gruyer, 2014 used two lateral cameras to detect the road markings and estimated the lateral and directional deviations by coupling the images with the map data in an extended Kalman filter (EKF) framework. Schreiber, 2013 used a stereo camera system to recognize the environmental features of lane markers and curbs. Then, the Iterative Closest Point (ICP) algorithm was used to match the pre-built accurate map data with the detected features. The accuracy of lateral and longitudinal position was improved. However, the position of the lane markers was detected and calculated under the assumptions of fixed vehicle posture and flat road surface. The intrinsic and extrinsic parameter sensitivity of camera was analyzed by Tao, 2013 and only the lateral position of lane markers was used to locate the vehicle. It is extremely difficult for cameras to accurately extract the road features in shadows or poor lighting environments.

Other than cameras which are sensitive to lights, LIDARs are insensitive to illumination. Schlichting, 2014 used an IBEO laser scanner for vehicle localization. The pole-like objects and planes were measured and matched to the landmark map using local pattern matching algorithm. It is hard to ensure the matching rate because of the sparsity of poles and planes. The curbs detected by LIDAR have been used for localization by Hata, 2014. The localization algorithm is performed under the assumption of flat road surface, which is hard to guarantee in most scenarios. The lane markers can also be detected by LIDAR sensors based on the difference in reflectivity between the lane marker and the surface of road. Kim, 2015 and Matthaei, 2014 proposed a lane-based algorithm to estimate position, and the lateral accuracy was improved. Due to the lack of longitudinal information, it was unable to provide accurate longitudinal position. To improve the longitudinal positioning accuracy, a probabilistic grid map was used for localization by Levinson, 2010 and Wolcott, 2014. The online sensor data were directly matched with the map by traversing the lateral and longitudinal search space. Nevertheless, the precision of localization algorithm is directly related to the size of grid. The smaller size of grid, the higher computational complexity and larger storage memory.

In this paper, a real-time localization method is proposed to obtain the accurate lateral position, longitudinal position and heading angle of the autonomous vehicle. A 3D-LIDAR sensor is used and multi-frame features are generated to match the digital map. The curb features are extracted through a robust curb detection algorithm. The intensity features are represented as probability distributions and an area probability search algorithm is used to match the map. Due to the different characteristics of curb feature and intensity feature, the Kalman filter is implemented to fuse the observations of two features.

2 MAP-BASED LOCALIZATION

This section introduces the detail of the high-precision map based localization algorithm. First, a robust curb detection algorithm is performed on the point cloud of single-frame. Based on the vehicle dynamics, the detected curbs are densified by projection former curbs into current vehicle coordinate system. Then, the beam model is applied to reject the outliers and the registration between the curb features and high-precision map is performed based on ICP algorithm. The intensity feature is matched to the pre-built intensity digital map. Finally, the Kalman filter is used to fuse the two matching results and output the estimated position of vehicle. The flowchart of the proposed algorithm is shown in Fig. 1.

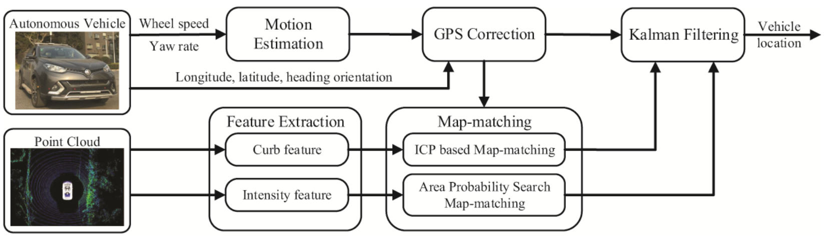


Figure 1. Flowchart of proposed method.

2.1 *Motion Estimation and GPS Correction*

Before applying map matching, the on-board wheel speed, inertial sensor and low-cost GPS are fused to obtain a rough position based on Kalman filter. The motion estimation model is defined as follows:

$$X(k) = AX(k-1) + Bu(k) + W \tag{1}$$

where

$$X(k-1) = \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ \psi_{k-1} \end{bmatrix}, \quad u(k) = \begin{bmatrix} \Delta x_k \\ \Delta y_k \\ \Delta \psi_k \end{bmatrix}, \quad A = B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

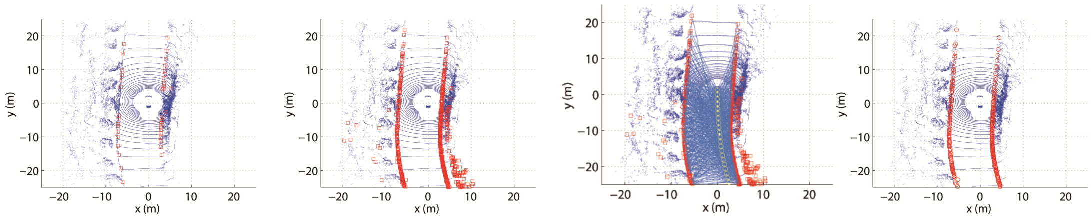
where W is the process noise. ($x_{k\text{-}1}$, $y_{k\text{-}1}$, $\psi_{k\text{-}1}$) are the lateral, longitudinal and heading angle of vehicle at time k-1, (Δx_k, Δy_k, $\Delta\psi_k$) is the deviation of lateral, longitudinal and heading angle between time k-1 and k. The deviation is calculated based on vehicle kinematics model and shown as follows:

$$\begin{cases} \Delta x_k = v_k \Delta t \cos(\psi_{k-1}) \\ \Delta y_k = v_k \Delta t \sin(\psi_{k-1}) \\ \Delta \psi_k = \dot{\psi}_k \Delta t \end{cases} \tag{3}$$

where Δt is the time step. v_k and $\dot{\psi}_k$ are the linear speed and yaw rate of vehicle measured by wheel speed sensor and inertial sensor. ($x_{k,\,gps}$, $y_{k,\,gps}$, $\psi_{k,\,gps}$) is the output of the Kalman filter.

2.2 *Curb detection*

In this paper, the LIDAR sensor is mounted on top of the autonomous vehicle. The raw data is obtained in a 3D polar coordinate. The curbs are detected from their spatial features. The height of curbs is uniform in most urban areas and it is often 10 to 15 cm higher than the road surface. Furthermore, the elevation changes sharply in the vertical direction. Based on these features, a robust approach was proposed by Zhang, 2015 to recognize curbs from a single frame. The detection result is shown in Fig. 2 (a). However, the density of the detected curbs decreases with the increase of distance. In this paper multi-frame curbs are transformed into current vehicle coordinate system based on the dynamics of the vehicle. An example of multi-frame curbs is shown in Fig. 2 (b).



(a) Single-frame curbs (b) Multi-frame curbs (c) Beam models (d) Extracted curbs

Figure 2. Curb detection procedure.

2.3 *Outlier rejection*

A few outliers exist in the densified multi-frame curbs because of false detection which need to be filtered. Beam model proposed by Thrun, 2005 is an approximate physical model of range finders and widely used in robotics. It is a sequence of beams with common initial point where the range finders are located and evenly spaced with angle resolution $\delta=2\pi/n$. In this paper, the beam model is applied to eliminate the outliers. Several beam models are set at each trajectory point of the autonomous vehicle. The beam model is denoted as follows:

$$\boldsymbol{Z}_k = \left\{ \frac{(k-1)\cdot\pi}{n} < \arctan\left(\frac{y-y_{\mathrm{ini},j}}{x-x_{\mathrm{ini},j}}\right) \leq \frac{k\cdot\pi}{n}, -25 \leq x, y \leq 25, k = 1,2,\cdots,n \right\} \tag{4}$$

$$d_k = \left\{ \underset{\boldsymbol{r}_i \in \boldsymbol{Z}_k}{\arg\min} \sqrt{x_i^2 + y_i^2} \right\} \tag{5}$$

where $\boldsymbol{r}_i=(x_i, y_i)$ is the ith curb coordinate. $\mathbf{Z}_k$ means the kth beam area. The coordinate ($x_{\mathrm{ini},j}$, $y_{\mathrm{ini},j}$) is the jth launching point of beam model. d_k is the index of the curb with the shortest distance among the curbs $\boldsymbol{r}_i$. Thus, all the d_k th curbs are extracted and used at the next step. The procedure is shown in Fig. 2 (c) and (d).

2.4 *Curb features Registration*

The registration process intends to estimate the deviation between curbs detected by the autonomous vehicle and curbs provided by the digital map. The high-precision map which contains curb features is shown in Fig. 3a. The blue dots represent the road boundary. The ICP algorithm is a matching algorithm proposed by Besl, 1992. After extracting the contour, the points of the contour are denoted by $\mathbf{C}$ and the feature points in the map are denoted by $\mathbf{M}$. The purpose of the ICP algorithm is to find a transformation $\mathbf{T}$ by minimizing the cost function:

$$J = \sum_{i}^{N} dist(\mathbf{T}\mathbf{C}_i, \mathbf{M}) \tag{6}$$

where $dist$ denotes the Euclidean distance function. The optimization problem can be solved by an iterative approach as follows:

a) Find the correspondence of each point $\mathbf{C}_i$ in $\mathbf{M}$ using a k-dimensional tree.
b) Compute the transformation $\mathbf{T}$ of the correspondence based on the singular value decomposition (Arun, 1987).
c) Apply the transformation $\mathbf{C}=\mathbf{TC}$ and calculate the J
d) Terminate the iteration when the change of J falls below a preset threshold τ.

The transformation matrix $\mathbf{T}$ is obtained after the iteration procedure.

2.5 *Intensity feature matching*

The intensity measurements of LIDAR sensor are also used to enhance the localization. The intensity map is considered as probability distributions over environment which is described in Levinson, 2010. The mean and variance of intensity are contained in each cell of the map. The advantage of this representation is an increased robustness to dynamic obstacles. In the matching procedure, first, the point cloud is projected into a grid. Then, the mean and variance of intensity of (i, j) cell are calculated and denoted as $S_{r,(i,j)}$ and $S_{\sigma,(i,j)}$. The mean and variance of intensity of (i, j) cell in the digital map are denoted as $m_{r,(i,j)}$ and $m_{\sigma,(i,j)}$. Thus, the possibility of vehicle locating at position (x, y) is computed:

$$P(z \mid x, y) = \prod_{i,j} \exp\left(\frac{-\left(m_{r,(i-x,j-y)} - s_{r,(i,j)}\right)^2}{2\left(m_{\sigma,(i-x,j-y)} + s_{\sigma,(i,j)}\right)^2} \right)^{\alpha} \tag{1}$$

where α is a parameter to control the influence of intensity for each cell. Finally, the estimated position is calculated by taking the average of $P(z|x, y)$ at all possible positions. The estimated position is denoted as $(x_{k,\mathrm{int}}, y_{k,\mathrm{int}})$ at time k.

2.6 *Localization*

In the localization process, the computed results of above steps are imported into another Kalman filter. The output $\left(\hat{x}_{k,gps}, \hat{y}_{k,gps}, \hat{\psi}_{k,gps}\right)$ of first Kalman filter is used as the prediction states of vehicle. The transformation matrix $\mathbf{T}$ and $(x_{k,\mathrm{int}}, y_{k,\mathrm{int}})$ is used as the observation. The prediction states and observation are fused through the second Kalman filter. The output of the second Kalman filter is the final localization result.

3 EXPERIMENTS

To evaluate the proposed method, experiments are carried out both offline and online. The high-precision curb-feature map and intensity-feature grid map are used as priori knowledge. RTK-GPS data is recorded as the benchmark positions. The intensity-feature grid map is generated through calculating the mean and variance of intensity information of each grid. Also, the curb detection method is applied to automatically extract the curbs. After that, we modify the map points manually to generate the high-precision map.

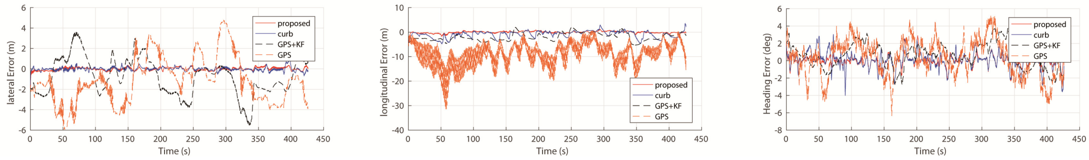
(a) Curb map

(b) Intensity map

Figure 3. High-precision curb and intensity maps.

3.1 *Offline experiment*

The dataset is recorded by our autonomous vehicle on the campus road in Tongji University. The recorded dataset composed of 4260 frames. Our autonomous vehicle is equipped with an Oxford Inertial+2 and NovAtel GPS receiver running at 100 Hz. The RTK-GPS provides the ground truth for evaluating the accuracy of localization algorithm. We compared our algorithm with only using low-cost GPS, low-cost GPS combined with INS, and low-cost GPS with INS plus curb features. The simulation is implemented with MATLAB. The waveforms of lateral, longitudinal and heading error of localization are shown in Fig. 4 and the statistical results of four methods are reported in Table 1. The proposed method has an approximately 70% improvement in longitudinal position error due to the fusion of curb feature and intensity feature. In addition, the average processing period of the proposed method is around 60 ms, which is acceptable in autonomous driving.



(a) Lateral position error (b) Longitudinal position error (c) Heading angle error

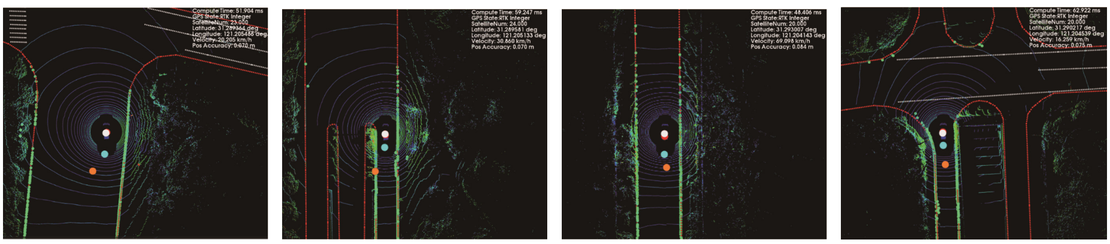
Figure 4. Waveforms of localization error in datasets.

Table 1. Performance index (RMSE).

	Lateral (m)	Longitudinal (m)	Heading (°)
GPS	2.564	9.969	2.118
GPS+KF	1.994	2.544	1.503
Curb-based	0.191	1.623	0.941
Proposed	0.170	0.443	0.697

3.2 *Online experiment*

After the comparison of four localization methods, the proposed algorithm is implemented with C/C++ under Windows-8 Operating System. The online experiment is tested on our autonomous vehicle platform. The controller is the ADLINK Industrial Personal Computer (IPC) with 16GB of RAM and Intel Core i7-3610QE CPU clocked at 2.3GHz. The online experiment is carried out on our campus lasting 3.1 km with average speed 26.9 km/h. The real-time operating window is shown in Fig. 5.



(a) (b) (c) (d)

Figure 5. Real-time experimental results. White dot represents the ground truth from RTK-GPS, red dot is the result of proposed method, light blue dot shows the result of curb-based method and orange dot is from GPS+INS.

4 CONCLUSION AND FUTURE WORK

This paper develops a real-time algorithm to locate an autonomous vehicle using a 3D-LIDAR sensor. The curb feature and intensity feature are used to match with high-resolution maps and a

Kalman filter is utilized to fuse the matching results. Through combining the two different environment features, the accuracy of lateral, longitudinal and heading angle of vehicle are improved. Experimental results have shown promising performance in most scenarios. However, the proposed algorithm may fail to locate the vehicle accurately when some obstacles block the curb. In the future, we will focus on the localization problem in dynamic environments.

5 ACKNOWLEDGMENT

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