

Rail Train Navigation System Based on GPS-IMU Combination

Wei Tan, Caihong Wang, Wei Ran, Yixuan Guo

School of Information Science and Engineering, Chongqing Jiaotong University, Chongqing, 400074, China

Abstract

A combined train navigation system based on satellite positioning and inertial measurement unit (IMU) is innovatively proposed for rail transit train operation control system, which overcomes the differential speed measurement accuracy error and positioning drift accumulation problem when using GPS and inertial navigation system (INS) separately. Based on the Kalman optimal filtering framework, the acceleration and angular velocity data from the IMU are used to integrate and predict the train running speed and position in real time, and the GPS-observed train position is used to calibrate the IMU positioning drift and solve the train speed adaptively and accurately. The experimental results show that the accuracy error and stability of speed measurement and positioning of the combined GPS-IMU navigation system are better than those of the INS and GPS systems used alone, which is conducive to the high-density and high-speed tracking operation of front and rear trains and the improvement of line transportation efficiency.

Keywords

Train navigation system, GPS, IMU, combined navigation.

1. Introduction

Urban rail transit has the advantages of large transportation volume, low energy consumption, low pollution, fast speed, and small land occupation, which can effectively relieve the pressure of urban travel, reduce traffic congestion and traffic accidents, and is strongly supported by the state. With the acceleration of urbanization, urban rail transit will gradually become the mainstream of urban bus passenger transportation system. Real-time, reliable and high-precision train speed measurement and positioning can ensure the safety and accuracy of front and rear train tracking, improve train operating density and speed, and improve driving safety and transportation efficiency. It is the core key technology of the train operation control system. The traditional wheel-rail positioning technology realizes the speed measurement and positioning of the train by means of wheel speed sensors such as tachometer motors. The main defects are: (1) the displacement deviation caused by the wear of the wheel diameter; (2) the wheel spins when the train starts or accelerates; When the train brakes, the wheels will slip, which will cause the speed and positioning deviation of the wheel speed sensor [1]. (3) As a moving part, the wheel speed meter has a high failure rate and is more complicated to install and maintain. . We found that the speed measurement and positioning method directly aimed at the vehicle body is an effective way to solve the above problems.

In the Next Generation Train Control System (NGTCS), the train positioning method based on the global navigation satellite system is generally regarded as the main development direction of the NGTCS positioning technology [2]. GPS is a relatively mature global positioning system at present. It has the advantages of all-round, full-time, high-precision, etc. It can provide high-precision navigation information for global users, but its signals are easily blocked and interfered. In particular, its dynamic performance is relatively high. Poor, that is, due to its limited positioning accuracy, the real-time speed measurement error based on position

difference is too large, and it is difficult to meet the safety requirements of train control [3]. It is worth mentioning that compared with other transportation scenarios, such as aviation, highway, etc., the mass (inertia) of the train is relatively large, and the slope and curvature of the track are relatively gentle, so that the running posture and acceleration of the train do not change sharply, so it is more suitable for the application of inertia navigation. The IMU-based inertial navigation system (INS, inertial navigation system) is a navigation system with strong autonomy. The IMU's accelerometer and gyroscope angular velocity data output frequency is high, and can effectively resist external interference, but the INS system belongs to The multi-dimensional integral accumulation working system, the speed measurement and positioning error will increase rapidly with time (the speed error increases with the 3 power of time, and the position error increases with the 6 power of time), which is not suitable for long-term speed measurement and positioning [4].

Therefore, for the rail train operation scenario, we propose an on-board navigation system based on the combination of GPS and INS. The combination uses the Kalman filter algorithm with global optimization for data fusion-based on the vehicle body acceleration and angular velocity data provided by INS. , real-time multi-dimensional integration, to predict the speed and position of the train; use the train position observed by GPS to calibrate the positioning offset of the INS in real time, adaptively calculate the accurate speed of the train, and realize the function of accurate speed measurement and positioning of the train [5, 6].

2. Design of GPS-INS Integrated Navigation System

2.1. System Components

As shown in Figure 1: First, obtain GPS data (longitude, latitude), and calculate the GPS movement speed according to the measurement time interval, and then calculate the GPS movement displacement; secondly, obtain the output of the inertial navigation component. Parameters, such as the acceleration of the x, y, z axes, are Kalman filtered. Integrate the acceleration data with the time interval to obtain the velocity of the inertial navigation component in three directions. By integrating the velocity, the motion displacement of the component can be obtained. By accumulating the displacement, the motion mileage of the inertial navigation component can be obtained.

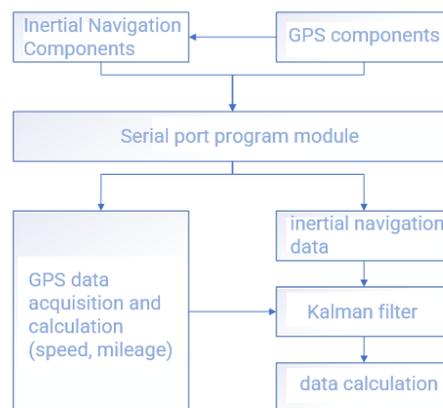


Figure 1 System logical structure diagram

2.2. System Workflow

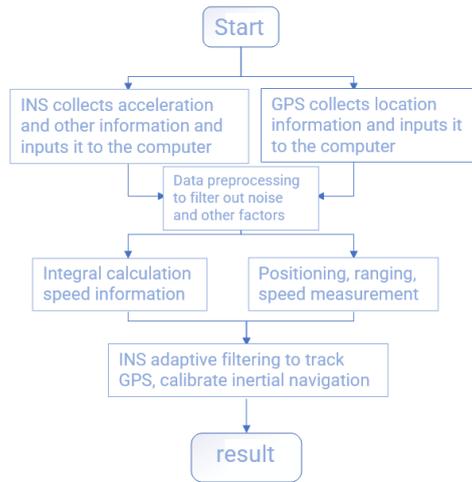


Figure 2 System work flow chart

The above flow chart generally summarizes the upper computer system framework of the integrated navigation system. The implementation process is divided into three parts. The first part is to obtain the carrier speed through the inertial navigation module, and the second part is to realize the acquisition of the carrier speed through the GPS module. , the third part is to process the speed information obtained in the first two parts and realize the image display.

3. Algorithm design

3.1. Equation of State of the System

When the height of the vehicle is basically unchanged, the state variable of the combined Kalman filter is $X = [x_e, v_e, a_e, x_n, v_n, a_n]^T$, where x_e, x_n are the displacement components of the vehicle in the north direction, v_e, v_n are the velocity components of the vehicle in the east and north directions, respectively, a_e, a_n are the acceleration components of the vehicle in the east and north directions, respectively. The "current" statistical model of the motor vehicle is used to describe the statistical distribution of vehicle acceleration, namely:

$$\begin{cases} a_e = \bar{a}_e + a_{e1}, a_{e1} = -\tau_e a_{e1} + w_e \\ a_n = \bar{a}_n + a_{n1}, a_{n1} = -\tau_n a_{n1} + w_n \end{cases}$$

Among them, a_{e1}, a_{n1} zero mean colored acceleration noise; \bar{a}_e, \bar{a}_n is the mean value of maneuvering acceleration, which is constant in each sampling period; τ_e, τ_n are the relevant time constants corresponding to the Markov process; w_e, w_n are Gaussian white noise with zero mean and variance $2\tau_e\sigma_e^2, 2\tau_n\sigma_n^2$, respectively. The continuous state equation of the system is obtained as:

$$\dot{X}(t) = \mathbf{A}X(t) + \mathbf{U} + \mathbf{W}(t) \quad (3)$$

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -\tau_e & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & -\tau_n \end{bmatrix}$$

$$U = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \tau_e a_e \\ 0 \\ 0 \\ \tau_n a_n \end{bmatrix}, W(t) = \begin{bmatrix} 0 \\ 0 \\ w_e \\ 0 \\ 0 \\ w_n \end{bmatrix}$$

Discretize the continuous state equation of the system to obtain the discrete state equation of the system:

$$X(k) = (k, k - 1)X(k - 1) + U(k) + W(k)$$

$$, X(k) = [x_e(k) \ v_e(k) \ a_e(k) \ x_n(k) \ v_n(k) \ a_n(k)]^T$$

3.2. Establishment of System Observation Equation

3.2.1. GPS data observation point

For the GPS signal update point sequence with a period of 200ms, the easting velocity information v_e and northing velocity v_n output by the GPS receiver and the easting acceleration a_e and northing acceleration a_n output by the accelerometer are used as external observation vectors. Then the observation vector $Z(k) = [z_1(k) \ z_2(k) \ z_3(k) \ z_4(k)]^T$ and the external observation vector and the state vector have the following relationship:

$$\begin{cases} z_1(k) = v_e(k) + v_1(k) \\ z_2(k) = v_n(k) + v_2(k) \\ z_3(k) = a_e(k) + v_3(k) \\ z_4(k) = v_n(k) + v_4(k)v_i(k) \end{cases}$$

($i = 1, 2, 3, 4$) is Gaussian white noise with a mean equal to zero and a variance of $\sigma_{v_i}^2$. The discrete linear system observation equation is:

$$Z(k) = HX(k) + V(k)$$

$Z(k) = [v_e(k), v_n(k), a_e(k), a_n(k)]^T$ is the observation matrix. $V(k)$ has a mean of zero, The variance $R(k) = \text{diag}\{\sigma_{v_1}^2, \sigma_{v_2}^2, \sigma_{v_3}^2, \sigma_{v_4}^2\}$ is a constant matrix.

3.2.2. Accelerometer data difference point

In the 200ms interval between the two GPS signals, the difference calculation is performed by using the accelerometer signal with a period of 5ms. Therefore, the absolute value component of the acceleration of the accelerometer signal along the direction of the car is used as the external observation vector ax_0 .so:

$$Z(k) = a_{x_0}(k) = \sqrt{a_e(k)^2 + a_n(k)^2} + v(k)$$

$v(k)$ is white Gaussian noise with mean equal to zero and variance σ_v^2 . Therefore, the discretized system observation equation is:

$$Z(k) = h[X(k)] + V(k)$$

$$h[X(k)] = \sqrt{a_e(k)^2 + a_n(k)^2}$$

The mean of $V(k)$ is zero, and the variance is $R(k) = \sigma_v^2$.

Since the observation equation is a nonlinear equation, in order to linearize it, the extended Kalman filter technique (EKF) is used, that is, it is transformed into a Taylor series at the one-step predicted value, and the high-order terms are ignored, we get

$$Z(k) = h[X(k, k - 1) + H(k)][X(k) - X(k, k - 1)] + V(k)$$

$$= H(k)X(k) + V(k) + h[X(k, k - 1)] - H(k)X(k, k - 1)$$

$$H(k) = \frac{\partial h[X(k)]}{\partial X(k)} \Big|_{X(k) = X(k, k-1)} = [0 \quad 0 \quad h_1 \quad 0 \quad 0 \quad h_2],$$

$$h_1 = \frac{a_e(k, k-1)}{\sqrt{a_e^2(k, k-1) + a_n^2(k, k-1)}}$$

$$h_2 = \frac{a_n(k, k-1)}{\sqrt{a_e^2(k, k-1) + a_n^2(k, k-1)}}$$

3.3. GPS and INS combined speed measurement algorithm

The GPS+INS combined system navigation designed in this design refers to using the GPS method to measure the position information, calculating the speed information through the position information, and using the speed and position information measured by the INS at the same time; using the adaptive filter, the GPS data is used as the desired signal. , take the INS data as the input signal, give the adaptive filter, the obtained INS output signal is compared with the expected GPS signal, and get the error, we adjust the parameters of the adaptive filter to reduce the error signal to the minimum and achieve the optimal Adaptive filtering to achieve the purpose of GPS calibration INS.

The combined navigation process of GPS and INS is shown in the following figure:

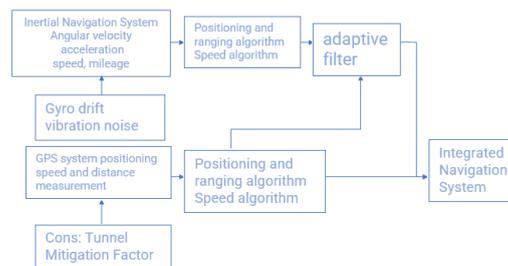


Figure 3 GPS and INS integrated navigation flow chart

3.4. Adaptive Filter Algorithm

The principle of the adaptive filter algorithm is shown in Figure 4-3,

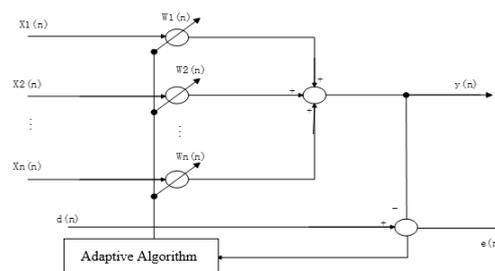


Figure 4 Multiple Input Adaptive Filter

In the case of a single input, the input-output relationship is:

$$y_{(n)} = \sum_{k=0}^m w_n(k)x(n-k)$$

Among them, the expression of $x(n)$ is:

$$x(n) = [x_{(n)} x_{(n-1)} \dots x_{(n-N)}]^T$$

In the case of multiple inputs, the input-output relationship:

$$y_{(n)} = \sum_{k=0}^N w_k(n)x_k(n)$$

As shown in Figure 4, the $m+1$ coefficients of the adaptive linear combiner form a weight vector " $w_{0:n}$ " (" n "), so

$$w(n)=[w_0(n) w_1(n) \dots w_m(n)]^T$$

The difference between the output signal and the reference signal is called the error signal, represented by $e(n)$, and its expression is:

$$e(n)=d(n)-y(n)=d(n)-x^T(n)w(n)=d(n)-w^T(n)x(n)$$

According to the principle that the mean square value of the error signal is the lowest, the mean square error of the error signal of the adaptive filter is:

$$\begin{aligned} \xi(n) = E[e^2(n)] &= E[d^2(n)] + \omega^T(n)E[x(n)x^T(n)]w(n) \\ &\quad - 2E[d(n)x^T(n)]w(n) \end{aligned}$$

4. System testing and results analysis

4.1. Comparative Analysis of GPS Navigation Data and Inertial Navigation Data

Figure 5 shows the derived image of the inertial navigation and GPS time distance data obtained from the simulated road section. It can be observed that after integrating the speed curve, the movement distance curves of GPS and inertial navigation are quite different. This shows that the accuracy of the inertial navigation output data and the actual error are relatively large. When the train enters the tunnel for a long time or the GPS signal cannot be received underground, the inertial navigation output data may not be able to reliably measure the speed and position. Therefore, using GPS data as expected information, adaptive filtering/calibration processing is performed on the inertial navigation output speed, so that the speed curve output by the inertial navigation is close to the GPS speed curve. The filtered inertial navigation velocity curve is shown in Figure 6, which also shows the GPS velocity curve for comparison.

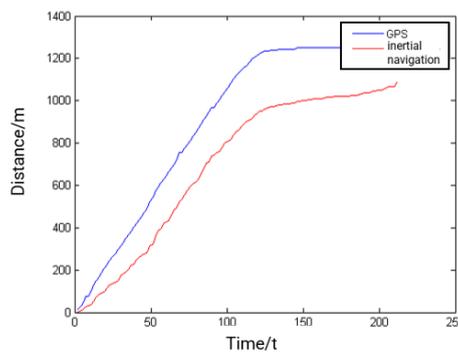


Figure 5 Time relationship between GPS and inertial navigation distance

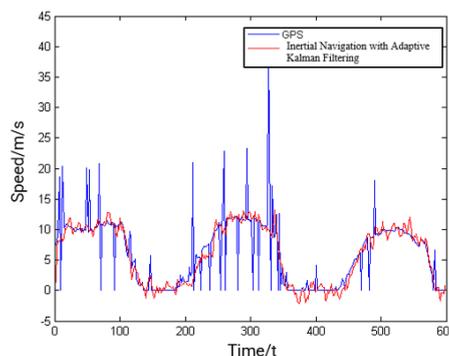


Figure 6 GPS and inertial navigation motion v-t diagram with adaptive kalman filtering

Figure 6 shows the GPS and the inertial navigation motion speed and time curve after adaptive Kalman filtering. It can be clearly seen that the inertial navigation speed curve after adaptive

Kalman filtering is more consistent with the GPS speed curve. At the same time, it can be seen that the inertial navigation speed curve after adaptive Kalman filtering is less affected by the impact of the GPS speed curve. Figure 3 shows the GPS and inertial navigation motion distance and time curves after adaptive Kalman filtering. It can also be seen that the GPS motion distance curve is in good agreement with the inertial navigation motion distance after adaptive Kalman filtering. Due to the large size shown in the figure, the difference between the two curves cannot even be seen. It can be seen that the motion speed obtained by using the adaptive Kalman filter to filter the inertial navigation speed curve can meet the use accuracy of replacing GPS in tunnels, underground and other environments.

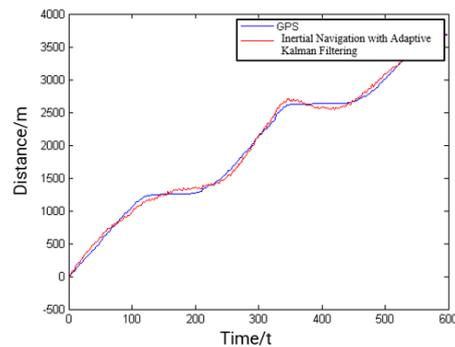


Figure 7 GPS and inertial navigation motion s-t diagram with adaptive Kalman filtering

4.2. Test Results

It can be clearly seen that before the Kalman filter, the speed curve of inertial navigation is constantly shifting to a decreasing direction, which is caused by the accumulation of errors in inertial navigation. In addition, it can also be seen that the high-frequency vibration of the speed curve of the inertial navigation is relatively large. After analysis, this is caused by the existence of more vibrations on the train. Not only that, due to the high sensitivity of the inertial navigation device, its register for storing acceleration information is up to 14 bits. Therefore, many tiny vibrations that are difficult for humans to perceive can be detected and amplified, and the inertial navigation element detects these vibrations through accumulation of errors and amplifies them to affect its speed measurement accuracy. After Kalman filtering, the phenomenon of high frequency vibration on the inertial navigation speed curve has been greatly improved. Not only that, because the adaptive algorithm is added to the filter, the error of the inertial navigation can be continuously corrected, and the speed curve is kept from shifting downward, thus ensuring the accuracy of the inertial navigation speed measurement and positioning.

It can be seen from the above test results that the test section needs to travel about 3.7km, which is consistent with the actual situation. From this, it can be concluded that the inertial navigation speed curve after Kalman filtering is roughly consistent with the GPS speed curve, which realizes the tracking of GPS by inertial navigation and achieves higher accuracy than any single navigation and positioning method.

5. Conclusion

The design of the train adaptive inertial navigation system based on GPS calibration proposed by us fully utilizes the technical characteristics of the two navigation methods, overcomes the speed measurement accuracy defect of GPS navigation and the drift accumulation of INS, and has higher accuracy and stability. It can reduce the construction and maintenance cost of the train operation system, and has a great application prospect. With the continuous development of society, more advanced technologies will serve the field of train navigation and positioning.

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