Research on Autonomous Driving Navigation in GNSS Denial Environment

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Abstract. With the development of the automotive industry, the status of autonomous driving technology is gradually increasing. It becomes a symbol of a country's technological strength in the automotive industry. China has also introduced a series of policies to promote the development of autonomous driving technology. In autonomous driving technology, there are three key modules: perception, decision-making, and planning. The research on positioning systems is highly valued by researchers. In positioning systems, satellite navigation systems represented by GPS and the Beidou system are the main sources of information for obtaining the location of autonomous vehicles. However, the reception of signals from satellite navigation systems is often disturbed in special weather conditions and terrain conditions. Therefore, relying on single satellite navigation systems for positioning does not satisfy the requirements of actual autonomous driving conditions. At present, to get precise positioning under the GNSS denial environments, various vehicular sensors are used to obtain the vehicle body position information. Single-sensor SLAM technology cannot satisfy the requirements of precise positioning because of the differences in working principles. The multiple sensors coupled with SLAM technology are necessary to be studied. This article mainly introduces the GNSS positioning and mapping technology based on IMU and LiDAR fusion and the advanced positioning system based on three-sensor fusion.

Keywords: Autonomous driving technology, GNSS denial environment, Vehicular Sensors; SLAM technology

1. Introduction

The automobile manufacturing industry has undergone a century of development and has become an economic pillar industry for industrial countries such as China, Japan, the United States, and Germany, making it a research hotspot for these countries. In the modern automotive industry, vehicles are not just playing a simple role as traffic transportation, they also integrate advanced technologies such as perception, navigation, and precision computing into intelligent mobile platforms. It brings a deeper in the operation of modern society. Autonomous driving technology is an important research direction for the development of the automotive industry in recent years, representing the innovation and breakthrough of technology in the traditional automotive industry. At present, autonomous driving technology has important application prospects in many fields. In the logistics industry, autonomous driving technology can be applied to the disassembly and transportation of goods industrial automation, and saving labor costs [1]. Also, autonomous mining machines can greatly improve the safety and efficiency of the mining process in the mining industry [2]. In addition, cruise vehicles equipped with autonomous driving technology can make many cumbersome tasks simple and efficient. The development of autonomous driving technology is an essential process for many areas of industries to be intelligent and automated in the future.

The core technologies of autonomous driving can be divided into three modules: perception, positioning, decision-making, and planning [3]. The positioning module can locate the current position of the vehicle by using satellite navigation systems represented by GPS or Beidou. It can also use map-matching or visual recognition systems to improve the accuracy of the positioning. The positioning module needs to make correct decisions and achieve precise control in complex environments. When a vehicle is driving, the Global Navigation Satellite System (GNSS) will sometimes fail to receive a signal due to various factors. For example, suffering from adverse weather conditions such as rain, snow, heavy fog, and sandstorms. It will affect the work of perception sensors and cameras. Roadworks will distort map data. When vehicles travel in tunnels or mountainous areas, satellite signals are also not able to be received. The following areas are known as GNSS denial environments [4]. It is difficult for vehicles to avoid driving in a GNSS denial environment. At this time, it is not feasible to obtain accurate positioning and map information solely through a single satellite navigation system. Therefore, how to maintain accurate positioning in such special environments has been a focus of research on positioning algorithms in recent years.

To maintain accurate positioning in the presence of GNSS signal interference, the position information of the vehicle and the three-dimensional features of the surrounding environment are required. To achieve these goals, vehicular sensors can generally be used to locate and perceive the environment through Simultaneous Localization and Mapping (SLAM) technology. SLAM technology can estimate the pose of a target and construct an environmental map by processing data from sensors [5]. It was initially used for route planning for robot walking and gradually expanded to the field of autonomous driving. The following text will provide a comprehensive overview and detailed analysis of the fusion processing method based on the SLAM algorithm using three types of sensors in the GNSS denial environment.

2. Requirements for SLAM technology for multi-sensor fusion

Autonomous driving intelligent vehicles are generally equipped with various sensors, including cameras, Lidar, and Inertial Measurement Units (IMU). Lidar can directly obtain three-dimensional point cloud data. It can also cooperate with IMU, achieving high-precision positioning while reconstructing the surrounding environment in three dimensions [6]. Cameras can also achieve simultaneous localization and mapping based on visual information and other sensors. The positioning based on a single sensor is always limited by external factors like temperature and light. That is because sensors have different kinds of functions and working principles. Therefore, it is necessary to integrate the performance of different sensors to make up for the defects of a single sensor and achieve mutual matching and complementarity. For example, point cloud data can compensate for the lack of depth information in image data, and image data can also supplement point cloud data in terms of feature extraction. Due to the market's demand for higher levels of automation, the requirements for positioning algorithms in automated systems are gradually increasing. It requires algorithms to possess accuracy, real-time performance, and robustness. Possessing accuracy means that the system's positioning information can provide precise position and attitude information for subsequent environmental perception and decision-making, thus achieving precise control operations to ensure driving safety. Possessing real-time means that the automatic train system can perceive and predict the surrounding environment promptly through real-time positioning information to make real-time decisions and control operations. Possessing robustness means that the positioning algorithm of the system can provide accurate and real-time positioning information in any situation. Therefore, to improve the accuracy, stability, and robustness of the algorithm, researchers couple the sensors in different ways.

3. Coupling technology of IMU and Lidar

The basic working principle of IMU is using Newton's second law to calculate short-term displacement and finally integrate it. It is mainly used for detecting and measuring acceleration and rotational motion. Most IMU sensors include accelerometer sensors and gyroscope sensors. The accelerometer sensor is used to measure the linear acceleration on three orthogonal axes and integrate the acceleration to obtain the changes in velocity and position. Gyroscope sensors are used to measure the angular velocity of three orthogonal axes. Through time integration, the angular velocity integration along the three axes will obtain the changes in roll, pitch, and yaw to obtain the changes in object attitude [7].

The IMU's measurements are based on physical laws, meaning that it does not rely on external conditions. Though the vehicle is driving in a GNSS denial environment, IMU is also able to send data continuously to ensure the safe direction of the vehicle. Although IMU navigation systems can perform relatively accurate navigation results in a short period. However, when IMU works in long-term navigation tasks, the accumulation of errors can lead to system divergence. So IMU sensors cannot be the only navigation method in driving [8]. To solve this problem, it is common to make a coupling of LiDAR and IMU. In traditional LIDIA multi-sensor fusion SLAM technology, Lidar Odometry and Mapping (LOAM), Lightweight and Ground-Optimized Lidar Odometry and Mapping on Variable Terrain (LeGO-LOAM), and tightly coupled Lidar Inertial Odometry via Smoothing and Mapping (LIO-SAM) are three of the most classic open-source algorithms. Researchers have made many modifications based on it. Wang improved the LIO-SAM algorithm in the research of a high-precision map generation algorithm based on GNSS/IMU/LiDAR [9]. The traditional LIO-SAM algorithm usually has three steps. The first step is using IMU's raw data to correct the distortion of LiDAR motion. Then the pre-integrate techniques to process the IMU data to achieve initial pose transformation between two frames of LiDAR point clouds. In this step, it will face two issues. The point cloud data near Lidar is redundant. Also, it will lack essential information when the point cloud data is in distance. To solve the problems, the article uses the conditional filtering algorithm and adds a pretreatment step for point cloud filtering. Providing the maximum and minimum values in the point cloud coordinates x, y, and z. When the coordinates of the data exceed any one of the three ranges, the algorithm considers that the data point is too far and deletes it. It also uses the radius filtering algorithm which limits the range of a circle with a radius of R to filter out the noise. The second step is to process the keyframes of the front-end odometer and use the point cloud registration algorithm based on curvature features to complete the point cloud registration between the current frame and the local map. The article added constraints on reflection intensity based on the point cloud registration algorithm. When the number of iterations approaches the threshold, compare the reflection intensity of the last 5 points. The strength difference between these 5 points and the current point is compared to determine whether the matching is successful. Finally, the impact of registration from moving objects is reduced. The third step is to optimize the backend global map by using the loop detection algorithm based on Euclidean distance and the optimization algorithm with the constraints of absolute valve data from GNSS. In this step, the author proposes a loop detection algorithm based on the combination of Scan Context and Euclidean distance. This algorithm weights the score coefficients of the two algorithms, increasing the robustness of the algorithm and improving the accuracy of loop detection. Finally, it is successful in reducing the displacement error of the dataset through the improved method mentioned above.

In addition to improving traditional algorithms, Liu proposed a method of using factor graph fusion for tightly coupled lidar and IMU, optimizing the Lidar odometer generated by the front-end registration method based on point and line feature extraction and the created map [10]. The article introduced the concept of windowing to reduce computational complexity based on the factor graph and improved the speed of optimization. It also uses the edge probability method to preserve the constraint relationship of the old framework deleted in the sliding window, adding a loopback detection module to deal with large-scale mapping problems. Then, the scanning context loop back detection method is combined with backend optimization methods to reduce mapping errors. Finally, the constraint relationships provided by loopback detection are put into the factor graph as factors to enhance the effect of optimization. Chang proposed a robust and accurate LiDAR GNSS/IMU self-calibration system consisting of two modules: the parameter initialization module and the parameter refinement module [11]. The working principle is that the time synchronization submodule first synchronizes the GNSS/IMU system measurement values based on the interpolation of the laser radar timestamp. Then the Lidar odometer estimates the pose of the Lidar by applying feature-based matching algorithms. Finally, the parameter initialization solver constructs a cost function based on the relative motion constraints between Lidar and the GNSS/IMU system, using the Levenberg Marquardt optimization to calculate the initial calibration parameters.

The parameter refinement module reduces the impact of drift in the Lidar odometer and enhances the calibration constraints in the 6-DoF parameter space. This module consists of three sub-modules: mapping, localization, and parameter update. The mapping submodule constructs a global map by concatenating point cloud data with GNSS/IMU data and estimated calibration parameters. The positioning submodule estimates the pose of the Lidar based on scanning global map matching. The parameter submodule refines the calibration parameters by minimizing the cost function constructed by relative and absolute motion constraints. Overall, the system does not rely on calibration marks and has the advantages of simple operation and a high degree of automation.

4. Three-sensor coupling technology

In recent years, with the emergence of low-cost solid-state Lidar, Lidar multi-sensor technology has been widely used in the field of autonomous driving technology. However, this system will still fail without receiving sufficient geometric features. Therefore, it is necessary to integrate other sensors such as camera sensors to enhance the robustness and accuracy of the system.

R3LIVE is a new fusion framework consisting of Lidar inertial and visual sensors. This framework utilizes the Error-State Kalman Filtering (ESKF) to tightly couple Lidar Inertial Odometry (LIO) with Visual Inertial Odometry (VIO) to achieve mutual state optimization. It allows to structure of the geometry by LIO and rendering texture by VIO at the same time, facilitating real-time dense 3D reconstruction of environment RGB-D maps. However, in the VIO sub-system, when laser map points are projected onto image frames, problems such as point duplication, occlusion, and discontinuous levels of depth in edge often occur between contiguous image frames, seriously affecting the accuracy of the VIO system. To deal with the issues, Geng et al. proposed an improved R3LIVE algorithm based on outlier rejection and boundary rendering [12]. The author projects the previously scanned map points onto the camera coordinate system in the VIO system and takes a selection process to only reserve the map points with the best state for visual localization and mapping. In the global mapping thread, contiguous pixels are compared, and edge rendering points are identified based on the specified pixel chromatism threshold. Non-edge points are smoothed by using bilinear interpolation, while edge points are directly rendered by using nearest neighbour interpolation. This method preserves the smooth rendering effect. Also, it reduces the impact of noise colours on the map, effectively solving the problem of the appearing blue points and the building of edges when the dense point cloud map is constructed. Lang et al. proposed a realistic Lidar inertial camera SLAM with 3D Gaussian scattering, named Gaussian LIC. This system integrates the Neural Radiance Fields (NERF) SLAM system and the 3D Gaussian Scattering (3DGS) [14, 15, 16]. It also integrated the system with 3D Lidar, IMU, and camera sensors. The system uses sequentially coloured LiDAR point clouds as before to reconstruct Gaussian maps online. Using a carefully designed series of strategies, gradually expand the Gaussian map and adaptively control its density to achieve high efficiency and accuracy. It achieved highly accurate posture tracking and realistic online map construction. It can keep its robustness under harsh conditions like highly dynamic motion, low lighting, and the absence of geometric structure and visual texture, having significantly better generalization ability in indoor and outdoor scenes.

5. Conclusion

With the problem of inaccurate positioning results caused by the disturbance of signal reception in the GNSS denial environment, the article introduced the research direction of using vehicular sensors for assisted positioning. The article summarized the traditional LIDIA multi-sensor SLAM technology and the current research on its optimization and improvement from different directions. In response to the requirements to achieve higher accuracy and robustness in map construction, it also summarized an advanced fusion framework consisting of Lidar, inertial, and visual sensors.

With the development of autonomous driving technology, precise positioning in GNSS denial environments has become an increasingly important research emphasis to meet the requirements of driving in complex terrains. The research on vehicle sensor positioning algorithms has also become an essential topic. At present, single SLAM technologies such as laser SLAM and visual SLAM algorithms have become mature. However, due to the limitations of receiving information from a single sensor, the accuracy and robustness of the system are not able to satisfy the requirements of the safety driving in GNSS denial environments. Therefore, it is necessary to integrate more kinds of sensors to receive various site information accurately and reduce errors. However, the mutual matching and coupling of different sensors is still a major difficulty in the research. It is necessary to optimize the algorithm or introduce new technologies in other fields to solve the problem. It can be two of the feasible directions in future research.

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