Research on indoor positioning and navigation method of AGV based on multi-sensor fusion

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Abstract. In comparison with current AGV indoor positioning and navigation methods, the combination of IMU+2D LiDAR is prone to signal loss and cumulative error in indoor, so we propose an AGV indoor navigation and positioning method with multi-sensor fusion of odometer, IMU, LiDAR, and UWB. The model is based on the traceless Kalman filter fusion algorithm, and the UWB positioning provides accurate initial coordinates for the traceless Kalman filter. To verify the feasibility of the method, simulations and experiments are done on MatlabR2020a and experimental platform. The results show that the UWB localization can reduce the accumulated errors brought by IMU, the traceless Kalman filter has good trajectory fitting, the method has good performance in system stability and localization accuracy, and achieves the expected goal.

Keywords: Multi-sensor fusion; AGV; Traceless Kalman filtering; Indoor positioning and navigation.

1. Introduction

Traditional storage AGVs mostly use magnetic stripe navigation and laser navigation as the main means. The advantage of magnetic stripe navigation is that the technology is mature, the installation and construction cost is low, and the AGV moves according to the predetermined line with high accuracy. However, the disadvantage is also prominent, the line is fixed, less flexible, and the magnetic stripe is easy to wear and tear in the process of use, thus causing the failure of navigation. At present, the combination of IMU + LIDAR has become the mainstream of AGV automatic navigation nowadays by virtue of its high positioning accuracy and flexible and variable use scenarios. However, LIDAR has high requirements for light, and IMU will produce cumulative errors after long working hours, which will eventually affect the accuracy of AGV indoor positioning.

In order to adapt to the complex use environment and improve the accuracy of navigation and positioning, AGV indoor navigation based on multi-sensor fusion is gradually becoming a new solution. UWB positioning technology is a new type of high-precision positioning method, which does not depend on the environment and can provide AGVs with accurate positioning information at all times. Hao Liu improved the positioning and navigation system with the software reusability of the ROS system [1], which has a more compact structure and is convenient to use, but is prone to positioning inaccuracy in the face of complex scenes. Songhua Liao proposed a new data fusion method using the data measured by microphone array and odometer [2], but also could not obtain good positioning accuracy. Donghai Qian proposed the transform-traceless Kalman filter (NDT-UKF) algorithm based on the traceless Kalman filter, which plays a good effect in optimizing the Kalman calculation.

This paper proposes a fusion odometer, IMU, LIDAR, and UWB navigation and positioning model based on the traceless Kalman filter. After simulation and experiment, the model can adapt well to the complex environment and the navigation and positioning accuracy is relatively high.

2. Sensor positioning principle

2.1 Odometer positioning principle

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Mileage line speed:

\[ v = \frac{v_r + v_l}{2} \]  

(1)

Mileage angular velocity:

\[ \omega = \frac{v_r - v_l}{T} \]  

(2)

\( v \) indicates linear speed, \( \omega \) indicates angular velocity, \( v_r \) indicates the speed of the left wheel of the trolley, \( v_l \) indicates the speed of the right wheel, \( T \) indicates the horizontal distance between the left and right wheels.

From the obtained linear and angular velocities, we can deduce the current position of the car in the two-dimensional plane \((x_t, y_t, \theta_t)\).

\[
\begin{align*}
    x_{t+1} &= x_t + u_t + v_t \cos(\theta_t)d_t \\
    y_{t+1} &= y_t + u_t \sin(\theta_t)d_t \\
    \theta_{t+1} &= \theta_t + \omega_t d_t
\end{align*}
\]  

(3)

Among them \((x_t, y_t)\) Indicates the current position, \((u_t, \omega_t)\) Indicates the current linear and angular velocities.

### 2.2 IMU Positioning Principle

The Inertial Measurement Unit (IMU) is a parametric measurement device consisting of a gyroscope and an accelerometer that provides the position and velocity of the AGV in a navigation coordinate system. In use, the IMU relies on the built-in accelerometer to provide the acceleration of the cart, and the gyroscope to establish the navigation coordinate system with the cart as the carrier. The IMU has rich characteristics, as it acquires its own driving state, so it is continuous and complete in data acquisition and has no requirements for the environment, but the disadvantage is that the error will become bigger and bigger with the increase of using time and distance, which eventually affects the accuracy of positioning.

### 2.3 Ultra-wideband positioning technology

UWB is a short-range wireless carrier communication technology with good positioning accuracy indoors. It has been widely used in warehouse robots, shopping mall supermarket personnel navigation. A comparison of common indoor positioning technologies is shown in Table 1.

| Positioning Technology | Hardware Deployment | Positioning accuracy | Anti-interference | Power consumption |
|------------------------|---------------------|----------------------|-------------------|------------------|
| WIFI                   | None                | 5-15m                | Weak              | High             |
| Bluetooth              | Large number        | 5-15m                | Weak              | Low              |
| RFID                   | Large number        | 3-5m                 | Weak              | Low              |
| ZIGBEE                 | Large number        | 3-5m                 | Moderate          | Low              |

### 2.3.1 Distance measuring principle.

![Bilateral bi-directional ranging method](image)

Fig. 1 Bilateral bi-directional ranging method
UWB ranging is calculated based on the time difference of the signal passing back and forth between the base station and the tag. According to the number of signals passed, it can be divided into two forms: unilateral bidirectional ranging and bilateral bidirectional ranging. In order to obtain a smaller time error, this paper uses bilateral bidirectional ranging method. As shown in Figure 1.

The signal flight time is:

$$T_{flight} = \frac{(T_4-T_1)(T_6-T_3)-(T_3-T_2)(T_5-T_4)}{T_5-T_1+T_6-T_2}$$  \hspace{1cm} (4)

Where $T_1$, $T_3$, $T_5$ is the signal transmitting time; $T_2$, $T_4$, $T_6$ is the signal receiving time.

$$L = c \times T_{flight}$$ \hspace{1cm} (5)

Where $c$ is the speed of light and $L$ is the distance from the base station to the tag.

Three-sided ranging method. From equation (5), the distance from the base station to the tag is known. The three-sided ranging method is shown in Figure 2.

![Fig. 2 Trilateral distance measurement method](image)

Set the base station A1 coordinates as $(x_1, y_1)$, A2 coordinates as $(x_2, y_2)$, A3 coordinates as $(x_3, y_3)$, respectively, so that the label coordinates is $(x, y)$, Make circles of radius R1, R2 and R3 respectively with the base station as the center and intersect the tag. From this, the system of equations can be obtained as follows:

$$\begin{align*}
(x-x_1)^2 + (y-y_1)^2 &= r_1^2 \\
(x-x_2)^2 + (y-y_2)^2 &= r_2^2 \\
(x-x_3)^2 + (y-y_3)^2 &= r_3^2
\end{align*}$$ \hspace{1cm} (6)

Using the least squares method, the label coordinates can be solved as:

$$\begin{bmatrix} x \\ y \end{bmatrix} = \left[ \frac{2(x_1-x_3)\ 2(y_1-y_3)}{2(x_2-x_3)\ 2(y_2-y_3)} \right]^{-1} \begin{bmatrix} x_1^2 - x_3^2 + y_1^2 - y_3^2 - r_1^2 + r_3^2 \\ x_2^2 - x_3^2 + y_2^2 - y_3^2 - r_2^2 + r_3^2 \end{bmatrix}$$ \hspace{1cm} (7)

2.4 Lidar positioning principle

![Fig. 3 Triangulation method](image)
There are two commonly used LIDAR positioning methods: triangulation and TOF ranging. The triangulation method can be simplified to the model shown in Figure 3.

First of all, the LIDAR laser emits laser light, which is reflected by the object and captured by the signal receiver, and the captured place is “x2”. Make a vertical line S intersecting the reflection line at the focal point “O,” and make “a” line “L” parallel to “d” over the focal point “O”, and its reverse extension intersects the signal receiver at the point “x1”. Let the laser emitting angle be “u”, the distance between the laser and the object is “d”, the distance between “x1” and “x2” is “x”, and the dashed lines “f” and “q” are the left and right triangular plumb lines. From the similarity of the triangles, we know that:

\[
\frac{q}{f} = \frac{s}{x} \quad (8)
\]

Also,

\[
\sin \beta = \frac{q}{d} \quad (9)
\]

So

\[
d = \frac{s f}{x \sin \beta} \quad (10)
\]

Then the laser transmitter and signal receiver combination are rotated with a mechanical structure, so that the distance of the obstacle for one week is obtained. From Equation (10), it can be seen that “x” is inversely related to “d”. For accuracy reasons, the measurement error of “x” becomes larger when d is too large. Therefore, LIDAR using triangulation is mostly applied in the case of close distances. In this paper, the AGV cart is experimented indoors, which is suitable for triangulation method.

3. Multi-sensor fusion based indoor navigation and positioning system

Both the extended Kalman filter and the traceless Kalman filter can be applied to nonlinear Gaussian models. The difference between the two is that the Kalman filter simply omits the second-order and higher terms in the Taylor expansion of the nonlinear function, which can produce large errors when the model threads are very high. The traceless Kalman filter, on the other hand, is a linear approximation of the higher order terms of the nonlinear equation, and thus has a higher accuracy. In order to obtain the driving trajectory of the car more accurately, this paper integrates IMU, LIDAR and ultra-wideband positioning system (UWB) on the basis of the traceless Kalman filter. The indoor positioning system is shown in Figure 4.

![Fig. 4 Composition of the positioning system](image)

4. Based on UKF data fusion

Unlike the extended Kalman filter which linearizes a nonlinear function, the traceless Kalman filter approximates the probability density of the nonlinear function. This has the advantage of not requiring the computation of the Jacobi matrix, which is greatly reduced in computational effort,
preserves the higher order terms, and is more accurate in accuracy, but the disadvantage is that it is not as stable as the extended Kalman filter.

**Table 2. Filter Comparison**

| Filtering                  | Speed  | Precision | Accuracy     |
|---------------------------|--------|-----------|--------------|
| Extended Kalman Filter (EKF) | Quick  | Difference | More stable  |
| Particle filtering (PF)    | Slow   | High      | More stable  |
| Unstained Kalman filter (UHK) | Faster | Higher    | More unstable|

The most important step of the traceless Kalman filter is the UT transform, which essentially selects 3 special Sigma points and uses these 3 points to replace the original standard normal distribution. After the UT transformation, the Sigma point has the following properties.

1) Since the set of Sigma points is symmetrically distributed around the mean and the symmetric points have the same weights, the sample mean of the Sigma set is, therefore, the same as the mean of the random vector x.

2) The sample variance of the Sigma point set is the same as the variance of the random vector x.

3) The set of Sigma points of an arbitrary normal distribution is obtained from the set of Sigma of a standard normal distribution by a transformation.

Thus, we transform a nonlinear problem into a Kalman problem.

### 4.1 The process of unstained Kalman filter:

1) Calculate 2n+1 Sigma points, where n refers to the number of dimensions of the state.

\[
\begin{align*}
X^{(0)}(0) & = \bar{X}, i = 0 \\
X^{(i)}(0) & = \bar{X} + (\sqrt{n + \lambda}P)^{i}, i = 1 \sim n \\
X^{(i)}(0) & = \bar{X} - (\sqrt{n + \lambda}P)^{i}, i = n + 1 \sim 2n
\end{align*}
\]  

(11)

2) Calculate the corresponding weights of these sampling points.

\[
\begin{align*}
\omega_m^{(0)} & = \frac{\lambda}{n+\lambda} \\
\omega_c^{(0)} & = \frac{\lambda}{n+\lambda} + (1 - \alpha^2 + \beta) \\
\omega_m^{(i)} & = \omega_c^{(i)} = \frac{\lambda}{2^{(n+\lambda)}}, i = 1 \sim 2n
\end{align*}
\]

(12)

Where \( m \) denotes the expectation and \( c \) denotes the variance. For Sigma points, the variance and expectation are equal thereafter, except for the first expectation and variance, which are different. \( \lambda \) is a parameter indicating the scaling ratio. \( \alpha, \beta \) are parameters, where \( \beta \) is greater than or equal to 0.

3) A set of sampled points (called Sigma point set) and their corresponding weights are obtained using equations (11) and (12).

\[
X^{(i)}(k|k) = \left[\begin{array}{c} \hat{X}(k|k) \\
\sqrt{(n + \lambda)P(k|k)} \\
\hat{X}(k|k) - \sqrt{(n + \lambda)P(k|k)} \end{array}\right]
\]  

(13)

4) Compute one-step predictions for the set of 2n+1 Sigma points, \( i = 1, 2, \ldots, 2n+1 \).

\[
X^{(i)}(k + 1|k) = f[k, X^{(i)}(k|k)]
\]  

(14)

5) The obtained Sigma point set predictions are added to the sum of the weights to obtain the prediction and covariance matrix for calculating the system state quantities. The weight \( \omega^{(i)} \) is calculated from equation (12).

\[
\hat{X}(k + 1|k) = \Sigma_{i=0}^{2n} \omega^{(i)} X^{(i)}(k + 1|k)
\]  

(15)

\[
P(k + 1|k) = \Sigma_{i=0}^{2n} \omega^{(i)} \left[ \hat{X}^{(i)}(k + 1|k) - X^{(i)}(k + 1|k) \right] \left[ \hat{X}^{(i)}(k + 1|k) - X^{(i)}(k + 1|k) \right]^T + Q
\]  

(16)

6) The new Sigma point set is obtained by further using the UT transformation on the one-step predicted values.
\[ X^{(i)}(k + 1|k) = \begin{bmatrix} \hat{X}(k + 1|k) \\ \hat{\dot{X}}(k + 1|k) - \sqrt{(n + \lambda)}P(k + 1|k) \end{bmatrix} \] (17)

7) The predicted observations are calculated by substituting the new set of Sigma points obtained in step (6) into the observation equation, \( i = 1, 2, \ldots, 2n+1 \).

\[ Z^{(i)}(k + 1|k) = h^{(i)}(X^{(i)}(k + 1|k)) \] (18)

8) The mean and covariance of the system predictions are obtained by weighting and summing the observed predictions of the Sigma point set obtained in step (7).

\[ Z_{\overline{z}}(k + 1|k) = \sum_{i=0}^{2n} \omega^{(i)} (k + 1|k) \] (19)
\[ P_{z_{kz_k}} = \sum_{i=0}^{2n} \omega^{(i)} [Z^{(i)}(k + 1|k) - \overline{Z}(k + 1|k)] [Z^{(i)}(k + 1|k) - \overline{Z}(k + 1|k)]^T + R \] (20)
\[ P_{x_{kz_k}} = \sum_{i=0}^{2n} \omega^{(i)} [X^{(i)}(k + 1|k) - \overline{Z}(k + 1|k)] [X^{(i)}(k + 1|k) - \overline{Z}(k + 1|k)]^T \] (21)

9) Calculate the Kalma gain matrix.

\[ K(k + 1) = P_{z_{kz_k}} P_{x_{kz_k}}^{-1} \] (22)

10) In the last step, the state and covariance of the system are updated.

\[ \hat{X}(k + 1|k) = \hat{X}(k + 1|k) + K(k + 1) [Z(k + 1) - \overline{Z}(k + 1|k)] \] (23)
\[ P(k + 1|k + 1) = P(k + 1|k) - K(k + 1) P_{z_{kz_k}} K^T(k + 1) \] (24)

5. Experiment and Simulation

5.1 Simulation results and analysis

With the help of Matlab R2020a, IMU+LIDAR uniformly accelerated linear model and IMU, LIDAR, UWB uniformly accelerated linear model are simulated respectively. In the simulation process, let the vector of the mass point M at the moment be \( X(k) = [x_k, y_k, (x_k - \cdot), (y_k - \cdot), (x_k - \cdot\cdot), (y_k - \cdot\cdot)]^T \), \((x_k, y_k)\) denotes the coordinates of the point M, \((x_k - \cdot), (y_k - \cdot)\) denotes the velocity at the moment, and \((x_k - \cdot\cdot), (y_k - \cdot\cdot)\) denotes the acceleration at the moment. The plasmoid M makes uniformly accelerated linear motion along both X-axis and Y-axis in the Cartesian coordinate system, and the same noise is attached in both directions \( w(k) \). The motion trajectory diagram is shown in Fig. 5, and the tracking error diagram is shown in Fig. 6.

![Fig. 5 Movement trajectory diagram](image)
From the simulation results, it can be seen that the combination of IMU+LIDAR has a more stable trajectory fit in the early stage, but there is a problem of low stability in the later stage, and its motion trajectory will have a certain amount of fluctuation, which means that the combination of IMU+LIDAR cannot suppress the noise very well. LIDAR combination.

5.2 Experimental verification

The Ros System is widely used in robotics experiments and simulations due to its efficient software reusability. For ease of use, the Ros system is pre-installed on a Linux system. This experiment is based on the Ros system and conducted on the experimental platform YOOH AGV. The sensor is Hokuyo LIDAR and the UWB is D-DWM-PG. Firstly, Xiaomi laptop with Linux system was connected to the AGV cart via network cable and USB, and the port name was checked to be consistent with the one prompted by the system file. Then open a new terminal on the linux desktop respectively and execute the following command:

```
roslaunch my_navigation odom.launch
roslaunch my_navigation laser.launch
rosrun my_navigation odom_tf
```

When finished, continue to open a new terminal and execute the build order:

```
roslaunch my_navigation gmapping.launch
```

Control the AGV trolley through the keyboard to finish building the map. After the completion of map building, open the rviz view, select the appropriate target point for navigation, and the AGV is planning the appropriate path. As shown in Figure 7.

![Fig. 6 UKF tracking position error](image)

The feasibility and stability of the IMU+LIDAR+UWB multi-sensor fusion system are experimentally verified.
6. Summary

The experimental and simulation results show that the fusion of multiple sensors has a good effect on improving the indoor positioning of AGVs, and the traceless Kalman filter simplifies the calculation compared with the extended Kalman filter, and the model achieves the expected results.

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