Development of a self-driving car prototype for educational and research purposes

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Abstract. Self-driving car (SDC) is one of the most challenging topics in artificial intelligence. However, current off-the-shelf SDC platforms are expensive and difficult to modify, which prevents more researchers from working towards the improvement of self-driving technologies. This paper presents the development of a SDC prototype with low-cost sensors and an open-source software platform for educational and academic research purposes. The goal of such a SDC prototype is to serve as a testbench, which allows students and researchers to easily test new algorithms of SDC. Localization is one of the most basic and important problems in SDC. To achieve high performance using low-cost sensors, a localization method based on Lidar-INS fusion was investigated under the framework of Kalman filtering. Autonomous driving experiments were conducted on roads of a university campus environment and the results are used to show the performance.

1. Introduction
Self-driving cars, also known as autonomous vehicles, are becoming a new trend of infrastructure. Automobile companies, electronics manufacturers, and IT service providers are all interested in this technology, and academic research in artificial intelligence has contributed significantly to producing their prototype systems.

The architecture of a SDC system is generally organized into two main parts: perception and decision-making. The perception system is typically divided into many subsystems, which are responsible for tasks such as localization, obstacle detection and tracking, road mapping, traffic signal recognition, etc. The decision-making system commonly consists of many subsystems as well, which are responsible for tasks such as mission planning, path planning, behavior selection, motion planning, and vehicle control. To define the autonomy levels of SDCs, SAE International published a classification system ranging from level 0 to level 5 [1], which is based on the amount of required human driver intervention and attentiveness.

Research on self-driving has accelerated in both academia and industry around the world. Notable examples of university-conducted research comprise Carnegie Mellon University, Stanford University, and MIT. However, most of self-driving studies at university focus only on a specific technological area, such as ADAS [2], vehicle control [3], visual environment perception [4], etc. Notable examples of company-conducted research include Google/Waymo, Uber, Baidu, Tesla, Intel/Mobileye, Toyota, and Volvo.

Naturally, in education and research fields, there is an increasingly demand for a self-driving platform that combines flexible, off-the-shelf hardware with an open software development
environment to create user-defined prototyping and test perception or decision-making solutions. However, there are two problems in existing SDC platforms:

- Given that commercial vehicles protect their in-vehicle system interface from users, third-party developers cannot easily test new components of autonomous vehicles.
- Most of current SDC platforms are expensive, mainly due to the use of high-resolution multi-layer Lidars.

Motivated by the above problems, we have developed a SDC prototype, which consists of relatively inexpensive sensors. It uses Autoware as its software platform, which is a fully-open-source development environment for self-driving [5]. Such a SDC prototype aims to allow researchers and students easy to testify algorithms from perception to decision, integrate all modules, in lab environments. Localization is one of the most basic and important problems in SDC. To achieve better performance with low-cost sensors, a localization method based on Lidar-INS fusion was investigated under the framework of Kalman filtering. Autonomous driving experiments were conducted on roads of a university campus environment and the results are used to show the performance.

The remainder of the paper is organized as follows. Section 2 introduces the hardware configuration of our SDC prototype. Section 3 gives a brief description of Autoware. In Section 4, we explain the localization method employed in the proposed system. Section 5 presents the results of autonomous driving experiments. Finally, conclusions are drawn and further work is briefly suggested in Section 6.

2. Vehicle and sensors

We introduce a SDC platform with a set of sensors that can be purchased in the market. Intelligent modules of self-driving, such as scene recognition, path planning, and vehicle control, are located in a plug-in computer. The computer is connected to the vehicle platform through a CAN card. The computer and the set of sensors, such as cameras and Lidar sensors, were added to this basic platform so that the results of scene recognition, path planning, and vehicle control could apply to autonomous driving.

The specification of sensors and computers highly depends on the functional requirements of self-driving. As shown in figure 1, various sensors and computers are used in our prototype system:

- Velodyne Lidar sensors produce 3D point-cloud data, which can be used for localization and mapping, while also being used to measure the distance to surrounding objects. In our case, a VLP-16 is used instead of an expensive HDL-64.
- A front-looking camera (AVT Mako G-223B) is used to detect and track objects.
- The GPS/INS sensor (OxTS RT2500-RT2) can receive global positioning information from satellites. It is also coupled with gyro sensors and odometers to fix the positioning information.
The MMW Radar (Delphi ESR 77GHz) provides mid-range (60m) measurements with a wide field of view (±45°). It can be used to improve the accuracy of moving object detection by fusion with other sensors.

5G V2X communication unit (OBU) provided by ZTE Corporation can be used in the research of cooperative vehicle infrastructure systems.

A high-performance workstation, Nuvo-6108GC (Intel® Core™ i7-6700TE, NVIDIA® GPU), serves as the main computer to run most of the intelligent modules. The OS is Ubuntu 16.04 installed with ROS Kinetic. These sensors can be connected to commodity network interfaces, such as Ethernet and USB 3.0. The car is Drive-by-Wire retrofitted so that a plug-in computer can send operational commands (such as pedal strokes and steering angles) to the vehicle platform.

3. Autoware

Autoware is a software stack comprising a wide range of autonomous-driving algorithms. It can be used as a basic software platform for autonomous vehicles driven in urban areas. A brief overview regarding modules implemented in Autoware was given in [5]. It has been known as the first and probably the largest open-source project for self-driving technology.

Autoware is based on ROS (Robot Operating System) and other well-established open-source software libraries, such as PCL, CUDA, and OpenCV. Autoware uses such tools and libraries to compile a rich set of software packages, including sensing, perception, decision making, planning, and control modules. Many drive-by-wire vehicles can be transformed into self-driving vehicles with an installation of Autoware [6].

Localization is one of the most basic and important modules in self-driving. Particularly in urban areas, localization precision dominates the reliability of self-driving. Autoware use the 3D version of NDT (Normal Distribution Transform) to perform scan matching over 3D point-cloud data and 3D map data. However, as pointed in [7], 3D registration may fall into misalignment due to measurement errors, especially when using a low-definition Lidar. Our approach resolves this problem by fusing the result of 3D-NDT with the result from INS on the basis of a Kalman filtering algorithm, which will be described in the next section.

4. Localization

4.1. INS-based DR localization

Let \( x \) represents a 3D pose of the vehicle, defined at the center of its rear axle. \( x = (x, y, \theta)^T \), where \( \theta \) is the heading angle of the vehicle. \( u_i = (\Delta d_i, \Delta \theta)^T \) represents the measurement of INS from \( t-1 \) to \( t \), where \( \Delta d_i \) is the distance from \( t-1 \) to \( t \).

Given the motion model of the vehicle \( f \),

\[
f(x_{t-1}, u_t) = \begin{pmatrix} x_t \\ y_t \\ \theta_t \end{pmatrix} = \begin{pmatrix} x_{t-1} \\ y_{t-1} \\ \theta_{t-1} \end{pmatrix} + \begin{pmatrix} \Delta d_i \cos \theta_{t-1} \\ \Delta d_i \sin \theta_{t-1} \\ \Delta \theta_i \end{pmatrix}
\]

a predicted pose \( x_{p, t} \) at time \( t \) can be calculated from \( u \), and the pose at time \( t-1 \) \( x_{t-1}, P_{t-1} \).

\[
x_{p, t} = f(x_{t-1}, u_t) = \begin{pmatrix} \hat{x}_{t-1} \\ \hat{y}_{t-1} \\ \hat{\theta}_{t-1} \end{pmatrix} + \begin{pmatrix} \Delta d_i \cos \hat{\theta}_{t-1} \\ \Delta d_i \sin \hat{\theta}_{t-1} \\ \Delta \theta_i \end{pmatrix}
\]

Its uncertainty is denoted as follows:

\[
P_{p, t} = F_t P_{t-1} F_t^T + G_t Q G_t^T
\]
where \( F \) and \( G \) are Jacobian matrices of the model \( f \) upon \( x \) and \( u \) respectively. \( Q \) is the process noise covariance.

\[
F_i = \frac{\partial f}{\partial x}_{k_{i-1}, u_{k_{i-1}}} = \begin{bmatrix} 1 & 0 & -\Delta t, \sin \hat{\theta}_{i-1} \\ 0 & 1 & \Delta t, \cos \hat{\theta}_{i-1} \\ 0 & 0 & 1 \end{bmatrix}
\]

\[
G_i = \frac{\partial f}{\partial u}_{k_{i-1}, u_{k_{i-1}}} = \begin{bmatrix} \cos \hat{\theta}_{i-1} & 0 \\ \sin \hat{\theta}_{i-1} & 0 \\ 0 & 1 \end{bmatrix}
\]

### 4.2. Localization by 3D-NDT matching

To reduce the number of points, both the ND map and 3D point cloud from the Lidar are down-sampled using a voxel grid filter (VGF). The voxel size was set to 1m in this work.

Let \( Q = (q_1, q_2, ..., q_M) \) be the filtered scan points. With these notations the NDT matching problem can be stated as:

\[
\arg\max_x J(x) = \sum_{i=1}^{M} \exp \left\{ -\frac{1}{2} (p_i^n - T(x, q_i))^T \Sigma_i^{-1} (p_i^n - T(x, q_i)) \right\}
\]

where \( J(x) \) is the cost function, \( T(x, q_i) \) is the transformed point \( q_i \) relative to the center of the point distribution of the voxel to which it belongs, \( p_i^n \) and \( \Sigma_i \) are the mean point and covariance of voxel \( i \) which corresponds to \( T(x, q_i) \).

The Gauss Newton method is used to maximize the cost function. Finally, we obtained the estimated pose using NDT, \( \hat{x}_t \). More details can be found in [8].

To determine the uncertainty of \( \hat{x}_t \), we use Hessian matrix to compute its covariance matrix \( R_t \).

\[
R_t = \sigma^2 \left( \frac{\partial^2 J(x)}{\partial x^2} \right)_{k_{i-1}}^{-1}
\]

where \( \sigma^2 \) is the noise level, indicating the scale of the covariance [9]. As suggested in [10], we set this value as \( \sigma^2 = 2\varepsilon / (M-3) \), where \( \varepsilon \) is a sum of errors between corresponding points computed in the scan-matching algorithm.

### 4.3. Fusion using Kalman filtering

With the above notations and estimated covariance matrices, the localization results from 3D-NDT and INS can be fused in the framework of Kalman filtering. The pose estimation \( x_t \), and its covariance \( P_t \), are obtained as follows:

\[
e_t = \hat{x}_t - x_{gt-1}
\]

\[
S_t = R_t + P_{gt-1}
\]

\[
K_t = P_{gt-1} S_t^{-1}
\]

\[
x_t = x_{gt-1} + K_t e_t
\]
5. Experiments
Autonomous driving experiments were conducted on roads of Qianfoshan Campus (figure 2), Qilu University of Technology (Shandong Academy of Sciences). We built a 3D point cloud map of the environment in advance. As mentioned in Section 4, the initial 3D map was processed by VGF to reduce its size. Then the down-sampled map is stored in a PCD file. The route is about 530 meters long and the PCD file size is 2.3 GB. Evaluation was performed using recorded ROSBAG data during experiments. The navigation speed of the vehicle was below 25 km/h.

The robustness and accuracy of localization is being investigated using the method described in Section 4. During the localization experiment, we manually drove the car through the environment and 3D-NDT localization was performed to obtain the trajectory of the car. Then the smoothness of the trajectory was improved by using spline interpolation as described in [11]. The interpolated trajectory was used as the target path. The initial experimental results indicated that the smoothness of the estimated trajectory could be improved by fusing the 3D-NDT and INS results. This is because the trajectory estimated by INS is smoother than that determined by 3D-NDT. Detailed results will be reported in our following papers.

Figure 3 shows the process of path planning and trajectory generation based on the results of localization. As a result, a set of waypoints were generated, containing the information of pose and velocity. Then path following using the Pure-Pursuit algorithm was performed along the waypoints. Based on the results of environment perception provided by Autoware, we further established the driving risk field for our SDC prototype by using the theory described in [12]. Figure 4 represents the driving risks caused by the vehicles on a road. The driving risk field gives a quantitative evaluation of driving risks, which can serve as a foundation for decision-making and vehicle control of a SDC under complex traffic environments.

\[ P_{x} = (I - K_{x})P_{x-1} \]  

(13)
6. Conclusions and future work

Using the methodology described in this article, a SDC prototype for educational and research purposes was developed. The SDC prototype was equipped with relatively low-cost sensors (Camera, Radar, Lidar) for environment perception. It used Autoware as its software platform which provides function modules covering from sensor data processing to vehicle control and decision-making. To achieve high performance with low-cost sensors, the localization method was improved by fusing the result from 3D-NDT and the result from INS under the framework of Kalman filtering. Other function modules, such as driving risk field, were also developed. Autonomous driving experiments were conducted in a university campus environment and the results are used to show the performance.

Our future work will consider the use of a combination of multiple low-cost Lidars to further improve the localization accuracy. A localization method based on low-cost Lidars but with a HD map (created by a high-definition Liar in advance) will also be considered.

7. References

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