3D LiDAR-GPS/IMU Calibration Based on Hand-Eye Calibration Model for Unmanned Vehicle

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***Abstract*—For the unmanned vehicle, multi-line LiDAR (Light Detection and Ranging) and GPS/IMU are often used in conjunction for SLAM or the production of high-precision maps. To improve the accuracy of navigation as well as map building, the extrinsic parameters calibration of LiDAR and GPS/IMU is often required. In response to the problem of insufficient conditions in the calibration of LiDAR and GPS/IMU for unmanned vehicle, this paper proposes a decoupling method, grouping the extrinsic parameters for calibration, and finally merges the point clouds with the pose obtained by the GPS/IMU before and after calibration to get environment reconstruction results. With the reconstruction results before and after calibration, it is verified that the method proposed is effective.**

***Index Terms*—LiDAR-GPS/IMU joint calibration, distortion correction, multi-sensor fusion**

I. Introduction

In the field of autonomous driving, certain tasks require more than one kind of sensor to complete. Multi-sensor fusion has become one of the common technical methods for automatic driving. For example, the camera and the LiDAR are required for target ranging and the camera and the IMU are required for VIO (Visual-Inertial Odometry). The first step of the multi-sensor fusion algorithm is the calibration of the parameters between the sensors. The sensor calibration of autonomous driving needs to use the data collected by sensors to calculate the intrinsic parameters of the individual sensor and the extrinsic parameters between multiple sensors, so that the coordinate systems of the multiple sensors can be unified. On unmanned platforms, 3D LiDAR is devoted to sense the environmental information around the vehicle, usually installed on the top of the vehicle near the front of the vehicle, as shown in Fig. 1, and the GPS/IMU is responsible for measuring the vehicle's latitude, longitude and angles around the axises of the world coordinate system. On the steering vehicle platforms, GPS/IMU is usually installed on the vertical centerline of the rear axle of the vehicle. 3D LiDAR and GPS/IMU are common sensor configurations in LiDAR SLAM(Simultaneous Localization and Mapping) and high-precision map building. For high-precision mapping, if the point cloud is stitched with the pose that directly output by GPS/IMU without calibration, it will be easy to produce erroneous results.

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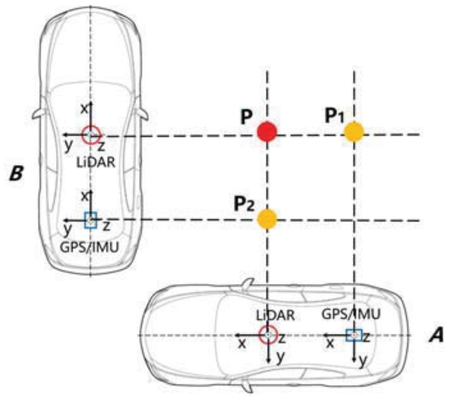


Fig. 1. The importance of LiDAR-GPS/IMU joint calibration. Without calibration, the point P will be recognized as P_1 and P_2 in different places.

As shown in Fig. 1, when the unmanned vehicle is at the position A, if the point P observed by the LiDAR is represented by the position output by the GPS/IMU, the point P will be changed to P_1. When the vehicle travels to the position B, similarly, if an uncalibrated GPS/IMU pose is used, it will cause point P in the LiDAR coordinate system to be moved to point P_2. Due to the inconsistency of the coordinate system, the point P produces two points P_1 and P_2, and it is easy to produce misalignment of the point cloud during the construction of the map and cause ghosting of the object. For SLAM, point cloud from LiDAR needs to use data from GPS/IMU for point cloud distortion correction and initial pose selection, etc. Without calibration, errors are likely to occur, especially in tightly-coupled LiDAR-IMU SLAM, the accuracy of the localization will be lowered. Therefore, the joint calibration of LiDAR and GPS/IMU is of great significance for the map-building and navigation of driverless vehicles.

Since the intrinsic parameters of IMU and LiDAR are usually provided by the manufacturer when sensors are shipped, this paper mainly solves the extrinsic parameter calibration between LiDAR and GPS/IMU. For the joint calibration between different sensors, a lot of researches have focused on the joint calibration of camera- LiDAR and camera-IMU. However, few works focus on the LiDAR-IMU calibration or LiDAR-GPS/IMU calibration. The extrinsic parameters of LiDAR-IMU can be solved by camera-IMU calibration and camera-LiDAR calibration mathematically. However, in fact, for driverless vehicles, it is difficult for GPS/IMU to obtain enough excitation in six degrees of freedom, which leads to the difficulty of camera-IMU and LiDAR-IMU calibration in driverless vehicles. This paper proposes a decoupling method of joint calibration of LiDAR and GPS/IMU based on the hand-eye calibration model. The extrinsic parameters of the LiDAR and GPS/IMU are divided into two groups separately by decoupling, and finally optimized to complete calibration.

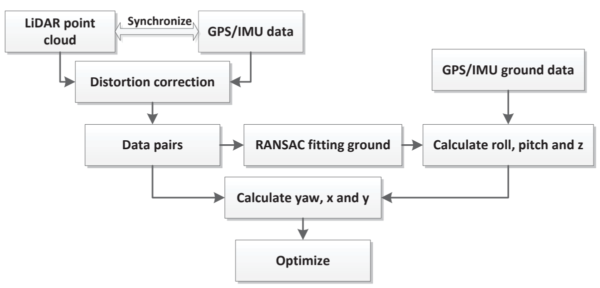


Fig. 2. The flow of the method proposed.

The flow of this method is shown in Fig. 2. It is mainly divided into three parts, including preparation of calibration data, calculation of $roll$, $pitch$ and z, and calculation of the remaining yaw, x and y.

The rest of this paper is arranged as follows: Section II introduces the related research on 3D LiDAR and GPS/IMU calibration; Section III introduces the preparation of calibration data; Section IV introduces the principle and method used for calibration; Section V evaluates the calibration results through the 3D reconstruction using point cloud; finally, Section VI summarizes the entire article and points out further work.

II. Related Research

In order to solve the transform relationship between the multi-line LiDAR and the IMU, Geiger et al. [1] propose an approach by solving a hand-eye problem [2]. This method needs to record a sequence with an '∞'-loop and gets two trajectories from the sequence with respect to the IMU and the LiDAR, respectively. Baidu's open source Apollo project [3] also requires an '∞'-loop and the driving time needs to be more than two minutes to ensure IMU has available data for calibration. Cedric et al. [4] present a probabilistic framework to recover the extrinsic calibration parameters of a LiDAR-IMU sensing system. The motion distortion of 3D-point clouds is removed based on preintegrated measurements over interpolated IMU readings. To recover the calibration parameters of Lidar and IMU, they fit the plane in the environment and construct an optimization equation according to the point-plane distance of the point cloud . Similarly, Jiajun Lyu et al. [5] construct an environmental point cloud map in advance and fits the plane in it, calculate the distance from the laser point to any plane and make the problem expressed as a maximum likelihood estimate.

These methods are effective for robots that can be calibrated indoors, because they can use strong constraints such as indoor corner planes or vertical walls for registration. However, for outdoor driverless vehicles, the constraints between them and the surrounding buildings are weaker. Insufficient plane constraints can easily lead to the failure of calibration. The Autonomous Driving Laboratory of ETH Zurich has released its LiDAR-IMU calibration source code [6]. According to the conversion between LiDAR and IMU, they merge multi-frame point clouds into one single point cloud, computing the sum of the distance between each point and its nearest neighbor. The distance can be minimized by repeating this process until find the transformation. However, the above method relies on non-planar motion, which is not easy for unmanned vehicles to provide such motion. Wu Yuhan et al. [7] use corner reflectors as markers to convert the joint calibration into point cloud matching to solve the coordinate transformation between LiDAR and IMU.

III. Calibration Data Preparation

A. Point Cloud Distortion Correction

For LiDAR, the coordinate value of the single point is relative to the origin of the LiDAR coordinate system at the time of laser emission. Since the mechanical rotating LiDAR takes a certain time to make one revolution, the movement of the vehicle will cause the origin of the LiDAR change constantly, resulting in a certain deviation of the obtained point cloud from the actual environment, which is point cloud distortion. The faster the vehicle moves or the faster the attitude angle changes, the greater the distortion of the point cloud will be. If a distorted point cloud is used for calibration, it will obviously cause errors, so the distortion of the point cloud should be corrected before the calibration data is used. According to the GPS/IMU, the vehicle speed ν and angular velocity ω can be obtained. Based on the constant-velocity moving model, the point cloud of each frame can be converted to the vehicle coordinate system at the reference time stamp t_0 of the frame using ν and ω. The original point is taken as $P_{s,k}$, the obtained time is t_k, and the point after distortion correction $P_{d,k}$ can be solved:

$$\begin{cases} R_k = F\left(\omega\left(t_k - t_0\right)\right) \\ p_k = \nu\left(t_k - t_0\right) \\ P_{d,k} = R_k P_{s,k} + p_k \end{cases} \tag{1}$$

where $F(\boldsymbol{.})$ represents the conversion function of euler angle to rotation matrix, R_k represents the rotation matrix between the original point and the correction point, and p_k represents the translation vector. After correcting each point in the point cloud, the point cloud of the current frame can be converted to the coordinate system at the reference time t_0 to finish the point cloud distortion correction.

B. LiDAR-GPS/IMU Data Pairs Selection

The calibration data should be collected during the driving of the vehicle. During the collection, time synchronization between point cloud from LiDAR and pose from GPS/IMU is necessary. Each frame of point cloud after distortion correction and its corresponding pose data form a point cloud-pose data pair. The range of the change of the angle between different data pairs should be within a reasonable range. Data pairs with a variation range of 10 ° to 50 ° are selected. To simplify calculation, the position information such as latitude and longitude given by the GPS/IMU is converted to a plane coordinate system.

IV. Methodology

A. Establishment of Calibration Equations

Let us consider a system with a rigidly mounted 3D LiDAR and a GPS/IMU, as shown in Fig. 3, $O_1X_1Y_1Z_1$ is the GPS/IMU coordinate system, $O_2X_2Y_2Z_2$ is LiDAR the coordinate system, the purpose of LiDAR-GPS/IMU joint calibration is to find the transformation matrix between the two coordinate systems, which can be expressed as $T_L^I = \begin{bmatrix} R_L^I & t_L^I \\ 0^T & 1 \end{bmatrix}$, where $t_L^I = \begin{bmatrix} t_x & t_y & t_z \end{bmatrix}^T$, and R_L^I can be expressed by pitch angle θ, roll angle γ and yaw angle ψ:

$$R_L^I = \begin{bmatrix} c\gamma\, c\psi + s\gamma\, s\theta\, s\psi & s\gamma\, s\theta\, s\psi - c\gamma\, s\psi & -s\gamma\, c\theta \\ c\theta\, s\psi & c\theta\, c\psi & s\theta \\ s\gamma\, c\psi - c\gamma\, s\theta\, s\psi & -c\gamma\, s\theta\, c\psi - s\gamma\, s\psi & c\gamma\, c\theta \end{bmatrix}$$

c means $\cos(\cdot)$ and s means $\sin(\cdot)$

When six parameters are calculated, the conversion relationship of the coordinate system can be obtained.

As shown in Fig. 1, T_{LA}^W and T_{LB}^W are the pose of the LiDAR coordinate system relative to the world coordinate system and T_{IA}^W and T_{IB}^W are the pose of the GPS/IMU coordinate system relative to the world coordinate system when the vehicle is at the A and B position respectively. The equation can be established as

$$T_W^{IA} \cdot T_{IB}^W \cdot T_L^I = T_L^I \cdot T_W^{LA} \cdot T_{LB}^W \tag{2}$$

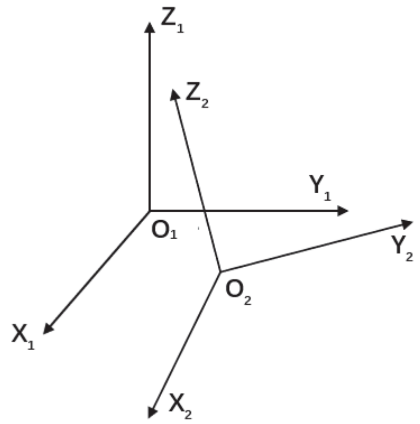


Fig. 3. The relationship between the LiDAR and GPS/IMU coordinate systems.

Furthermore , we can get:

$$T_{IB}^{IA} \cdot T_L^I = T_L^I \cdot T_{LB}^{LA} \tag{3}$$

which is the classic hand-eye calibration equation. This equation can be solved by decoupling rotation and translation. Expand (2) into:

$$\begin{bmatrix} R_I & t_I \\ 0^T & 1 \end{bmatrix} \cdot \begin{bmatrix} R_L^I & t_L^I \\ 0^T & 1 \end{bmatrix} = \begin{bmatrix} R_L^I & t_L^I \\ 0^T & 1 \end{bmatrix} \cdot \begin{bmatrix} R_L & t_L \\ 0^T & 1 \end{bmatrix} \tag{4}$$

the following equations can be got:

$$R_I R_L^I = R_L^I R_L \tag{5}$$

$$\left(R_I - I\right) t_L^I = R_L^I t_L - t_I \tag{6}$$

Equation (5) is only related to rotation, so the rotation parameters can be solved firstly from (5), and then are substituted into (6) to solve the translation parameters. T_L^I can be obtained as long as multiple sets of data are collected theoretically.

However, the solution of T_L^I needs to meet the 'non-parallel' condition, which means the rotation axes of the vehicle movement can not be all parallel or nearly parallel, otherwise it will be hard to find an unique solution or get an accurate solution. For unmanned vehicles driving on flat ground, the changes of pitch angle and roll angle are both very small, while a large change can be created in the yaw angle. Consequently, when the vehicle is moving on the plane, only three linearly independent equations can be obtained and cannot solve uniquely of the transformation matrix between the two coordinate systems [8]. The only way to get the solution is to add more linearly independent equations, which requires the vehicle moves with a large change in roll angle and pitch angle, but the vehicle often cannot collect such data due to space constraints. A decoupling method is now proposed to supplement the linearly independent equations, so that the equations can have the unique solution.

B. Calibration of γ, θ and z

During the installation of Lidar and GPS/IMU, the Z axis of two coordinate systems should be parallel or nearly parallel. Since the SLAM system is not sensitive to height information, the parameter z can be obtained directly by measuring the height difference between the origins of the two coordinate systems. When calibrating γ and θ, GPS/IMU needs to be placed on the ground firstly and the output pose T_g at this time can be read directly. Then GPS/IMU is fixed at the installation place inside vehicle. In the same way, the pose T_I can be obtained when it is installed on the vehicle. The rotation matrix of the GPS/IMU installation position relative to the ground R_I^g can be obtained from T_I and T_g. To get the LiDAR pose relative to the ground R_L^g, the point cloud data is collected at that time, which including the ground, and the RANSAC-based plane-fitting algorithm [9] is applied to get the plane parameters of the ground $ax + by + cz + d = 0$, thereby obtaining the normal vector of the fitted ground plane in the LiDAR coordinate system $\begin{bmatrix} a & b & c \end{bmatrix}^T$. For the ground coordinate system where the vehicle is located, the normal vector can be regarded as $\begin{bmatrix} 0 & 0 & 1 \end{bmatrix}^T$, and the rotation information of the LiDAR coordinate system relative to the ground R_L^g can be obtained. After calculating the R_L^g and R_I^g, the relative pose between the GPS/IMU and LiDAR coordinate systems can be obtained:

$$R_L^I = R_g^I \cdot R_L^g \tag{7}$$

Since the yaw angle ψ is unobservable during this part of the calibration process, only the γ and θ are valid.

C. Calibration of ψ, x and y

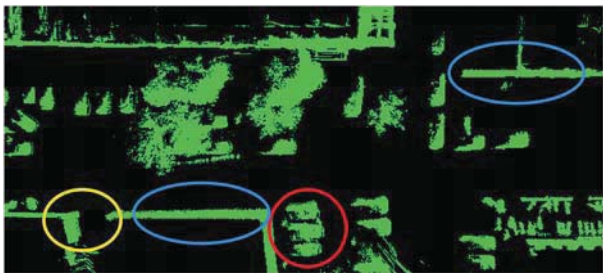
Since the z, γ and θ have been solved, substituting these parameters into the extrinsic matrix, the transform relationship between the corrected LiDAR and the GPS/IMU coordinate system only includes the translation in the X-Y plane and the rotation around the Z axis, which causes a dimensionality reduction, turning a 3D problem into a 2D problem and leaving three unknowns to solve. Therefore, these three parameters can be solved by the plane motion of the vehicle. Therefore, in (2), T_{IB}^{IA} can be calculated from data output by the GPS/IMU at the A and B positions and T_{LB}^{LA} can be obtained by applying the GICP algorithm or NDT algorithm for point cloud matching. Based on the collected several data pairs, the Ceres library [10] is used for calculation optimization, so as to obtain the yaw angle in the relative pose and the displacement in the x and y directions. It can be approved that the large-angle and small-displacement movement of the vehicle will improve the calibration accuracy [11].

V. Experiment

The unmanned vehicle platform shown in Fig. 4 is used in the experiment. A 32-line velodyne LiDAR and GPS/IMU are installed on the platform. For both coordinate systems, the axis X, Y, Z are in forward, left and upward dirction, respectively. In order to verify the validity of the method proposed, the pose of the GPS/IMU before and after calibration is used to merge multi-frame distortion-corrected point clouds for 3D reconstruction.

Fig. 4. Experiment platform.

Fig. 5(a) and Fig. 5(b) show the three-dimensional reconstruction results before and after calibration, respectively. The ground truth in the yellow part is an unfolded door, the blue part is actually wall surfaces, and the red part is several stationary vehicles. It can be seen that the ghosting occurs in the reconstruction result before the calibration, the wall surfaces appear thicker, and the contours of the doors, vehicles, or other objects are not clear and are difficult to recognize. In contrast, the reconstruction result after the calibration is much more clearer obviously.



(a) 3D reconstruction result before calibration

(b) 3D reconstruction result after calibration

Fig. 5. The calibration results.

VI. Conclusion and Future Work

This paper proposes an effective calibration method for LiDAR and GPS/IMU based on the hand-eye calibration model for unmanned vehicles. The decoupling method is used to divide the six degrees of freedom pose into two groups. By collecting the pose when the GPS/IMU is put on the ground and fitting the ground plane from point cloud, the pitch angle, roll angle and the translation on the Z axis are solved and successfully transforms the three-dimensional problem into a two-dimensional problem. According to the hand-eye calibration model, the final extrinsic matrix is obtained through several data pairs at different time. This method does not need to set a special calibration object and can obtain the unique solution by adding several linear equations, which are established by collectiong the ground data. Through the experiment performed in real vehicle, the three-dimensional reconstruction result before the calibration are compared with the reconstruction result after calibration to verify the calibration effect. Furthermore, manual measurment and lack of the evaluation indicators will be lucubrated to achieve the better results in the future.

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