Heading estimation algorithm for complex environment based on GPS single baseline

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Abstract. With the rapid development of unmanned technology, the high-precision heading angle determines the accuracy of this unmanned automatic navigation. However, traditional least square method is used to solve the vehicle's heading angle will jump in the complex terrain environment. Therefore, we propose an unmanned vehicle heading estimation algorithm based on single GPS baseline. First, we establish GPS single residual and double residual observation models to eliminate measurement errors, and combine code phase and carrier phase to form ambiguity combination. Second, in order to eliminate the effects of instability and noise that may be brought by complex environments, this paper proposes model equations based on the prediction and update equations of Kalman filter, the Kalman filtering performs real-time status update on the single residual ambiguity. Finally, the integer ambiguity is searched to find the heading angle of the vehicle. In addition, we performed an algorithm performance test in the actual unmanned vehicle operating environment. The test results shown that the estimated error of the heading when the vehicle is traveling straight and turning is within 1.5°.

Keywords: GPS, Heading estimation, Kalman filtering, Carrier phase.

1 Introduction

In recent years, unmanned and automatic navigation technologies have been greatly developed, the vehicle's attitude information is more important, in the automatic navigation system, vehicle course angle determines its direction, only accurately measure the position of the vehicle itself and can accurately control the movement direction of the vehicle yaw information, realizes the high precision automatic navigation.

GPS is a satellite navigation and positioning system authorized by the United States Department of Defense, which means a navigation system for timing and ranging[1]. The system was originally used to provide equipment with global three-dimensional precise positioning, timing, speed and attitude information[2]. Due to the relatively slow development of GPS hardware, the high price and lack of flexibility, the promotion of GPS attitude measurement technology has

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been limited. In recent years, the development of the chip industry and chip manufacturing processes has made GPS more and more miniaturized[3]. At the same time, the rapid development of GPS carrier phase difference technology, the use of GPS carrier phase to measure carrier attitude information has become another important branch of GPS application research.

The rest of the paper is organized as follows. Some related works are surveyed in Section 2. In Section 3, we introduce the proposed algorithm framework, and introduce the residual error elimination method and Kalman filter to solve the ambiguity principle. Section 4 shows the experimental results and finally the conclusion of this paper is given in Section 5.

2 Related Works

GPS aims to provide high-precision, high-reliability positioning, navigation, and timing services for various users around the clock and around the world. GPS has a wide range of uses, high positioning accuracy and full global ground coverage. Using GPS can not only perform navigation and positioning on the carrier, but also perform speed measurement, attitude measurement, and time service on the carrier. Cars, ships, airplanes, and other carriers can be equipped with GPS terminals for positioning and navigation; GPS can continuously provide three-dimensional position, three-dimensional speed, and time information of dynamic targets for various types of users; there are many GPS satellites And the distribution is reasonable, so any place on the earth can continuously observe at least 4 satellites synchronously, thereby ensuring global, all-weather continuous 3D positioning.

In recent years, more and more researchers have done a lot of research in the field of self-driving heading estimation. The literature[4] uses an adaptive Kalman filter algorithm with unit quaternion as the state vector to fuse three-axis gyroscope and three-axis accelerometer. And the triaxial magnetic sensor measures the signal to achieve the vehicle heading estimation. The literature[5] proposes an attitude angle estimation algorithm based on position correction and Kalman filtering. The literature[6] addresses the problem of cumulative error of attitude angle calculation using inertial navigation in a low-cost vehicle-fixing attitude system. A three-axis gyroscope, three-axis accelerometer, and magnetic force are used The design implements the attitude heading system, which effectively suppresses the influence of errors on the gyro attitude. Literature[7] the combined attitude measurement using GPS and MEMS sensors achieves high-precision vehicle heading angle measurement, but it is expensive and not suitable for large-scale promotion.

In order to solve the problem of vehicle heading angle instability in an unmanned system, we propose a GPS single-baseline heading estimation algorithm. It uses the GPS single-baseline carrier phase measurement model to solve the vehicle heading angle and uses Kalman filtering to solve the problem of instability of the heading angle under the dynamic environment of the unmanned vehicle, and provides the vehicle heading angle with high accuracy and stability.

3 Algorithm Description

The GPS single baseline model is to install the GPS antenna on the vehicle according to a certain structure, and calculate the vehicle's heading Angle by solving the GPS satellite data through two GPS receivers. This system adopts a single baseline course estimation system composed of two GPS receivers. The two antennas can be connected to form a baseline vector, and the vehicle's heading angle can be obtained through coordinate transformation.

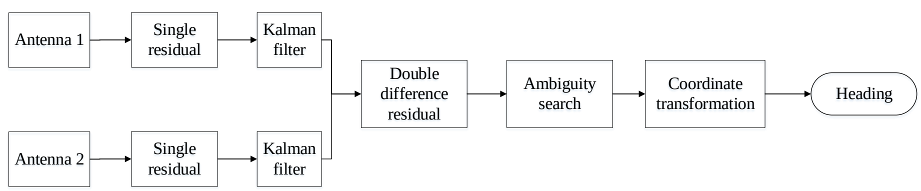

Fig. 1. Algorithm model.

Aiming at the characteristics of vehicle heading estimation in the unmanned system, we proposed the algorithm model based on GPS single baseline as shown in Fig.1. It consists of three parts: single difference processing, kalman filter status update and double difference residual processing.

3.1 Single baseline residual model

The original observation equation of pseudo-range is:

$$P^p = \rho^p + \mathrm{c}(\delta_i - \delta^p) + \mathrm{d}^p{}_{trop} + d^p{}_{iono} + \varepsilon_p{}^p \tag{1}$$

$\rho^p = \sqrt{(X^p - X_i)^2 + (Y^p - Y_i)^2 + (Z^p - Z_i)^2}$ is the geometric distance from the satellite to the reference station, δ_i is the receiver clock error, δ^j is the satellite clock error, $\mathrm{d}^p{}_{trop}$ is the tropospheric delay, $\mathrm{d}^p{}_{iono}$ is for ionospheric delay, ε^p is for observation noise.

The original carrier phase observation equation is:

$$\lambda \cdot \delta\Phi^p = \rho^p + c \cdot \delta - \lambda \cdot N^p - c \cdot \delta^p - c \cdot \delta^p_{ion} + c \cdot \delta^p_{trop} \tag{2}$$

$\delta\Phi^p$ is the actual measured carrier phase value, ρ^p is the actual distance between satellite p and receiver$i$, N^p is the ambiguity of the satellite p.

In the original pseudo-range and carrier phase observation models, there are error terms such as receiver clock error, satellite clock error, tropospheric error, and ionospheric error. In order to eliminate the errors, single-difference residual processing is performed on the data observed by the two antennas.

Residual term of antenna 1:

$$\begin{cases} y1_b^j = \phi_b^j \times \lambda - ({\rho_0}_b^j - c \times \delta^j + \mathrm{d}_{trop,b}^j) \\ y2_b^j = P_b^j - ({\rho_0}_b^j - c \times \delta^j + \mathrm{d}_{trop,b}^j) \end{cases} \tag{3}$$

Residual term of antenna 2:

$$\begin{cases} y1_r^j = \phi_r^j \times \lambda - ({\rho_0}_r^j - c \times \delta^j + \mathrm{d}_{trop,r}^j) \\ y2_r^j = P_r^j - ({\rho_0}_r^j - c \times \delta^j + \mathrm{d}_{trop,r}^j) \end{cases} \tag{4}$$

After the difference residuals, the code phase combination is used to solve the integer ambiguity floating point solution.

$$\begin{cases} P1_r^j - P1_b^j = [\rho_r^j + \mathrm{c}\delta_r] - [\rho_b^j + \mathrm{c}\delta_b] \\ \phi1_r^j - \phi1_b^j = [\frac{\rho_r^j}{\lambda_1^j} + f^j \delta_r + \mathrm{N}_r^j] - [\frac{\rho_b^j}{\lambda_1^j} + f^j \delta_b + \mathrm{N}_b^j] \end{cases} \tag{5}$$

it can eliminate atmospheric errors and get single difference ambiguity $\mathrm{N}_r^j - \mathrm{N}_b^j = (\phi1_r^j - \phi1_b^j) - (P1_r^j - P1_b^j)$.

After performing single-difference residuals on antenna 1 and antenna 2 and performing station-to-station difference, the receiver clock error is eliminated, and obtained the double-difference equation $\lambda\phi_{b,r}^{i,j}(t) = \rho_{b,r}^{i,j}(t) + \lambda N_{b,r}^{i,j}(t)$, after linearization

$$\lambda\phi_{b,r}^{i,j}(t) = [\rho_{r,0}^{i,j}(t) - \rho_b^{i,j}(t)] - [\, a_X^{i,j}(t) a_Y^{i,j}(t) a_Z^{i,j}(t) - \lambda\lambda \,] \begin{bmatrix} \Delta X_r \\ \Delta Y_r \\ \Delta Z_r \\ N_{r,b}^j \\ N_{r,b}^i \end{bmatrix}^T \tag{6}$$

$\begin{bmatrix} \Delta X_r & \Delta Y_r & \Delta Z_r \end{bmatrix}$ is baseline, $[N_{r,b}^j, N_{r,b}^i]$ is the ambiguity floating point solution.

Based on the single-difference ambiguity floating-point solution, the double-difference residual can be obtained

$$\begin{cases} {v_1}^j = [(y1_r^i - y1_b^i) - (y1_r^j - y1_b^j)] - [\lambda_1 \times (N_r^i - N_b^i) - \lambda_1 \times (N_r^j - N_b^j)] \\ {v_2}^j = [(y2_r^i - y2_b^i) - (y2_r^j - y2_b^j)] \end{cases} \tag{7}$$

i is the reference satellite, b is the main antenna, ${v_1}^j$ is the double difference residual corresponding to the carrier phase, and ${v_2}^j$ is the double difference residual corresponding to the pseudo range.

3.2 Kalman filtering

In order to eliminate the influence of instability and noise caused by complex terrain environment, this paper proposes the model equation based on the prediction and update equation of kalman filter.

Set state estimator is $x = (r_r^T, B_1^T, B_2^T)^T$, $B_i = (B_{rb,i}^1, B_{rb,i}^2, \ldots B_{rb,i}^m)^T$ is the carrier phase L_i single difference phase value between stations, $r_r = [x, y, z]$ is the position of antenna 2. Single residual observation vector $y = [\phi_1^T, \phi_2^T, P_2^T, P_2^T]$ based on pseudorange and carrier phase, set the observation equation $\mathbf{h}(\mathbf{x}) = ({\mathbf{h}_{\Phi,1}}^T, {\mathbf{h}_{\Phi,2}}^T, {\mathbf{h}_{P,1}}^T, {\mathbf{h}_{P,2}}^T)^T$, the observation error matrix is

$$\mathbf{R} = \begin{pmatrix} \mathbf{D}\mathbf{R}_{\Phi,1}\mathbf{D}^T & & & \\ & \mathbf{D}\mathbf{R}_{\Phi,2}\mathbf{D}^T & & \\ & & \mathbf{D}\mathbf{R}_{P,1}\mathbf{D}^T & \\ & & & \mathbf{D}\mathbf{R}_{P,2}\mathbf{D}^T \end{pmatrix} \tag{8}$$

Single difference factor

$$\mathbf{D} = \begin{pmatrix} 1 & -1 & 0 & \cdots & 0 \\ 1 & 0 & -1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 0 & \cdots & -1 \end{pmatrix} \tag{9}$$

Carrier phase and pseudorange observation error matrix

$$\begin{cases} \mathbf{R}_{\Phi,i} = \mathrm{diag}(2{\sigma^1_{\Phi,i}}^2, 2{\sigma^2_{\Phi,i}}^2, ..., 2{\sigma^m_{\Phi,i}}^2) \\ \mathbf{R}_{P,i} = \mathrm{diag}(2{\sigma^1_{P,i}}^2, 2{\sigma^2_{P,i}}^2, ..., 2{\sigma^m_{P,i}}^2) \end{cases} \tag{10}$$

where $\sigma^s_{\Phi,i}$ is the carrier phase standard deviation, $\sigma^s_{P,i}$ is the pseudorange standard deviation.

According to the state vector and observation vector set above, and P is the covariance matrix corresponding to the state quantity, the observation value x and covariance P can be updated according to the observation y at time t according to the following steps:

$$\begin{cases} \hat{\mathbf{x}}_k(+) = \hat{\mathbf{x}}_k(-) + \mathbf{K}_k(\mathbf{y}_k - \mathbf{h}(\hat{\mathbf{x}}_k(-))) \\ \mathbf{P}_k(+) = (\mathbf{I} - \mathbf{K}_k\mathbf{H}(\hat{\mathbf{x}}_k(-)))\mathbf{P}_k(-) \\ \mathrm{K}_k = \mathbf{P}_k(-)\mathbf{H}(\hat{\mathbf{x}}_k(-))(\mathbf{H}(\hat{\mathbf{x}}_k(-))\mathbf{P}_k(-)\mathbf{H}(\hat{\mathbf{x}}_k(-))^T + \mathbf{R}_k)^{-1} \end{cases} \tag{11}$$

$\hat{\mathbf{x}}_k$ and $\mathbf{P}_k$ are the state estimation vector and covariance matrix at the observation epoch t_k, $(-)$ and $(+)$ represent the observation value before and after the update, $h(x)$ represents the observation model vector, $H(x)$ is the partial derivative coefficient matrix, $R(k)$ is the observation error.

Combined with the above Kalman filter equation to perform the observation value filtering update, a floating-point solution can be obtained from the antenna position and carrier phase ambiguity at observation epoch.

3.3 Heading solution

The ambiguity single-difference floating-point solution obtained after Kalman filtering is converted into double-difference floating-point solutions between stations, and the true ambiguity solution is searched using the least square ambiguity reduction correlation adjustment method.

The double-difference integer ambiguity vector $\breve{a}$ is obtained through the ambiguity search, and the integer characteristic of the ambiguity is used to further improve the baseline vector estimation accuracy. $\breve{b} = \hat{b} - Q_{\hat{b}\hat{a}} \cdot Q_{\hat{a}}^{-1} \cdot (\hat{a} - \breve{a})$ obtained by LAMBDA[8] search can get $\breve{a}$, $\breve{b}$ is a fixed solution of the baseline vector correction number.

Since $\breve{b}$ is the correction number of the baseline vector, let the coordinate of the main reference antenna of the dual receiver in the WGS84 coordinate system[9] be $[X_m \ Y_m \ Z_m]^T$, then the coordinates of antenna 2 relative to antenna 1 is

$$\begin{bmatrix} X_s \\ Y_s \\ Z_s \end{bmatrix} = \begin{bmatrix} \delta X \\ \delta Y \\ \delta Z \end{bmatrix} - \begin{bmatrix} X_m \\ Y_m \\ Z_m \end{bmatrix} \tag{12}$$

Assuming that the antenna 1 is the coordinate origin, the baseline vector is equivalent to the baseline vector correction number

$$\breve{b} = \begin{bmatrix} X_s \\ Y_s \\ Z_s \end{bmatrix} = \begin{bmatrix} \delta X \\ \delta Y \\ \delta Z \end{bmatrix} \tag{13}$$

Since the baseline vector $\breve{b}$ is calculated in the WGS84 coordinate system, it is represented by $\breve{b}_e$, and it needs to be coordinate-converted to obtain the corresponding vector in the ENU coordinate system, coordinate transformation equation:

$$\begin{bmatrix} x_n \\ y_n \\ z_n \end{bmatrix} = \begin{bmatrix} -\sin\lambda & \cos\lambda & 0 \\ -\cos\lambda\sin\phi & -\sin\lambda\sin\phi & \cos\phi \\ \cos\lambda\cos\phi & \sin\lambda\cos\phi & \sin\phi \end{bmatrix} \begin{bmatrix} x_e \\ y_e \\ z_e \end{bmatrix} \tag{14}$$

where $\breve{b}_n = [x_n \ y_n \ z_n]^T$, $\breve{b}_e = [x_e \ y_e \ z_e]^T$, subscript n indicates the representation of the corresponding parameter in the navigation coordinate system, and λ is the longitude value of the position of the receiver antenna, and ϕ is the latitude value of the antenna position.

According to coordinate transformation[10], the heading can be directly calculated as:

$$\varphi = \arctan\left(\frac{x_n}{y_n}\right) \tag{15}$$

4 Experimental Results

In order to verify the effectiveness of the method proposed in this paper, we set up a test platform as shown in Fig. 1 on a golf unmanned golf cart. A single baseline heading angle solution model was composed of two GPS antennas.

For the performance of the algorithm on unmanned vehicles, we conducted straight-line and turning-path driving tests on a golf unmanned cart. The test environment was a golf course with more slopes and a larger slope.

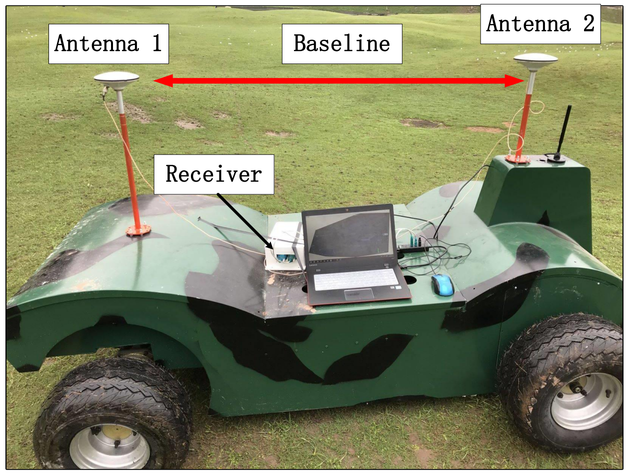

Fig. 2. Testing platform.

4.1 Straight path test

In straight path test, we set the start and end points on the map, plan the vehicle's predefined straight-line path, receive GPS signals during the automatic driving of the vehicle, the processor performs algorithm calculation to solve the heading angle, and performs automatic navigation control of the vehicle.

Fig. 3. Straight test track.

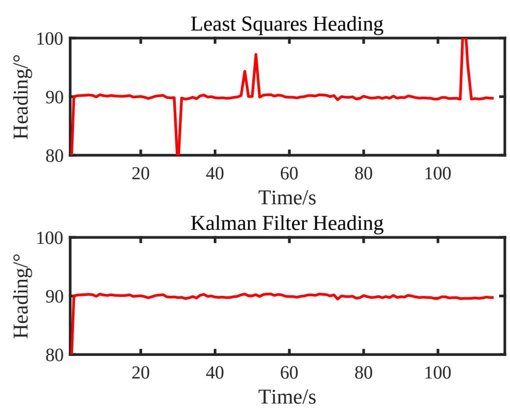

Fig. 4. Heading of straight path test.

First set the start and end points on the map, plan the vehicle's predefined straight-line path, receive GPS signals during the automatic driving of the vehicle, the processor performs algorithm calculation to solve the heading angle, and performs automatic navigation control of the vehicle.

The track of the straight test path is shown in Fig.3. The unmanned vehicle travels straight from south to north on the golf course. Fig.4 shows the vehicle heading angle calculated by the algorithm. There is a singularity in the heading angle for the ambiguity calculation using the least squares method, and there is no singularity in the heading angle for the ambiguity update using the Kalman filter.

4.2 Turning path test

The turn test path is shown in Fig. 5. A 90° turn path is planned on the golf course. The algorithm solves the heading angle in real time during the driving of the unmanned vehicle.

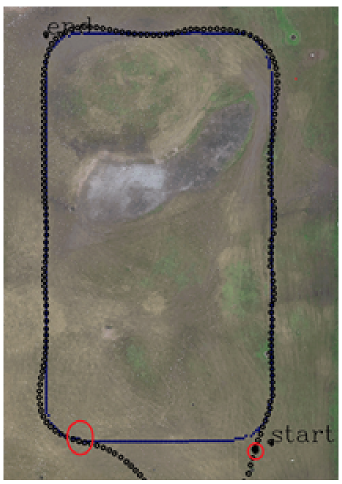

Fig. 5. Turning test track.

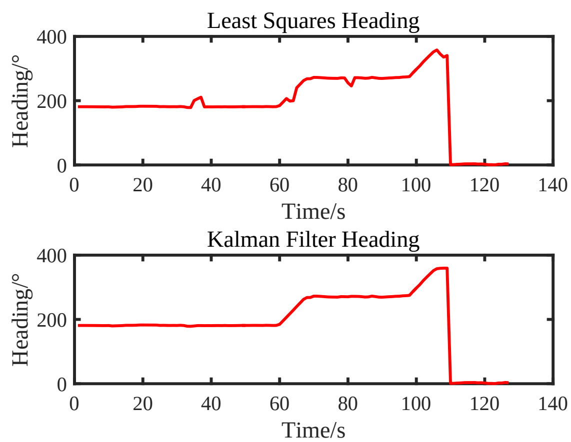

Fig. 6. Heading of turning path test.

Fig. 6 shows the solution of the heading angle of the turning test of the unmanned vehicle. Combined with the driving path analysis, the vehicle first travels straight in the direction of 180° and then turns 90°. During the turn, the output of the heading angle is smooth and stable. Steady heading angle output during cornering.

4.3 Test Result Analysis

At last, we counted several experimental tests results and calculated the standard deviation respectively. The comparison of the standard deviation between Kalman filtering and least squares is shown as Tab 1.

Table 1. Heading angle error statistics for straight line test

IDs	Testing Time $/s$	Mean $/^\circ$	Variance of ILS $/^\circ$	Variance of KF $/^\circ$
1	118	90.2	3.552	0.856
2	141	181.6	4.224	1.076
3	145	1.432	4.958	0.721
4	110	1.469	6.881	1.326

From the above results, it can be seen that the standard deviation calculated by the Kalman filtering is smaller than the least squares whether the vehicle is stationary or in motion. Therefore, in a complex terrain environment, using Kalman filter to update the integer ambiguity can solve the problem of singular points in the vehicle's heading angle.

5 Conclusion

In order to improve the accuracy of the heading estimation of the unmanned vehicle and reduce the equipment cost, the GPS single-baseline heading estimation algorithm proposed in this paper uses the GPS single-baseline model and Kalman filtering to provide real-time status updates to provide high-precision and stable heading angles. In addition, the algorithm test was verified in the actual application environment. The test results of the unmanned vehicle driving straight and turning show that the algorithm can calculate the heading angle for high accuracy and high stability.

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