Automatic Docking Optimization Method of Bed and Chair Based on Multi-sensor Information Fusion

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Abstract

Automatic docking is a basic function of intelligent wheelchair bed system. In order to achieve high-precision docking between intelligent wheelchair and U-shaped bed, this paper proposes an optimization method of automatic docking between bed and chair based on multi-sensor information fusion. By installing a variety of sensors, such as depth vision camera and lidar ranging, there is usually cross sensitivity when multiple sensors work together. Based on real sensing technology，wireless sensor network technology and lidar ranging equipment l, a dynamic Bayesian multi-mode information fusion method with asynchronous constraints is proposed. Wireless sensors are used to collect wheelchair pose information in real time. By analyzing the characteristics of the observation information of various sensors, the complementary and redundant information of various sensors in space and time is combined according to optimization criteria. The data fitting between multi-sensor information is carried out efficiently and quickly by surface fitting method. Based on the extended Kalman filter algorithm, the information fusion of IMU and combined sensing unit is realized, and the analysis model is established. Finally, the feasibility of the method is verified by Matlab simulation and the use of Gazebo in ROS to build a simulation experiment environment for fusion algorithm verification.

Keywords: Multi-sensor information fusion, Automatic docking, Extended Kalman filtering algorithm, surface fitting, Inertial navigation measurement unit

1 Introduction

At present, the aging of the population and the aging of fewer children coexist, and the demand for social pension services, especially nursing services, will continue to rise. The intelligent pension service model has important social significance. To improve the quality of life of the elderly, the intelligent bed and chair system has become the research focus of the elderly service robot. Among them, automatic docking has become a basic function of intelligent wheelchair bed system.

In the early days, Stephen Mascaro et al. [1] designed a bed and chair system, whose wheelchair was driven by spherical omni-directional wheels and equipped with force feedback sensors. The bed and chair system adopted a force-guided automatic docking method based on force sensors. Ning M et al. [2] put forward a docking method based on lidar and force sensor. In the early stage, the bed shape is identified according to the lidar data and the relative posture between the beds and chairs is calculated. In the later stage, when the beds and chairs are in contact, the wheelchair posture is adjusted according to the feedback signal of the vehicle-mounted force sensor and the automatic docking is completed. Liang [3] proposed a wheelchair remote vision guidance method based on artificial road signs and a bed chair short-range docking guidance method based on vision and ultrasonic sensors. In this paper, the remote visual guidance, short-range bed-chair docking guidance and wheelchair docking control methods in the process of automatic docking are studied in depth Li et al. [4] put forward a bed-chair docking strategy based on the fusion of vision and ultrasonic data, which uses the calibration point vision sensor to determine the horizontal position center, and the ultrasonic sensor to obtain the current depth information relationship. Thereby obtain that relative position and posture information of the bed and chair; Li et al. [5] designed an embedded automatic docking system for nursing beds based on lidar. In the early stage, intelligent wheelchairs were used to autonomously navigate and move to the target area in front of the bed frame. In the later stage, lidar performed feature extraction and local positioning on the preset artificial marks of the bed. On the basis of local positioning, PID algorithm is used to automatically adjust the posture of wheelchair.

To sum up, at present, the docking mode of bed and chair mostly adopts the docking mode of remote vision guidance and proximity sensor feedback signal guidance. The docking process of short-distance bed and chair requires higher precision, and the precise positioning of the bed body depends on a single sensor, which has a large error. The way of fusing multiple sensor data is getting more and more favor from experts and scholars. Ke et al. [6] designed a multi-sensor positioning system including infrared positioning system, auditory positioning system and visual positioning system. The proposed weighted average fusion algorithm can make the weight change with the target position and external environment, and the environment adaptability is stronger. The whole positioning accuracy and reliability of the interactive system are effectively improved. In the selection of sensors, the use of force feedback sensors has strict requirements on the initial position, posture and contact point of the bed and chair, and the docking accuracy of the bed and chair is low Ultrasonic and infrared ranging sensors are often difficult to complete the docking task with high precision; The docking of bed and chair based on vision, Standard points need to be preset in the use environment, which requires higher light use environment.

To solve the above problems, this study designed an automatic optimization method for bed and chair docking based on

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multi-sensor information fusion. At present, most bed-chair docking modes are adopted, which are divided into two steps: remote positioning and short-range precise docking [7]. In the early stage, the characteristics of the U-shaped bed are used, and the depth vision camera is installed to collect the image behind the wheelchair body, extract the characteristics of the U-shaped bed, and realize the bed positioning; In the later stage, the position and posture of the bed and chair were adjusted based on the measurement results of camera, gyroscope, accelerometer and lidar. Aiming at the processing of multi-sensor data fusion, a dynamic Bayesian multi-mode information fusion method with asynchronous constraints is proposed. By analyzing the characteristics of various sensor observation information, Combining the complementary redundant information of various sensors in space and time according to the optimization criteria, and carrying out data processing on multi-sensor information through a surface fitting method to optimize output data, reducing the influence of external non-difference variables on measured parameter variables and reducing the coupling relationship between parameter variables detected in multi-sensors [8], Improve the precision and stability of bed and chair butt joint.

Therefore, the main contribution of this paper is to aim at the low accuracy of the current automatic docking of wheelchairs, beds, and chairs, and cross-sensitivity problems usually occur when multiple sensors work together, and propose an optimization method for automatic docking of beds and chairs based on multi-sensor information fusion. Based on real sensing technology, wireless sensor network technology, lidar ranging and other equipment, by analyzing the characteristics of the observation information of various sensors, combining the complementary and redundant information of various sensors in space and time according to optimization criteria and multi-sensor The data fitting between the information is carried out efficiently and quickly through the surface fitting method, which can better solve the cross-sensitivity problem of the multi-sensor cooperative work, thereby improving the accuracy and stability of the bed and chair docking.

The main arrangements of this paper are as follows: After the first part of the research status analysis, summarizes the current problems in the docking of the bed and chair; the second part is the modeling and analysis of the wheelchair bed, from the selection of sensors to the establishment of vision, lidar, and inertial models , Analyzes the characteristics of various sensor observation information; the third part analyzes the multi-sensor fusion from the calibration of the sensor, the selection of Kalman filter algorithm and the steps of multi-sensor fusion; the fourth part focuses on the characteristics of various sensor observation information, According to the optimization criteria, the complementary and redundant information of various sensors in space and time are combined for multi-modal information fusion analysis. The fifth part uses the visualization tools provided by ROS to build an algorithm simulation environment. Lidar, depth camera and fusion data were used to carry out simulation experiments to compare and verify the effect of the fusion algorithm. The sixth part summarizes the optimization technology of wheelchair-bed docking based on multi-sensor information fusion.

2 Modeling and Analysis of Wheelchair Bed

The wheelchair bed used in the experiment is Medster's multifunctional electric wheelchair bed, which is based on ROS operating system and adopts four-wheel differential design, and the driving wheels on the same side run at the same speed. The camera adopts Obi Zhongguang 3D sensor camera, and the laser radar adopts Sugawa Lidar scanner, a ranging radar based on ToF principle, which is installed at the top of wheelchair. Hall AB double-channel incremental photoelectric encoder is used as driving motor, and inertial measurement unit PA-IMU488B is used as inertial measurement unit. The positioning problem is divided into remote positioning and short-range precise docking, and the docking function of intelligent wheelchair bed is explored by combining theory with practice. The experimental results show that each sensor has its own advantages, as show in Figure 1. For example, short-distance measurement sensor can obtain accurate wheelchair posture in the process of short-distance precise docking of bed and chair, which is an important parameter for wheelchair docking motion control; Long-distance measuring sensors help us detect and predict long-distance obstacles in the process of long-distance positioning of U-shaped bed. The advantages and shortcomings of the sensors used should be fully considered in practical application, and some redundant systems are added to ensure that the automatic docking function of the bed and chair can still be ensured under the condition that some systems cannot work.

2.1 Sensor selection

In the state estimation process of multi-sensor fusion, the following two factors should be considered when selecting sensors:

(1) Error irrelevance: if a single sensor fails in the sensor used for sensor fusion, it will not cause other sensors to fail at the same time for the same reason.

(2) Complementarity of sensors: for example, inertial sensors can fill the positioning output of the camera during two positioning intervals, which is used to smooth the positioning results of the camera; the camera provides the initial value for the inertial sensor, which eliminates the offset problem when the inertial sensor is used alone. Lidar sensor can make up for the problem of positioning accuracy.

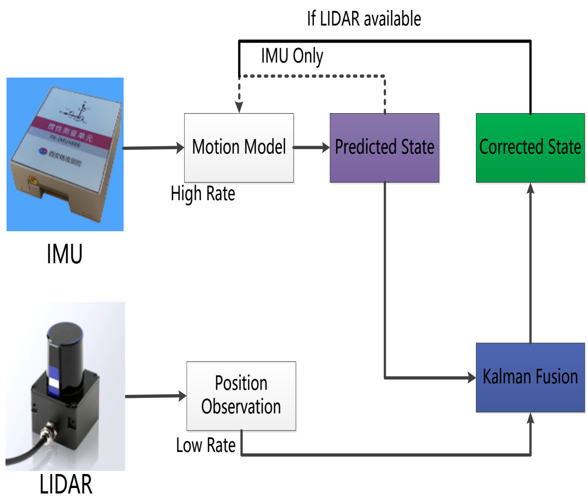


Figure 1. State estimation and positioning of automatic docking of bed and chair

2.2 Wheelchair bed sensor model

2.2.1 Depth vision camera model

The camera is fixed at the upper end of the rear side of the wheelchair, with the view backward, and the camera keeps a certain angle with the ground, so as to ensure that the effective positioning characteristics of the bed can be detected within a certain range. When the wheelchair moves in the horizontal plane, the pose of the camera, the horizontal ground and the bed plane are fixed, and a homography matrix H representing the homogeneous transformation between the planes is obtained by calibration. The matrix contains the pose information and internal reference information of the camera plane corresponding to the bed plane. With the help of homography matrix H, the points on the image plane can be transformed into the points on the U-shaped bed plane [9]. According to the characteristics of U-shaped lathe bed, if 8 contour lines are taken as effective features, the relationship between 8 contour lines in the image plane and the lathe bed plane is shown in Figure 2: In which straight lines a, b, c and d are parallel, straight lines e, f, g and h are parallel, and straight lines a, b, c and d are perpendicular to straight lines e, f, g and h, and the distance between these straight lines is determined. The distance between straight lines a and b, c and d are equal to 19cm, which is denoted d1. The distance between e and f is 21cm, which is denoted d2. The distance between b and c is denoted d3, the distance between a and d is denoted d4, and the distance between f and g and h is denoted d5.

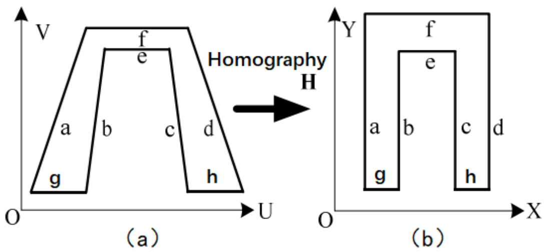


Figure 2. Linear transformation of U-shaped bed contour
(a) the image plane; (b) Bed plane

The endpoint coordinates of a straight line segment are known (x_1, y_1) and (x_2, y_2), the straight line equation is:

$$y = ax + b \tag{1}$$

among them $a = \frac{y_2 - y_1}{x_2 - x_1}$, $b = \frac{y_2 x_1 - y_1 x_2}{x_1 - x_2}$; Two straight lines (a_1, b_1), (a_2, b_2) the formula of the included angle is:

$$\tan\theta = \left|\frac{(a_2 - a_1)}{1 + a_1 . a_2}\right| \tag{2}$$

Straight line (a_1, b_1) which one endpoint (x_1, y_1) of is distance, the distance d from the point to the straight line is:

$$d = \left|\frac{a_2 - y_1 + b_2}{\sqrt{a_2^2 + 1}}\right| \tag{3}$$

First, by looking for parallel pairs of straight lines and dividing them into five groups according to the distance $\{d_1, d_2, d_3, d_4, d_5\}$ between the parallel straight lines, denoted as $\{s_1, s_2, s_3, s_4, s_5\}$. For the straight line pair (l_1, l_2) of s_4, if the straight line pair (l_1, l_3) and (l_2, l_4) can be found in s_1, and the straight line pair (l_3, l_4) is in s_3, then (l_1, l_3, l_4, l_2) is the U-shaped bed contour straight lines a, b, c, d, if in s_3 can be found and the straight line pair perpendicular to the straight line a finds the U-shaped bed contour straight lines e and f. If the straight line perpendicular to the straight line a can be found in s_3, the U-shaped bed contour straight lines g and h are found.

2.2.2 Lidar sensor observation model

The measurement model of lidar is distance-azimuth-pitch angle model. As shown in Figure 3, where P is the observation point of lidar and r is the distance from point P to lidar sensor, which is obtained by multiplying the propagation time of laser pulse by the speed of light and dividing by 2; α is the Azimuth, ϵ is the Elevation, α and ϵ is the emission angle of the laser beam.

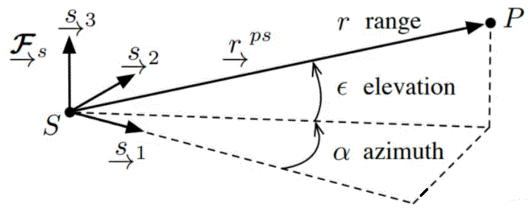


Figure 3. Lidar measurement model

The coordinates of point P in lidar coordinate system are: (x, y, z), and the relationship between coordinate values and measured values is:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} r\cos(\alpha)\cos(\epsilon) \\ r\sin(\alpha)\cos(\epsilon) \\ r\sin(\epsilon) \end{bmatrix} . \tag{4}$$

It is known that (x, y, z) solves (r,α,ϵ), the corresponding calculation formula is as follows:

$$\begin{bmatrix} r \\ \alpha \\ \epsilon \end{bmatrix} = \begin{bmatrix} \sqrt{x^2 + y^2 + z^2} \\ \tan^{-1}(y/x) \\ \sin^{-1}\left(z/\sqrt{x^2 + y^2 + z^2}\right) \end{bmatrix} \tag{5}$$

After processing the data of the lidar by using the merging and segmentation algorithm, in order to further realize the local positioning, that is, the relative position relationship between the intelligent wheelchair and the bed frame, the coordinate transformation between the lidar and the coordinate system and the robot coordinate system is needed. After the posture transformation, Figure 4 is obtained, and the rectangular coordinate system is established with the vertex angle of the reflector as the center. Then the pose coordinates of the intelligent wheelchair in this coordinate system can be used (x, y, θ). It can be seen that θ represents the angular deviation of the orientation of the smart wheelchair from the ideal pose, x represents the horizontal deviation of the current ideal pose of the smart wheelchair, and y represents the vertical distance deviation of the smart wheelchair from the ideal pose. Thus, the relative positional relationship between the smart wheelchair and the bed is obtained.

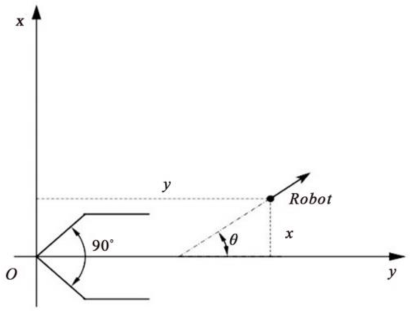


Figure 4. Schematic diagram of local positioning

2.2.3 Inertial measurement unit model

The inertial measurement unit has the characteristics of sensitivity and high frequency, and is often used as an auxiliary sensor for other sensors [10-13]. Assuming that the initial position of the smart wheelchair is $p_0 = (0,0,0)^T$, the initial posture is $\varphi_0(0,0,0)^T$, and $R(\varphi_0)$ represents the rotation matrix corresponding to the initial posture. Using the acceleration a and the sampling interval Δt, the speed and displacement changes of the smart wheelchair in the three-dimensional space can be obtained:

$$V_{k+1} = V_k + R_k a_k \Delta t \tag{6}$$

$$p_{k+1} = p_k + V_k \Delta t + \frac{1}{2} R_k a_k \Delta t^2 \tag{7}$$

In the formula: a_k represents the acceleration value measured by the IMU at the moment k; R_k represents the posture of the IMU in the world coordinate system at the moment k.

3 Multi-Sensor Fusion

3.1 Calibration of sensors

If you want each sensor to cooperate with each other, it is necessary to calibrate the sensor, as show in Figure 5. Sensor calibration is usually divided into three types: internal reference calibration, external reference calibration and time calibration [14].

(1) Internal reference calibration: the internal reference of the sensor has been fixed when the sensor is manufactured, and the fixed parameters in the sensor model are all internal references, which need to be determined in advance through Intrinsic Calibration.

(2) Calibration of external parameters: the external parameters of sensors mainly express the relative positions of the sensors, which is an essential parameter to unify the data coordinates of the sensors.

(3) Time calibration: Time calibration is very important for data fusion of each sensor. For example, the output frequency of IMU is 200 Hz, and that of Lidar is 20HZ. Only by aligning according to the closest time can IMU and LiDAR data be accurately fused. In practical application, the relative time error of each sensor is unknown. These errors may be caused by different pretreatment time of each sensor, and may also be caused by different timer accuracy of each sensor [15].

Figure 5. Calibration of sensor-time calibration

3.2 Extended Kalman Filter-Multi-sensor Fusion

Extended Kalman filter is an algorithm for solving nonlinear problems with the help of linear filtering theory. If it is used for multi-sensor data fusion, one sensor data can be regarded as a measured value and the other sensor data as an estimated value for fusion [16-21]. The main idea of extended Kalman filter approximation is linearization, which is usually done by Taylor expansion. Then the system state is estimated.

In the process of realizing the bed-chair docking function, electric wheelchairs generally need to be equipped with Camera, Lidar and inertial measurement units (IMU). These sensors always send different types of data at different frequencies during operation. The multi-sensor fusion module needs to fuse this information to update the wheelchair status constantly. The process of state estimation by multi-sensor fusion is shown in Figure 6:

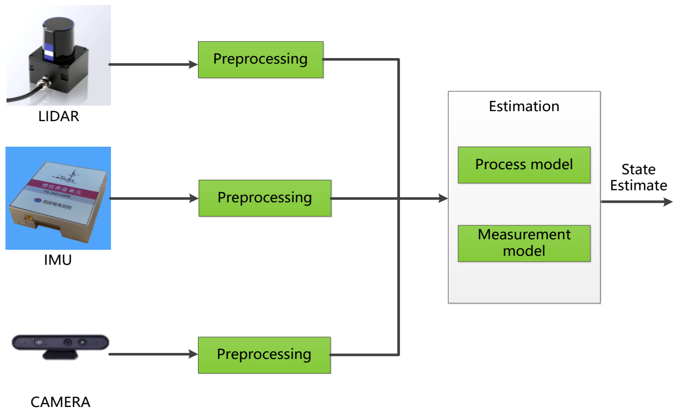


Figure 6. Multi-sensor fusion state estimation process

3.3 IMU + Lidar + Camera multi-sensor fusion

Step 1: use IMU to input the update status

$$\check{x}_k = \begin{bmatrix} \check{p}_k \\ \check{v}_k \\ \check{q}_k \end{bmatrix} \tag{8}$$

$$\check{p}_k = p_{k-1} + \Delta t v_{k-1} + \frac{\Delta t^2}{2}(c_{ns} f_{k-1} + g_n) \tag{9}$$

$$\check{v}_k = v_{k-1} + \Delta t(c_{ns} f_{k-1} + g_n) \tag{10}$$

$$\check{q}_k = \Omega\big(q(\omega_{k-1}\Delta t)\big) q_{k-1} \tag{11}$$

Step 2: Uncertainty of Communication

$$\check{P}_k = F_{k-1} P_{k-1} F_{k-1}^T + L_{k-1} Q_{k-1} L_{k-1}^T \tag{12}$$

Step 3: when a LIDAR measurement result arrives, enter step 4, otherwise enter step 1

Step 4:

A. calculate the Kalman gain of Lidar:

$$K_k = \check{P}_k H_k^T \left(H_k \check{P}_k H_k^T + R\right)^{-1} \tag{13}$$

B. calculation error status:

$$\delta x_k = K_k(y_k - \check{p}_k) \tag{14}$$

C. correctly predict the state:

$$\hat{p}_k = \check{p}_k + \delta p_k \tag{15}$$

$$\hat{v}_k = \check{v}_k + \delta v_k \tag{16}$$

$$\hat{q}_k = q(\delta\varphi) \otimes \check{q}_k \tag{17}$$

D. calculating the modified covariance:

$$\hat{P}_k = (1 - K_k H_k)\check{P}_k \tag{18}$$

4 Multi-modal Information Fusion

Information fusion is a real-time, continuous process. It uses relevant reasoning rules to detect, associate, estimate and combine multi-source information in multiple levels and in many aspects, so as to obtain accurate measured target state, consistency estimation and complete real-time evaluation, and comprehensively evaluate the target from a system perspective [22-26]. In the intelligent wheelchair bed system composed of multiple sensors, the information provided by each sensor may reinforce and complement each other, and may also contradict and repel each other. The basic process of multi-modal information fusion is to make full and efficient use of the information obtained by multiple sensors, and obtain redundant or complementary information in space or time from multiple sensors. Through the organic combination of fusion algorithm, the measured object or perceived object can be interpreted or described in a consistent way, thus obtaining better performance than a single sensor system.

In the application of automatic docking of bed and chair in intelligent wheelchair bed system, multi-modal information fusion has been well applied and embodied, as shown in Figure 7. It can realize the functions of positioning, path planning and automatic docking of U-shaped bed. This is achieved by fusing information obtained from various sensors mounted on the wheelchair [27].

In a multi-sensor system, the information provided by various sensors may have different characteristics: time-varying or non-time-varying, real-time or non-real-time, fast-changing or slow-changing, vague or definite, and may be contradictory or conflicting. The multi-modal information fusion makes full use of the information with different characteristics provided by multiple sensors. The complementary and redundant information of various sensors in space and time are organically combined to form a consistent interpretation and description of the surrounding environment [28-34].

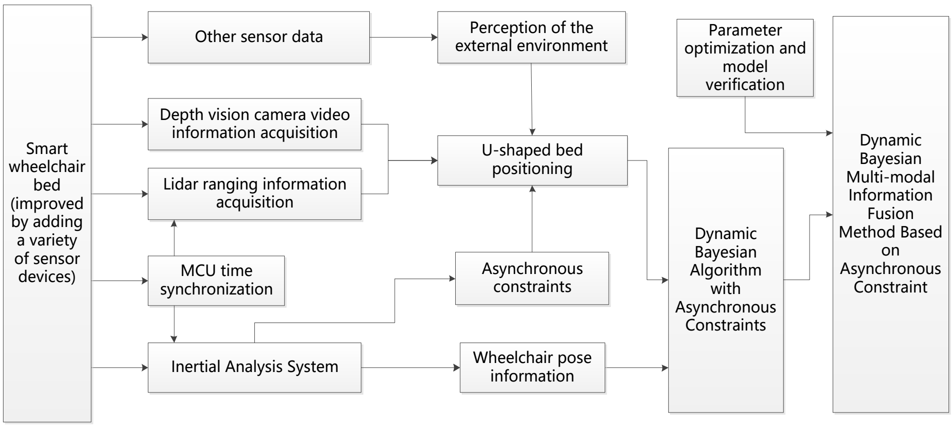


Figure 7. Block diagram of information fusion method based on multimodal perception

5 Multi-sensor Fusion Simulation Experiment

In the process of positioning the U-shaped bed, the electric wheelchair starts from the known position, first obtains its own state information by using the installed inertial measurement sensor and odometer, then uses the extended Kalman filter algorithm to fuse the information of odometer and IMU to roughly estimate the position and posture of the wheelchair [35-38], and then uses the lidar sensor and camera to scan the surrounding environment. Thereby obtaining the position and posture information of the wheelchair in the global situation [39]. The subsequent data analysis and algorithm verification in this article are all based on the real-time operation of the platform. The overall scheme of automatic docking function of bed and chair is shown in Figure 8:

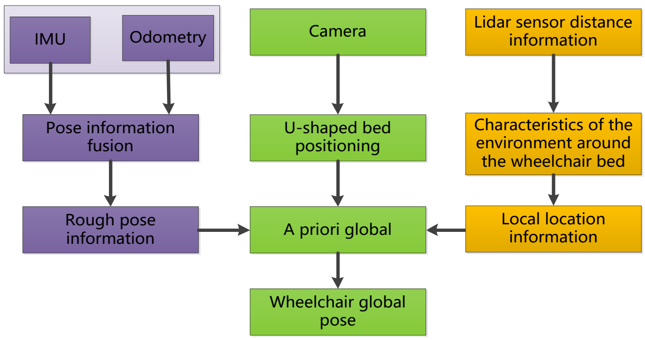


Figure 8. Automatic docking and positioning scheme of bed and chair

In order to fuse the sensor data, it uses a Kalman Filter. Actually, it provides 2 different types of filters: Extended Kalman Filter (EKF)、Unscented Kalman Filter (UKF). As shown in Figure 9, you can see the true state of the wheelchair through the blue line. You can see the state of the robot based on its sensor readings through the red line, which in this case is a little bit noisy. You can see the state of the robot we get after we have applied the Kalman filter, which is much more similar to the real one through the green line.

As shown in Figure 10, the X-axis is the timestamp, and the Y-axis represents the posture of the robot published by each theme in X. As the robot moves in a straight line on the map from x, y = 0,0 to x, y = 10,0, this value will start at 0 and move up to 10. A jagged line, such as the position of a laser scanner, shows fluctuations due to sensor noise. Some drift in filtering estimates is unavoidable, further corrected by GPS algorithms [40]. After filtering, the results are both smooth and insensitive to range drift.

Each element of the data dictionary is stored as an item in the data dictionary, and we store it in a local variable. Correctly calibrated rotation matrix, corresponding to Euler angle RPY, respectively represents roll angle, pitch angle, and yaw angle (0.05, 0.05, 0.1); incorrectly calibrated rotation matrix, corresponding to Euler angle RPY is (0.05, 0.05, 0.05). After the data is set, prepare for the solver. By setting some constants, these constants will not change for any iteration of the solver. One of the most important aspects of the filter is the correct setting of the estimated sensor variance. Table 1 records the variance of sensor data involved in this algorithm.

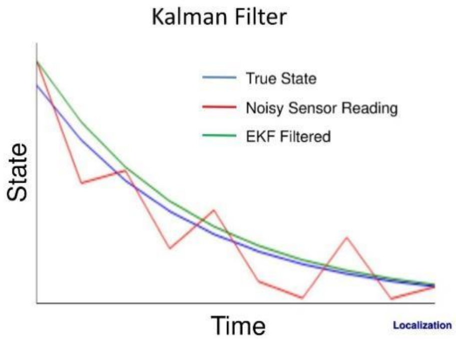
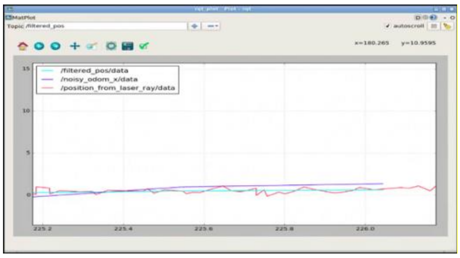
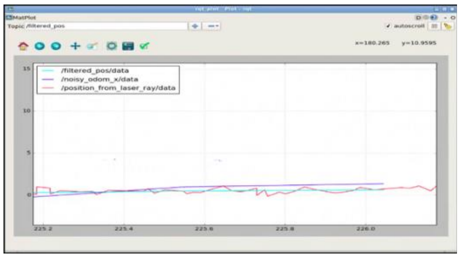


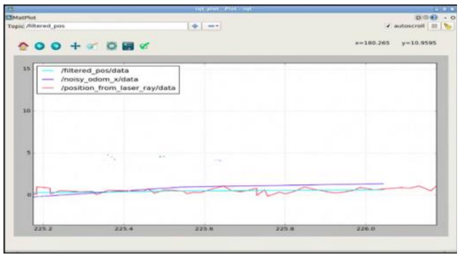
Figure 9. Use Kalman filter to fuse data



(a) Start



(b) Random time node



(c) End

Figure 10. Simulation diagram of robot attitude at different time points in linear motion process

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Table 1. Data variance of different sensors

Data collection	variance	
IMU	$\overline{a_x}$	0.00008
	$\overline{a_y}$	0.00022
	$\overline{\omega}$	0.05763
Motion sensor	$\overline{v_{xr}}$	0.00230
	$\bar{\delta}$	0.00121
Perceptual signpost	$\overline{Z^{L}_{lm,\iota}}$	Diag (0.05,0.05)

In this experiment, the actual trajectory of the automatic docking process of bed and chair is drawn first, and the actual trajectory is shown in Figure 11. Our lidar data is actually only a set of positions estimated from a single scanning matching system, so we can insert it into our solver as another position measurement. However, the LIDAR frame is different from the frame shared by IMU and Camera. To solve this problem, we use the known external calibration rotation matrix and translation vector to transform LIDAR data into IMU framework.

After everything is set up, we can start receiving sensor data and create estimates for our state in the loop. With the state estimation monkey year of all sensors, the experiments of straight trajectory and curve trajectory were carried out, and the outliers of the test results were detected and eliminated. The estimated trajectory and real trajectory after processing were shown in Figure 12, and the estimated trajectory exceeded the ground truth of the actual bed-chair docking process, because the estimated posture was evaluated from the trajectory without ground truth.

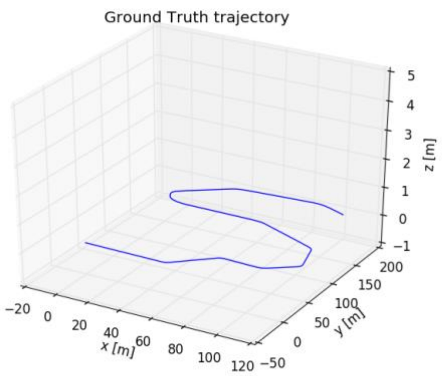

Figure 11. Actual trajectory

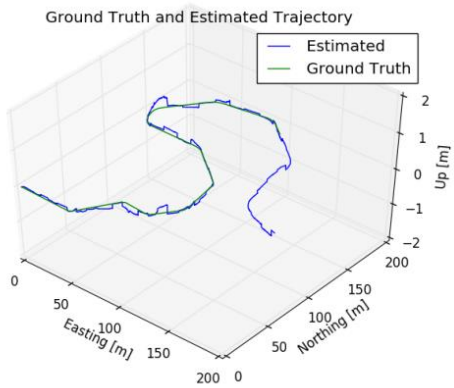

Figure 12. Real trajectory and estimated trajectory

Next, the error of each of the six degrees of freedom is plotted, including the estimation of uncertainty. The error estimate is blue, and the uncertainty limit is red and dashed. According to our uncertainty (covariance), the uncertainty limit is +/- 3 standard deviation. The error plot is shown in Figure 13:

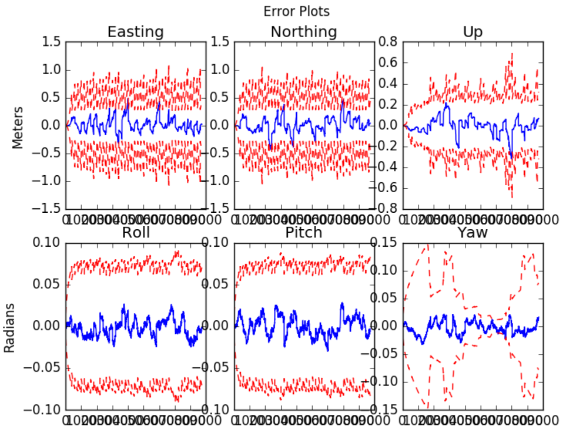

Figure 13. Error plotting

Finally, it can be seen from the partial graph of Figure 14 that, by comparing with the literature [41], the positioning of the literature is based on the correction of different sensor data related to the current posture, so the ride comfort is poor, and there is a comparison. Obvious shaking or even backwards (while the wheelchair actually keeps moving forward). Therefore, the positioning of the U-shaped bed and the estimation of the trajectory of the wheelchair are more realistic in this paper.

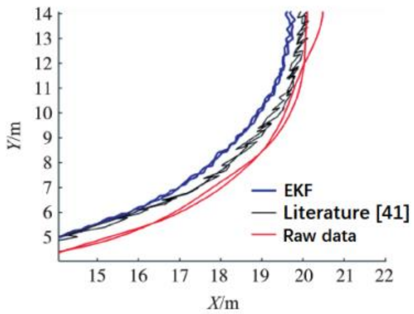

Figure 14. Comparison of observation trajectory and raw data

6 Conclusion

In view of the current wheelchair bed structure and docking problems, the wheelchair bed in the laboratory was transformed, and a variety of sensors such as depth vision camera and liDAR ranging were installed, and the parameters of the sensor system were modified. Combining theory with practice, based on the devices such as real sensing technology and laser radar ranging, a dynamic Bayesian multi-mode information fusion method with asynchronous constraints is proposed. By analyzing the characteristics of the observed information of various sensors, the complementary and redundant information of various sensors in space and time is combined according to the optimization criteria, the data fitting between multi-sensor information is carried out efficiently and quickly by surface fitting method. The measurement data of odometer and IMU are fused by extended Kalman filter algorithm, and the adaptive mechanism is introduced into the process of particle swarm resampling, which reduces the positioning error and improves the convergence speed of particle swarm. In addition, in this paper, surface fitting method is used to reduce the quantitative value of cross sensitivity of nonparametric variables. The performance parameters are further improved, which can overcome the one-sidedness and uncertainty in the detection process. The sensor group information fusion model is established. Finally, the feasibility and docking accuracy of this method are verified by experiments and simulations, and the problem of autonomous mobility of disabled patients is solved to a certain extent. At present, the improved algorithm is tested in the laboratory simulation environment, and the feasibility of the improved key technology algorithm can be verified by the wheelchair bed in the practical application environment in the future.

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