INTEGRATED NAVIGATION METHOD OF ELECTRIC FORKLIFT BASED ON IMPROVED UKF ALGORITHM
/
基于改进扩展卡尔曼滤波算法的电动叉车组合导航定位方法

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ABSTRACT
When forklifts are used to move stored crops in a storage environment, the positioning system is severely affected by the presence of multiple stored crops and shelves and other complex factors in the environment. Aiming at the problems of low positioning and navigation accuracy and large accumulated error of forklift system, a Lidar/IMU integrated navigation and positioning method is proposed in this paper, which can improve the positioning accuracy of forklift truck in storage environment. Meanwhile, the improved EKF filtering algorithm is proposed in this paper which can optimize the navigation and positioning system. This method first extracts the environmental information obtained from Lidar scan measurements and the attitude information collected by the IMU. Then the output data from the two sensors are processed with the improved EKF filtering algorithm, which can improve the navigation and positioning accuracy when the forklift is working. The Lidar/IMU integrated navigation and positioning method proposed in this paper is validated by experiments simulating forklifts working in a warehouse environment in the laboratory. Through simulation experiments, it is verified that the improved EKF filtering algorithm in this paper can improve the positioning accuracy of forklift truck, accuracy of forklift movement trajectory, closer to the expected trajectory.

摘要
叉车在仓储环境中搬运储存农作物时，定位系统受环境中多储存农作物以及置物架等复杂因素影响严重。本文针对叉车系统定位导航精度低、累积误差大的问题，提出了一种 Lidar/IMU 相融合的导航定位方法，可以提高叉车在仓储环境下的定位精度。同时改进 EKF 滤波算法，能够优化本文提出的导航定位系统。此方法首先将 Lidar 扫描测量得到的环境信息提取，然后使用改进 EKF 滤波算法处理两个传感器的输出数据，能够提高叉车工作时的导航定位精度。通过在实验室内模拟叉车在仓储环境工作的实验，验证了本文提出的 Lidar/IMU 组合导航定位方法的有效性。又通过仿真实验，验证了本文改进的 EKF 滤波算法，可以提高叉车的定位精度，能够提高叉车移动轨迹的精度，更接近于预期轨迹。

INTRODUCTION
With a large number of intelligent equipment used in the crop storage and transportation industry, warehouse intelligent forklift as a new kind of handling and stacking equipment, the storage protection of agricultural products has been greatly improved (*Goran., et al., 2016*). In the task of moving agricultural products to warehouses for storage, warehouse forklifts are commonly used in the warehousing industry because of their compact body, flexible movement, light weight and good environmental performance, which can greatly save manpower and time when moving and storing agricultural products (*Nguyen., et al., 2020*). As the electric forklift adopts new navigation and positioning technology, it makes forklift more convenient and flexible to run in the narrow aisles in the warehouse. The warehouse forklift is specifically transformed on the basis of ordinary forward-moving electric forklift, which is a kind of equipment specially used for small-scale handling and stacking. It retains the original stacking and handling characteristics of the forklift, but adds the function applicable to autonomous navigation, which is very suitable for working in agricultural products storage warehouses with low operational intensity and low stacking height requirements.

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The traditional positioning methods mainly include: odometer projection positioning, magnetic guide positioning, ultrasonic positioning, visual positioning, etc. A method based on robust laser-inertial odometry and map building is proposed to be applied to the positioning system, which can jointly optimize Lidar and INS measurement data. But the data volume of this method is too large and the real-time performance of positioning cannot be guaranteed (*Zhao S. et al., 2019*). Tightly coupled frame-based Lidar inertial state estimator can be used in low-noise indoor environments, but not in high-noise environments (*Neuhaus et al., 2018*). Monocular vision methods are proposed for navigation working, but the system takes too long time to process the image information from the camera (*Faessler et al., 2015*). Since forklifts work in a complex environment with many stacked crops and storage racks, the requirements for getting accurate information about the current environment and their own precise positioning are very high. To solve the problem that electric forklifts can be accurately navigated and positioned indoors, this paper proposes a combined navigation and positioning system based on electric forklifts in complex environments, using the combined navigation technology of Lidar (Light Detection and Ranging) and IMU (Inertial Measurement Unit) to enable forklifts to perform high-precision navigation and positioning work in complex warehouse environments.

In navigation and positioning, the system models all have some degree of nonlinearity. To solve the problem of nonlinear filtering, scholars have focused on the fusion of multiple sensor data to achieve better localisation algorithms. An improved Rao-Blackwellized Particle Filter (RBPF) method combines motion odometer and laser measurement data to obtain an accurate map, which can solve the problem of particle weight degradation, but the structure model is complicated (*Wang X. et al., 2020*). A Kalman filter based on the minimum error derived under the Gaussian assumption and the minimum mean square error criterion improves the robustness to pulses. But the effect is not ideal for the case of non-Gaussian noise (*Benzerrouk. et al., 2020*). A Kalman filter based on the inertial navigation error compensation model has higher accuracy than ordinary navigation systems and can monitor the accuracy of error estimation in real time (*Zhao X. et al., 2019*). An adaptive fading Kalman filter is used as a processing algorithm for target tracking, which improves the filter gain and effectively improves the progress of target tracking, but the ability to adapt to noise is not ideal (*Yan C. et al., 2020*).

When there is an error in the system or there is external noise, the filtering ability of the EKF algorithm is lower than its normal accuracy, even divergence occurs (*Kayacan E. et al., 2019*). To solve the problems of low positioning and navigation accuracy and large accumulated error of forklift system, a Lidar /IMU integrated navigation and positioning method is proposed in this paper (*Gentil C.L. et al., 2018*). Meanwhile, an improved filtering algorithm for Lidar/IMU integrated navigation is proposed based on the fading algorithm. The improved filtering algorithm is obtained by improving from the traditional EKF algorithm (*Mouayad S., et al., 2020*). Through simulation experiments, it is verified that the improved filtering algorithm can effectively combine the position and attitude observations from Lidar with the position and attitude results from IMU. It can improve the positioning accuracy of the motion trajectory of the forklift system. The combined Lidar/IMU navigation method is proved to be feasible by simulating forklift work in the laboratory. This method is able to obtain higher accuracy and robust positioning results when forklifts work in noisy and complex crop storage environments.

MATERIALS AND METHODS

Integrated navigation solution

The use of Lidar alone for positioning and navigation not only requires a lot of calculation, but also has the problem of slow map construction, and it also causes accumulated errors as the composition time increases. In an indoor environment, the traditional GNSS method fails and cannot be positioned (*Wang J., et al., 2017*). The introduction of multiple sensors can improve the shortcomings of the traditional positioning system. The IMU has a high update frequency per unit time, and the introduction of IMU can effectively reduce the cumulative positioning error of the Lidar. At the same time, it also avoids accumulated navigation errors caused by long-term use of IMU alone. Therefore, this paper adopts the combined positioning method based on Lidar/IMU to improve the accuracy of the mobile robot's indoor positioning. By the Kalman filter algorithm, different sensor data can be effectively fused to obtain more accurate positioning information. The paper uses an improved EKF algorithm to process sensor data to improve the stability and positioning accuracy of the system. The system block diagram is shown in Fig. 1.

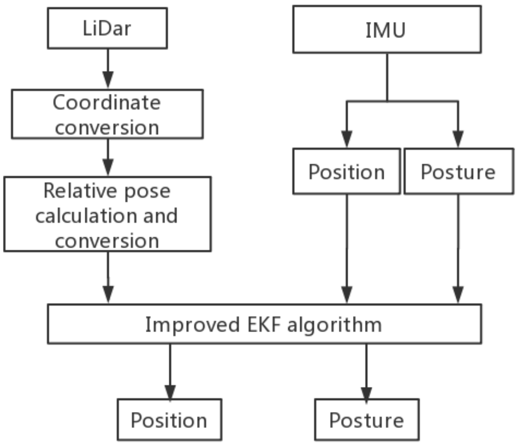


Fig. 1 – Lidar and IMU Combined System Model

Lidar Measurement model

The Lidar scanning environment has a relatively long range and it is suitable for working in a warehouse environment where attitude and position information can be obtained by scanning the environment. Lidar is widely used in the field of SLAM (Simultaneous Localization and Mapping) (*Li Xinlei., et al., 2020*), and the original data collected are polar points in the local coordinate system. Based on the feedback time from the laser pulse to the received pulse, the angle and distance between the measured object and the sensor are calculated and measured by the Lidar, which continuously updates the IMU data by scanning the indoor environment and processing the extracted information. Lidar measurement model is shown in Fig. 2. The Lidar is placed on the top of the forklift in the electric forklift system designed in this paper, as shown in Fig. 3.

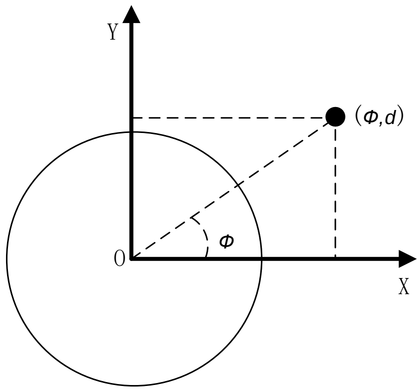


Fig. 2 – Lidar measurement model

Fig. 3 – Forklift equipment with Lidar

The formula commonly used in the conversion of polar coordinates collected by Lidar to direct coordinates is:

$$\left.\begin{aligned} x &= d\cos\phi \\ y &= d\sin\phi \end{aligned}\right\} \tag{1}$$

Lidar, forklift and world coordinate systems are shown in Fig. 4. Lidar scans 360° on forklift to get feature points, and Q is assumed to be a point returned by the laser beam.

For any feature point Q, the vector from the Lidar to point Q is:

$$T_{LQ} = T_{WQ} - (T_{WF} + T_{FL}) \tag{2}$$

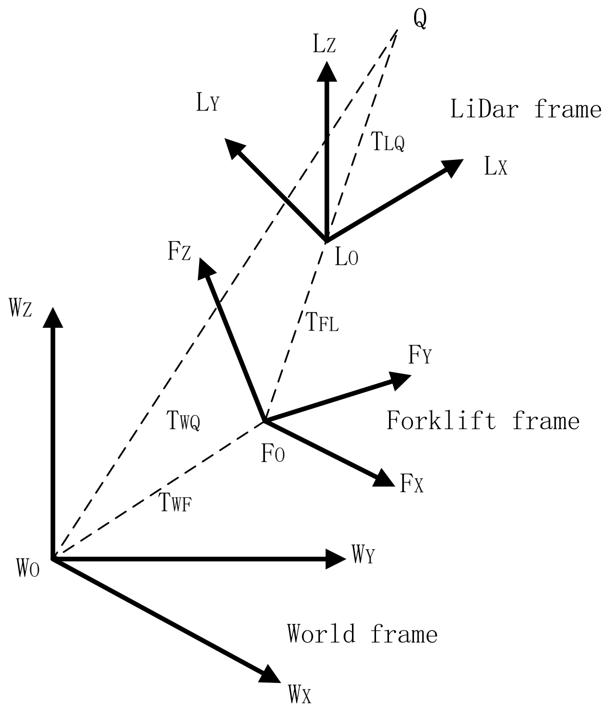


Fig. 4 – Lidar, Forklift and World Coordinate System and feature point Q

When the forklift is moving crops in a storage environment, the Lidar placed on top of the vehicle scans for obstacles with height h. Thus, ${T_{WQ}}^{W}(h)$ denotes the vector of height h from T to the feature point Q in the world coordinate system, the vector equation is:

$${T_{WQ}}^{W}(h) = {T_{LQ}}^{W} + h\, e_1 \tag{3}$$

where: h is a scalar, $h \in (0, +\infty)$, vector e_1 parallel and perpendicular to the line, e_1 = [0, 0, 1]^T.

For any feature point Q with height h, the equation (2) still holds in all coordinate systems.

In vector equation (2) and in Fig.4, T_{WQ} is a known constant in the world coordinate system. T_{WF} can be calculated in the world coordinate system, T_{FL} is known in the forklift coordinate system and it can be determined by pre-calibration. Define R_F^L as the rotation matrix from the forklift coordinate system to the Lidar coordinate system. So, this yields the vector of feature point Q in the Lidar coordinate system denoted as:

$$T_{LQ}^{L} = R_F^L\left(R_W^F\left(T_{WQ}^W - T_{WF}^W\right) - T_{FL}^F\right) \tag{4}$$

Substitute equation (3) into equation (4) to obtain the equation, which is the vector from the Lidar origin to the feature point with height h :

$$T_{LQ}^{L} = R_F^L(R_W^F(T_{LQ}^W + h\, e_1 - T_{WF}^W) - T_{FL}^F) \tag{5}$$

Expanding the equation (5), the theoretical coordinates of $T_{LQ}^{L}(h)$ in the -LZ direction are obtained as:

$$Z(h) = e_1^W\ T_{LW}^L(h) = h\ e_1^W\, R_F^L\ R_W^F\ e_1 + e_1^W\ R_F^L\left(R_W^F\left(T_{WQ}^W - T_{WF}^W\right) - T_{FL}^F\right) \tag{6}$$

For single plane Lidar, scan plane *LZ=0* in the coordinate system.

The Lidar measurement model is obtained as:

$$T_{LQ}^{L}(h) = R_F^L \left(R_W^F \left(T_{WQ}^W - \frac{e_1^W \, R_F^L \, \left(R_W^F \left(T_{WQ}^W - T_{WF}^W \right) - T_{FL}^F \right)}{e_1^W \, R_F^L \, e_1} \, e_1 - T_{WF}^W \right) - T_{FL}^F \right) \tag{7}$$

Inertial Measurement Unit measurement model

IMU is a motion sensing sensor, different from the environmental sensing sensor Lidar. It measures the angular velocity of the carrier relative to the coordinate axes and the acceleration of the carrier in the carrier coordinate system using 3-axis gyroscope and 3-axis accelerometer. Based on the acceleration and angular velocity of the IMU in 3D space, the system solves for the attitude of the carrier. During the initial operation of the IMU, environmental problems will cause errors, and the error will accumulate as time increases. Error and noise caused by environmental factors should be considered during IMU operation. Due to the existence of deviation, the measured value of IMU will drift over time. This paper adopts the method of IMU and Lidar integration. Assuming that e is the error and n is the noise, the noise is Gaussian white noise and mean value is 0. The schematic diagram of the IMU system is shown in Fig.5.

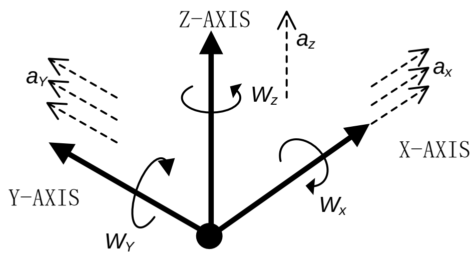


Fig. 5 – Schematic diagram of the IMU system

The data output from the IMU is the information measured by the gyroscope and accelerometer. The speed, position and attitude of the forklift truck can be obtained after these data are calculated. The state *C* of the forklift can be expressed as:

$$C = [R^T, P^T, v^T, b^T] \tag{8}$$

where R refers to 3×3 rotation matrix, P refers to 1×3 location matrix, v refers to forklift speed, b refers to bias of IMU. b can be expressed as:

$$b = [b^g, b^a] \tag{9}$$

where b^g, b^a refer to bias of gyroscopes and accelerometers.

Based on IMU raw data angular velocity w and acceleration a, measured values $\hat{w}$ and $\hat{a}$ are influenced by the white noise n and the bias b :

$$\hat{w}(t) = w(t) + b^w(t) + n^w(t) \tag{10}$$

$$\hat{a}(t) = R_W^F(t)(a(t) - g) + b^a(t) + n^a(t) \tag{11}$$

where define R_W^F as the rotation matrix from the world coordinate system to the forklift coordinate system, g refers to acceleration of gravity in world coordinates.

Based on the measured values of the IMU, the rotation, position and speed of the forklift at time t are shown in (12)-(14):

$$R(t + \Delta t) = R(t)\, exp((\hat{w}(t) - b^w(t) - n^w(t))\Delta t) \tag{12}$$

$$P(t + \Delta t) = P(t) + v(t)\Delta t + \frac{1}{2} g t^2 + \frac{1}{2} R(t)(\hat{a}(t) - b^a(t) - n^a(t))\Delta t^2 \tag{13}$$

$$v(t + \Delta t) = v(t) + g\Delta t + R(t)(\hat{a}(t) - b^a(t) - n^a(t))\Delta t \tag{14}$$

Laser SLAM model

Laser SLAM takes IMU data, odometer data, and Lidar data as input information, and outputs the scanned raster map. Laser SLAM mainly includes five steps, and the process is shown in Fig.6.

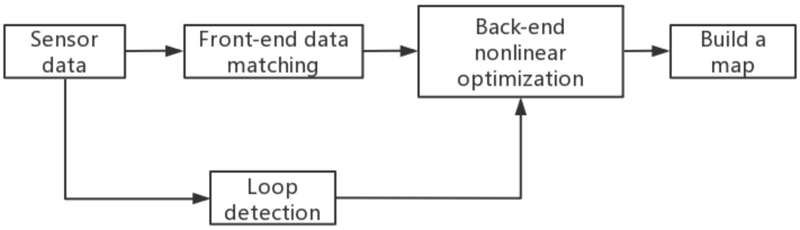


Fig. 6 – The General Flow of Laser SLAM

This map-building method requires information on the coordinate transformation (TF) between the robot base coordinates and the sensor, Lidar information and IMU information. Forklift systems have met the requirements for building maps. After inputting the Lidar data and IMU data, the system will get the a priori bit attitude at the first time. It will determine whether the two sensors' data are valid according to the defined data flow. Then it incorporates the corresponding data of the valid flag bits into the filter for processing. Finally, the posterior pose is obtained and it outputs the map information. The indoor environment map obtained from the forklift system scan is shown in Fig. 7. The Gray areas and black blocks are obstacles.

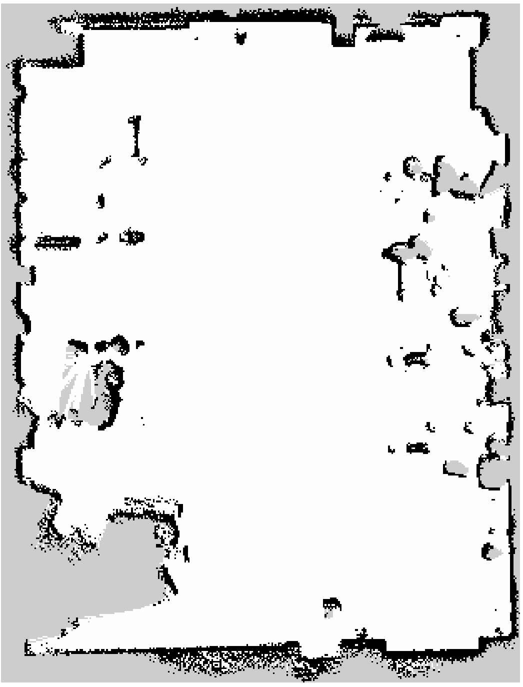


Fig. 7 – Laser SLAM Scans the Map

Fusion navigation and positioning based on Lidar/IMU

Firstly, solve the Lidar data to obtain position and attitude observations of the forklift. Then, blend the information obtained from Lidar and position, attitude information obtained from IMU data calculated by SINS (Strapdown Inertial Navigation System) algorithm. Finally, the fusion information is used as input to the EKF algorithm. Both Lidar and IMU are independent in terms of acquiring data that can be calibrated against each other based on the results of the solution. So, the positioning accuracy obtained is more reliable. If one of the Lidar and IMU sensors stops collecting due to environmental influences or its own factors, then another sensor can still provide the forklift system with navigation parameters for positioning.

Improved extended Kalman filter algorithm

This paper presents an attitude estimation algorithm based on EKF algorithm, which accords to laser scanning matching pose estimation system and IMU motion estimation system. The method has two main processes: the position and attitude of the forklift truck estimated from the first Lidar scan is used as Lidar's attitude information.

IMU sensor is used to provide the Lidar with a positional position. In order to obtain the attitude estimation information of the Lidar, the scan information of Lidar and the information provided by IMU need to be fused into EKF filter data.

Collect IMU and Lidar data at the current time, then the IMU attitude information is acquired by means of SINS algorithm and derive the Lidar pose at the current moment. There is noise in the forklift system and observation, assuming that its distribution is a conditionally independent Gaussian white noise distribution. The system is not linear and the Gaussian distribution cannot be used directly in a non-linear system. In this paper, an improved EKF filter algorithm is used to solve this problem, specifically it is used in bite-position fusion.

The prediction model uses IMU data. However, if only the angular velocity and acceleration data predicted by the IMU are used to derive velocity and position through integral estimation, the system must be unstable, and additional measurement data must be available to assist with updates. Moreover, in terms of the hardware system, there are insurmountable errors inherent in the system, the data itself produce errors. This hardware level error is also the cause of drift in the system data. Facing such problems, it is necessary to use algorithms to pre-process the data for live correction.

To solve this problem, the improved EKF filter algorithm is chosen for prediction and update in this paper, and the following is a brief procedure:

Estimating the covariance of errors:

$$(P^{+})^{-1} = (1-k)\,P^{-1} + k\,C^{T}R^{-1}C \tag{15}$$

State prediction equations for the Lidar attitude:

$$\hat{x}^{+} = P^{+}[(1-k)\,P^{-1}\hat{x} + k\,C^{T}R^{-1}\xi^{*}]^{-1} \tag{16}$$

Kalman gain solution:

$$K = PC^{T}\left(\frac{1-k}{k}\,R + C^{T}PC\right)^{-1} \tag{17}$$

Update Lidar attitude status:

$$\hat{x}^{+} = \hat{x} + K(\xi^{*} - C\hat{x}) \tag{18}$$

Update error covariance:

$$P^{+} = P - (1-k)^{-1}KCP \tag{19}$$

where: x refers to posture information of Lidar scans, $x = (L_T, \Omega_T, V_T)^T$, $L = (L_x, L_y, L_z)^T$, L refers to location information, Ω refers to Euler angles, $V = (V_x, V_y, V_z)^T$ refers to the instantaneous speed. P refers to covariance of states x, R refers to directional cosine matrix, ξ^* refers to attitude information output by Lidar, k refers to weighting parameters, $k \in (0, 1)$. The size of the k value is proportional to the confidence level of the matching result.

The information data fused by the improved EKF filtering algorithm exhibits greater robustness to process parameter variations and environmental noise disturbances. The improved filter algorithm is able to reduce the influence of historical observations on the system by autonomously adjusting the prior probability density estimates. The combination of attitude information collected by the IMU and position and attitude information from the Lidar scan with the improved EKF filter algorithm can effectively improve the positioning accuracy of the robot movement. The angular velocity after filtering is shown in the Fig. 8.

RESULTS

Experiment and Analysis

The experiment was divided into two parts. Simulation experiments are used to verify the positioning accuracy of the forklift system in an indoor storage environment using the improved EKF filtering algorithm proposed in this paper. Indoor experiments are used to verify the effectiveness of the proposed combined Lidar/IMU navigation and positioning method for forklifts working in a simulated warehouse environment.

Simulation experiments and analysis

The simulation experiments were conducted in the ROS (Robotics Operating System) based on the LINUX system. The electric forklifts model was built in Gazebo Physical Simulation Platform, which can reflect the movement of forklift under different methods in a more realistic way. The physical properties of the forklift are set in detail in the Link tab, which includes data such as shape, size, turning radius, power parameters and crash parameters, etc. The connection diagram position posture and connection relationship are shown in Fig.9. The simulation control model of the forklift is shown in Fig. 10.

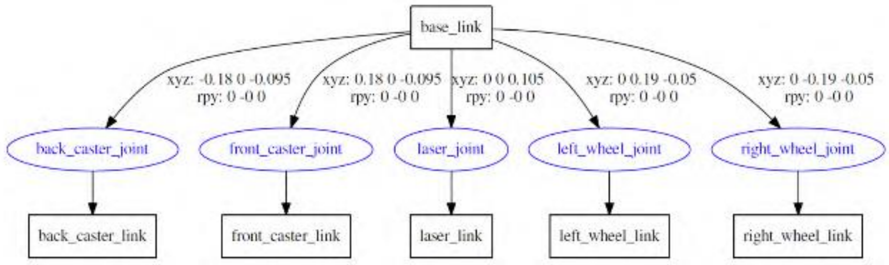


Fig. 9 – Link-joint connection

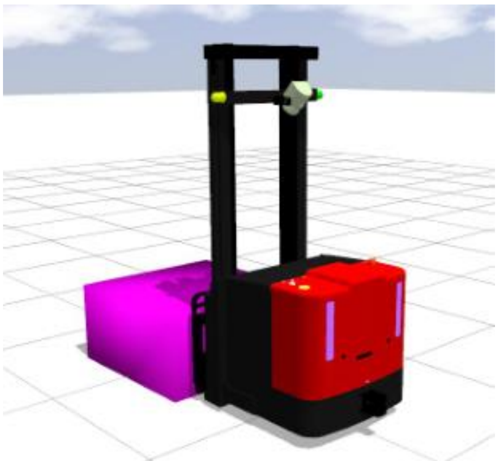


Fig. 10 – Forklift motion control simulation model

The forklift uses a backward approach when loading cargo and a forward approach when operating on the normal path. The forklift uses the same backward approach when unloading cargo. Based on this situation, an expected forklift travel route is planned in the simulation environment at first. Then, let the forklift use Lidar data alone for navigation and positioning, use IMU data alone for navigation and positioning and use the fusion data obtained by Improved EKF filtering algorithm. Placement of the travel paths into the same diagram for comparison is shown in Fig. 11.

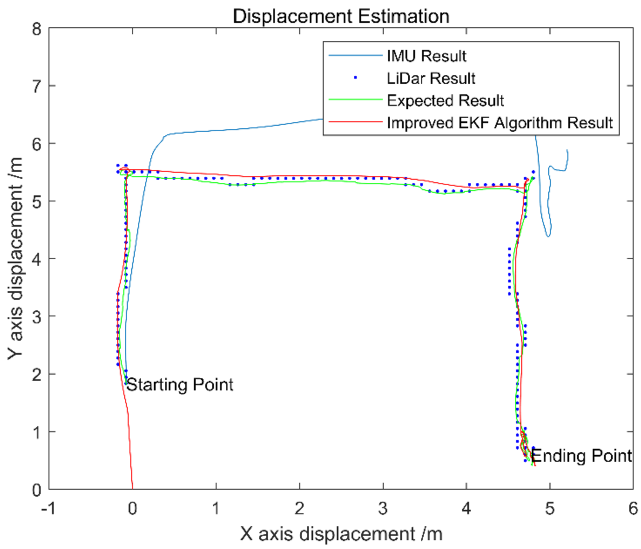


Fig. 11 – Navigation and Positioning Results

If only measurements from the IMU are used over a period of time, it will cause the forklift to move in a different route than expected. Although the path using Lidar data alone matches the expected path, there is no noise factor interfering in the simulation environment which is precisely the most serious problem affecting Lidar. Use traditional and improved filtering algorithms in the simulation environment. The error results of the multiple trials in the simulation environment are shown in Table 1.

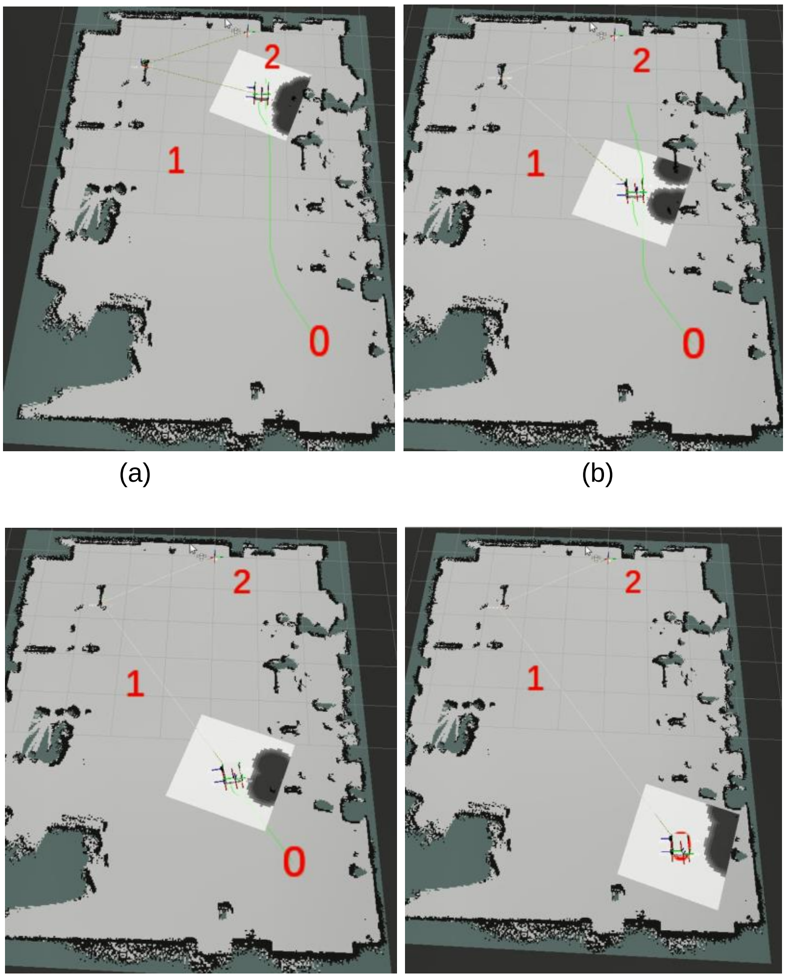
Table 1

Statistic Table of Positioning and Velocity Measurement

State estimation	X-axis position error/m	Y-axis position error/m	X axis speed error/(m/s)	Y axis speed error/(m/s)
Mean	0.018	0.018	0.003	0.003
Mean square error	0.38	0.38	0.06	0.06

Indoor experiments and analysis

To simulate a forklift moving crops in a storage environment, obstacles and shelves are placed in the indoor environment of the laboratory. Let the forklift work in this environment to verify the effectiveness of the combined Lidar/IMU navigation and positioning. The forklift will load the boxes of crops to be transported at *Point 2* and transport them to the racks at *Point 0*. On the way, it will pass the area where the crop is stacked (this area is simulated with some obstacles in the laboratory environment). The forklift system can avoid this area autonomously, avoid obstacles in the forward route and finally reach *Point 0* safely, the actual route is shown in Fig. 12. In Fig. 12 (a), the green line shows the forward path determined by the forklift, and in Fig. 12 (b) (c), the forklift updates the forward path to avoid obstacles.



(a) (b)

(c) (d)

Fig. 12 – Forklift simulation storage experiment

Considering whether the whole system would be affected if the forklift speed was changed, another experience is conducted: let the forklift arrive at the same target area from the same starting point at 50cm/s, 80 cm/s and 1 m/s. The path trajectory is shown in Fig.13. It can be seen that if the speed of the forklift is too fast, although the forklift can also reach the target area, it will rush out of the target area, because it could not reduce the speed in time. The right operating speed can improve the efficiency of the forklift.

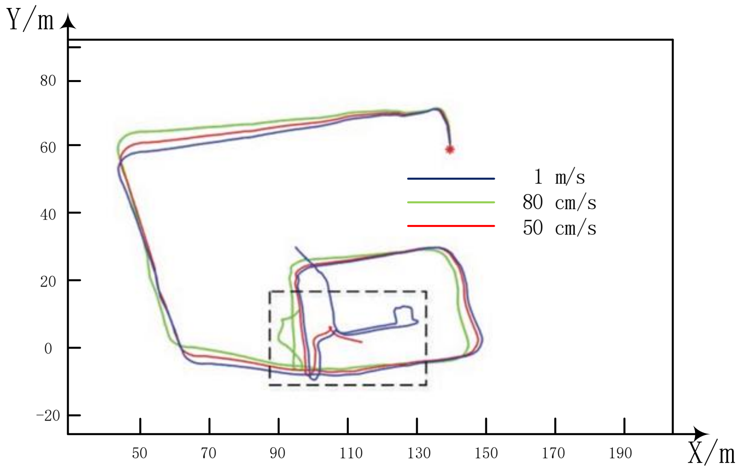


Fig. 13 – Results of running at different speeds

CONCLUSIONS

In order to improve the solution of positioning and navigation accuracy of forklift system in the warehouse environment with complex environment, the article proposes a navigation and positioning method with Lidar/IMU fusion. The system uses Lidar and IMU as posture information collection sensors for forklift. First, the forklift position and attitude information obtained from the Lidar scan is used as an input quantity. Then, the IMU decodes the gyroscope and accelerometer outputs, the forklift speed, position, and attitude information obtained is used as another input quantity. Finally, the data information obtained from Lidar is fused with the data information obtained from IMU by the improved EKF filtering algorithm. This enables accurate position and attitude updates of the forklift system.

The simulation experiment was done in order to demonstrate that the fused IMU data can reduce the trajectory error of Lidar ranging. And the fused Lidar ranging corrects for cumulative IMU errors. The proposed improved EKF filtering algorithm can improve the positioning accuracy of forklifts. Another experimentation of forklifts working in a warehouse environment was conducted in the laboratory. The forklift system can work effectively using the method proposed in this paper. Finally, a comparison experiment of forklifts at different speeds was conducted. The results show that the method proposed in this paper can meet the navigation and positioning needs of forklifts, but if the speed is too high, it will drive out of the target area. It has to work with the right speed.

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