Journal of Computers Vol. 28, No. 6, 2017, pp. 324-334
doi:10.3966/199115992017122806029

Multimode Information Fusion Based on Kalman Filter of Macro and INS

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Received 24 July 2017; Revised 19 September 2017; Accepted 19 October 2017

Abstract. Research based on intelligent information fusion filtering method. Using multi-sensor information to compensation of inertial navigation, the range of distance sensor integrated range positioning results and INS inertial measurement information synchronization, on the basis of combined kalman filter for fusion structure, through the kalman filter to estimate the states of the movement, using the results of the estimate to correct positioning, the positioning of the results after compensation algorithm is given, in order to improve the positioning precision of integrated navigation. In the experiment, the cumulative error is reduced from 4.75% to 2.47% after using the algorithm. The results show that the proposed algorithm can improve the positioning precision of integrated navigation.

Keywords: autonomous positioning, information fusion, Kalman filter

1 Introduction

IMU inertial navigation device will gradually drift until divergence, autonomous positioning error increases exponentially with the time [1, 4, 22]. In this study, the characteristics of emergency rescue personnel are realized by using the distance measurement device (ultrasonic, infrared, macro sensors) in the emergency rescue personnel and the finite state analysis of the human movement characteristics (distance, rate and range). By using the results of ultrasonic distance measurement and inertial measurement, the local information is formed by information fusion, which can improve the accuracy and efficiency of the dead reckoning. It provides a reference solution for the improvement of the positioning accuracy of wearable navigation equipment.

2 Realization of Multimodal Information Fusion

Multi sensor data fusion involves many aspects of theory and technology, such as signal processing, estimation theory, uncertainty theory, optimization theory, pattern recognition, neural network and artificial intelligence, etc.. Multimodal information fusion a method of data recognition and evaluation, through data association and combination to obtain the more accurate positioning, identification and evaluation of the measured object [2-3, 21].

Therefore, many researchers have studied the measurement error of inertial navigation system [6-7, 23]. The error model of strapdown inertial accelerometer is deduced by Yoon, Zihajehzadeh, Kang and Park [13]. Hu, Gao and Zhang Analyzed the gravity vector disturbance in the accelerometer measurement process [17]. According to the error model of MEMS gyroscope, Liu, Zhang, Zuo and Xie designed the calibration method of MEMS gyroscope [12]. Wu, Zhou, Chen, Fourati and Li proposed different calibration schemes for inertial measurement unit errors [16]. Chang, Zha and Qin proposed a general

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calibration method for inertial measurement units [14].

In this study, ultrasonic distance measurement is used to obtain the distance between the wearable navigation device and the ground, and the distance variation information is used as the observation value, and the INS inertial measurement information synchronous output. By using the Kalman filter to estimate the zero instantaneous state of INS, the zero calibration of INS is done, and the cumulative error of INS is corrected [5, 9]. The method is in line with the characteristics of unknown fire emergency environment and which is convenient for engineering realization. Two measurement systems are relatively independent, with the control unit of wearable navigation device to keep data synchronization, the positioning information of the settlement is redundant and which can meet the requirement of improving the positioning accuracy [8].

Fig. 1 is installed in the waist position of the wearable device map, Fig. 2 is the movement process of distance change model.

Fig. 1. Wearable equipment installed at the waist position

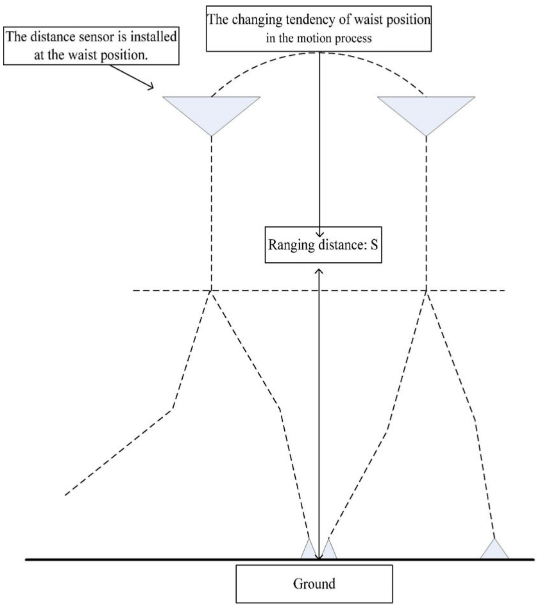

Fig. 2. Change in the motion process

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2.1 The State Estimation of Ranging Based on Distance Sensor

Wearable device for emergency rescue personnel has been equipped with ultrasonic sensors. The ultrasonic sensor can work in harsh environment, such as the limited sight distance, fire scene and so on. Ultrasonic distance measurement is a non-contact distance measurement based on ultrasonic wave propagation characteristics in the medium. The principle is that the ultrasonic wave is transmitted by the ultrasonic transducer. In the air, it is transmitted to the measured object, which is reflected by the ultrasonic transducer to receive the echo signal and determine the time of the ultrasonic pulse from the transmitter to the receiver. Under the premise of the known ultrasonic velocity V, the distance between the measured object and the ultrasonic transducer can be calculated, and the determination of the obstacle and the position of the object can be completed. Distance and distance variation information of wearable device to ground or surrounding walls can be obtained by the change of the ultrasonic sensor distance, and calculating the boundary points of the variation of distance, and INS zero transient judgment can be achieved based on finite state analysis.

The ultrasonic wave transmitting device sends out the ultrasonic wave, and which can calculate the distance according to the time difference when the receiver receives the ultrasonic wave. This is similar to the principle of radar ranging. Ultrasonic transmitter emits ultrasonic in a certain direction. At the start of the launch time, ultrasonic wave propagates in the air, on the way back to the obstacles on the way, and the ultrasonic receiver immediately stop receiving the reflection wave time (The propagation velocity of ultrasonic wave in air is 340m/s, the distance between the starting point and the obstacle can be calculated according to the time recorded by the timer. That is: s=340t/2), and then the boundary of the distance can be obtained. Take this moment as the motion feature point, and analyze the zero transient time of INS.

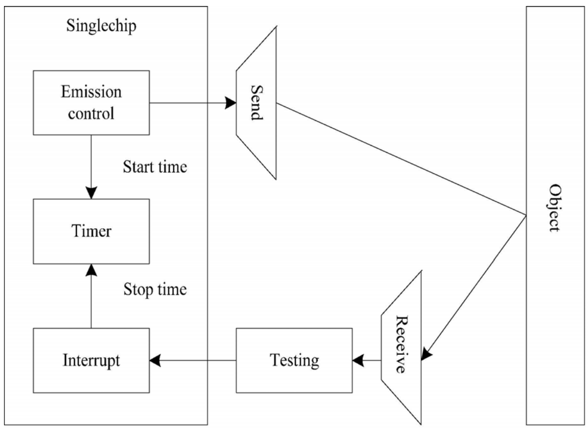


Fig. 3. Principle of ultrasonic measuring distance

2.2 Wearable Navigation Inertial Navigation Device

The wearable navigation device in this study is mainly composed of ranging sensor, inertial navigation system and MCU unit. The inertial navigation mainly includes the following three parts: accelerometer, gyro stabilized platform and navigation computer, which belongs to the autonomous navigation system. The main disadvantage is that with the growth of time, the error of the positioning system will continue to increase, that is, the long-term stability is relatively poor. The inertial navigation system is based on the gyro as the measuring element, and the two components are fixed in the direction of the three coordinate axes of the motion vector coordinate system. When the carrier in motion, the motion vector relative to the inertial reference system angular movement speed by installing gyroscope on the carrier to determine, and then use the motor angular velocity value to calculate the motion vector coordinate system to the navigation coordinate system the coordinate transformation matrix. Based on the calculated transformation matrix, the acceleration information is converted into the navigation and positioning coordinate system. Finally, the navigation parameters are obtained.

2.3 Multi-modal Information Fusion Algorithm Structure

The main task of multi-sensor information fusion is to estimate the state of the target using multi sensor information. In the combined positioning system, it is reasonable to use the Kalman filter to estimate the error state of the combined location system effectively [11]. By using the estimated value of the error state, the system can adjust the positioning system, and then improve the accuracy of the system. The biggest characteristic is that it can eliminate the random disturbance noise, and obtain the useful information to approximate the real situation. Joint Kalman filtering is more suitable for real-time fusion of dynamic low level redundant sensor data [24]. In this method, the statistical properties of the measurement model are used to estimate the optimal fusion data in the statistical sense.

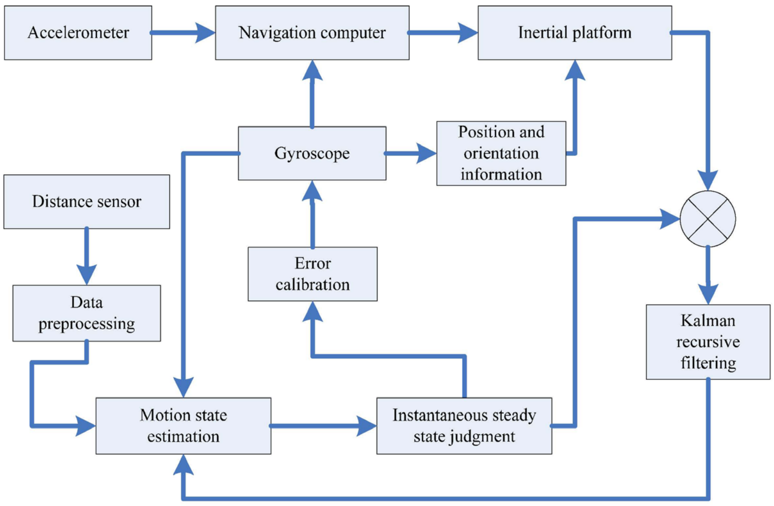


Fig. 4. Structure of information fusion algorithm based on Kalman filter

Kalman filter using recursive method to solve the discrete data linear filtering problem, in order to measure the error generated by the estimated value for correction, so that the state and parameters are estimated to be close to the true value. Kalman filtering algorithm is mainly divided into two processes of time updating and observation updating [19-20]. The effective operation of Kalman filter requires the system to be linear, and the state noise and observation noise are Gauss white noise. But in the actual application environment, the above conditions are difficult to meet, in order to solve the problem of nonlinear, non-stationary and non Gauss system, a variety of derivative algorithms came into being [6-7]. Autonomous navigation system with Kalman filter algorithm and its derivative algorithms such as the extended Kalman filter and unscented Kalman filter, Cubature Kalman filter and CKF, Robust filtering (RF) or Particle Filter (PF) for information processing core [24].

2.4 Macro and Inertial Navigation Multimode Information Fusion Based on Kalman Filter

Kalman filter is a state equation of linear system, which is used to estimate the state of the system by the system input and output data. Kalman filtering is able to estimate the state of the dynamic system from a series of measurement noises in the measurement variance. Kalman filter uses recursive method to solve the discrete data linear filtering problem, in order to measure the error generated by the estimated value for correction, so that the state and parameters are estimated to be close to the true value. Self-localization based on inertial navigation system has its own limitations. Due to the existence of accumulated error, it is not suitable for long distance and long distance. In this study, the Kalman filter algorithm is used to fuse the information of ultrasonic distance measurement and inertial navigation positioning data to eliminate the accumulated error and achieve accurate positioning. In the experiment, the test personnel carry on the wearable navigation device, going along a fixed route at a uniform speed, and eventually returning to the origin, to see whether the results can also be the origin to determine the effect of the system. For this purpose, the motion state estimation based on Kalman filter is established, and the distance between the human body and the ground is measured by the distance sensor, and the future trend of the human body is predicted according to the mathematical model. In the transient position inertial navigation system, the accelerometer and gyroscope are zero corrected. The main purpose is to reduce the accumulated error and improve the positioning accuracy.

As shown in Fig. 5, a distance sensor is expected to occur in the vicinity of dt at the time of n. According to the human body kinematics theory, S is the point of the minimum distance in the moment of changing the feet, and waist position has a moment of static state, that is, the Z axis of the accelerometer is measured as 0. Due to the existence of the error, the measurement results are often less than 0 values, which can be used to measure the results obtained from the measurement results of the instantaneous steady-state point.

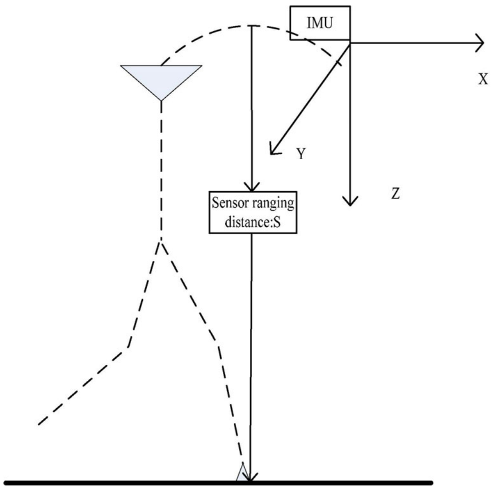


Fig. 5. Schematic diagram of distance measurement and IMU measurement in the course of motion

The following is a brief description of the process of Kalman filter. In the integrated navigation system, the ultrasonic distance measurement and the inertial navigation system can be described as the process equation and the observation equation.

(1) Process equation and observation equation

$$X_k = \Phi\, X_{k-1} + \mathrm{B}U_k + W_k \tag{1}$$

$$Z_k = HX_k + V_k \tag{2}$$

In the above (1) (2) two formulas, X_k is the K time ultrasonic distance measurement information, and U_k is the K time of the system control. Φ and B is a system parameter. For multi model systems, Φ and B is matrix. Z_k is the measurement result of the inertial navigation system in K time, and H is the parameter of inertial navigation system. For multi- measurement system, H is the matrix. W_k and V_k respectively represent processes and measurements of noise, and they are assumed to be Gauss white noise.

At the same time W_k and V_k meet the follow formula:

$$\begin{aligned} &\mathrm{E}\left[W_k\right] = 0, Cov\left[W_k, W_j\right] = E\left[W_k W_j^T\right] = Q_k \sigma_{kj} \\ &\mathrm{E}\left[V_k\right] = 0, Cov\left[V_k, V_j\right] = E\left[V_k V_j^T\right] = R_k \sigma_{kj} \\ &Cov\left[W_k, V_j\right] = E\left[W_k V_j^T\right] = 0 \end{aligned} \tag{3}$$

In the above formula, the Q_k is the variance matrix of the noise sequence of the ultrasonic measuring distance measurement system; R_k is the variance matrix of the noise sequence of the inertial navigation system, which is positive definite matrix. If the state X_k is estimated to satisfy the above equation, Z_k satisfies the above measurement equation, system noise and measurement noise V_k to meet the above formula (3), the system noise covariance matrix Q_k is not negative, the measurement noise covariance matrix R_k positive definite, K time measurement is Z_k, then can use the system process model to predict the next time. Assuming the current system state is k, according to the system model, we can predict the current state of the system based on the state of the system:

$$X_{k|k-1} = \Phi_{k,k-1} X_{k-1} + B\ U_k \tag{4}$$

In formula (4), $X_{k|k-1}$ is the use of the results of the last state prediction, X_{k-1} is the result of a state of the best, U_k for the current state of control, if not control, it can be 0. The covariance of the corresponding $X_{k|k-1}$ is expressed by P.

$$P_{k|k-1} = \Phi P_{k-1} \Phi' + Q \tag{5}$$

In equation (5), $P_{k|k-1}$ is the covariance corresponding to $X_{k|k-1}$, p_{k-1} is the covariance corresponding to X_{k-1}, Φ' said the transpose of Φ, Q is the covariance of the system process. Formula (4), (5) is the prediction of the system. Combining predictive values and measured values can be obtained from the present state of the estimated value of the optimization $X_{K/K}$.

$$X_{k|k} = X_{k|k-1} + Kg_k \bullet \left(Z_k - HX_{k|k-1} \right) \tag{6}$$

$$Kg_k = \frac{P_{k|k-1} H'}{HPk \mid k-1\ H' + R} \tag{7}$$

Where Kg is the kalman filter gain. In order to make the kalman filter to run continuously until the end of the system process, update the $X_{K/K}$ covariance at the K state:

$$P_{k|k} = (I - Kg_k H) \mathrm{P}_{k|k-1} \tag{8}$$

Where I is 1 matrix, when the system enters the state K + 1, $P_{k|k}$ is $P_{k-1|k-1}$ in the formula (7), such algorithm is can regression arithmetic down from the.

By the Kalman filtering process shows that the inertial navigation error compensation system of equation of state (4) Φ=E (E is the identity matrix), easy to get:

$$V_{k|k-1} = V_{k-1|k-1} + W_k + \frac{N_i L_i \tan\alpha}{L\sqrt{N_i^2 + L_i^2 - 2N_i L_i \cos\alpha}} a(k-1) t_0 \tag{9}$$

Among them, the $V_{k|k-1}$ is the first k-1 moments of the ultrasonic distance measurement algorithm velocity V of the predicted value for the relative motion of the K moments. W_k is Gauss white noise, which describes the uncertainty of the system. Then:

$$E(\mathrm{w}_k) = 0, \mathrm{E}[\mathrm{w}_k \mathrm{w}_k{}^T] = q\delta_{k-\tau} \tag{10}$$

q is the variance intensity for w_k.

According to the Kalman filter, the measurement variance is known to be able to estimate the dynamic state of the system from a series of measurement noise in the data [11]. In this system, the first k time variance is estimated by the k-1 time, adding process error Q:

$$P_{k|k-1} = \mathrm{P}_{k-1|k-1} + \mathrm{Q} \tag{11}$$

Formula (9) (11) to achieve the basic prediction of the system state, in order to further improve the accuracy of prediction, but also need to have the ability to learn independently. The Calman gain Gg is introduced, which is used as a measure of the closeness of the estimated value of the optimal estimate and the predicted value, and the prediction value of the variance of the first k time is determined according to the ratio of the k-1 and the measurement error.

$$\mathrm{Gg_k} = \frac{P_{k|k-1}}{P_{k|k-1} + \mathrm{R}} \tag{12}$$

Then the position of the optimal estimate in the predicted and measured values at the first k time is determined by using the Calman gain.

Finally, the optimal estimation variance of the first k time is determined by the close degree $[1 - \mathrm{Gg_k}]$ of the optimal estimate and the measured value (measured by the sensor).

$$P_{k|k} = (1 - \mathrm{Gg_k})\,\mathrm{P}_{k|k-1} \tag{13}$$

The formula (12), (13), (14) achieve the process of autonomous learning.

The above equations constitute the fusion mathematical model. As long as the given initial value X_0 and P_0, according to the measurement of K moments Z_k, you can estimate the state of the K moment estimates X_k.

3 Experimental Data Acquisition and Simulation Results Analysis

The initial conditions of the system are as follows: Personnel shoulder wearable navigation device, along the 30 degrees east of North Point to 1m/s speed motor; initial position as in figure shown in the position of the circle markers, the acceleration of gravity 9.7804m/s2; earth rotation psi to 15°/h. The gyro drift is 0.1°/h, the zero offset of the accelerometer is 10-3g; the first order Markoff correlation time is 300s; the filter period T=1s; the initial value of the filter covariance is:

$$\mathrm{X} = \begin{bmatrix} 1m, 1m, 0.5\mathrm{m/s}, 0.5\mathrm{m/s}, 0.8^{\circ}, 0.8^{\circ}, 0.16^{\circ}, \\ 0.1^{\circ}/h, 0.1^{\circ}/h, 0.1^{\circ}/h, \left(10^{-3}\right)\mathrm{g}, \left(10^{-3}\right)\mathrm{g}, \left(10^{-3}\right)\mathrm{g} \end{bmatrix}$$

The Initial value of system state:

$$P_0 = \begin{bmatrix} \left(0.0024^{\circ}\right)^2, \left(0.0046^{\circ}\right)^2, \left(0.1\mathrm{m/s}\right)^2, \left(0.1\mathrm{m/s}\right)^2, \left(1^{\circ}\right)^2, \left(1^{\circ}\right)^2, \\ \left(1^{\circ}\right)^2, \left(0.1^{\circ}\right)^2, \left(0.1^{\circ}\right)^2, \left(0.1^{\circ}\right)^2, \left(10^{-3}\right)\mathrm{g}, \left(10^{-3}\right)\mathrm{g}, \left(10^{-3}\right)\mathrm{g} \end{bmatrix}$$

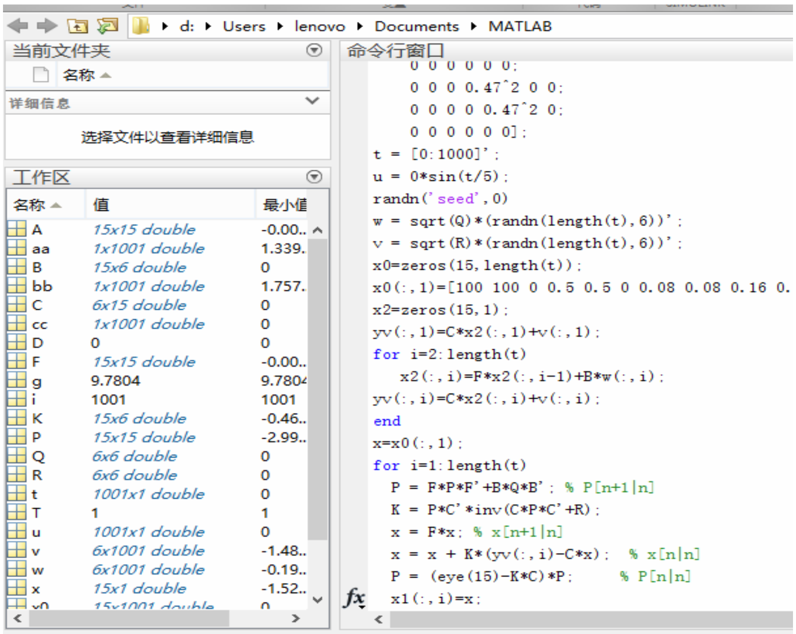
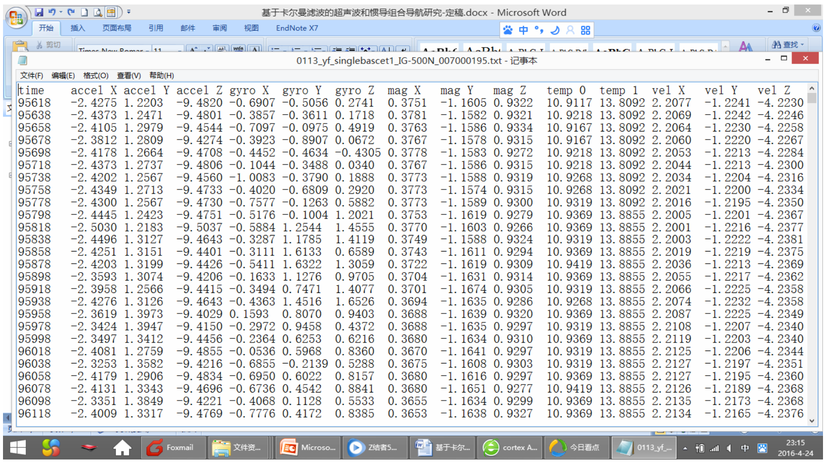


Fig. 6. Experimental data Matlab simulation interface

The experimental data are shown in the following Fig. 7.



time	accel X	accel Y	accel Z	gyro X	gyro Y	gyro Z	mag X	mag Y	mag Z	temp 0	temp 1	vel X	vel Y	vel Z
95618	−2.4275	1.2203	−9.4820	−0.6907	−0.5056	0.2741	0.3751	−1.1605	0.9322	10.9117	13.8092	2.2077	−1.2241	−4.2230
95638	−2.4373	1.2471	−9.4801	−0.3857	−0.3611	0.1718	0.3781	−1.1582	0.9321	10.9218	13.8092	2.2069	−1.2242	−4.2246
95658	−2.4105	1.2979	−9.4544	−0.7097	−0.0975	0.4919	0.3763	−1.1586	0.9334	10.9167	13.8092	2.2064	−1.2230	−4.2258
95678	−2.3812	1.2809	−9.4274	−0.3923	−0.8907	0.0672	0.3767	−1.1578	0.9315	10.9167	13.8092	2.2060	−1.2220	−4.2267
95698	−2.4178	1.2664	−9.4708	−0.4452	−0.4634	−0.4305	0.3778	−1.1583	0.9272	10.9218	13.8092	2.2053	−1.2213	−4.2284
95718	−2.4373	1.2737	−9.4806	−0.1044	−0.3488	0.0340	0.3767	−1.1586	0.9315	10.9218	13.8092	2.2044	−1.2213	−4.2300
95738	−2.4202	1.2567	−9.4560	−1.0083	−0.3790	0.1888	0.3773	−1.1588	0.9319	10.9268	13.8092	2.2034	−1.2204	−4.2316
95758	−2.4349	1.2713	−9.4733	−0.4020	−0.6809	0.2920	0.3773	−1.1574	0.9315	10.9268	13.8092	2.2021	−1.2200	−4.2334
95778	−2.4300	1.2567	−9.4730	−0.7577	−0.1263	0.5882	0.3773	−1.1589	0.9300	10.9319	13.8092	2.2016	−1.2195	−4.2350
95798	−2.4445	1.2423	−9.4751	−0.5176	−0.1004	1.2021	0.3753	−1.1619	0.9279	10.9369	13.8855	2.2005	−1.2201	−4.2367
95818	−2.5030	1.2183	−9.5037	−0.5884	1.2544	1.4555	0.3770	−1.1603	0.9266	10.9369	13.8855	2.2001	−1.2216	−4.2377
95838	−2.4496	1.3127	−9.4643	−0.3287	1.1785	1.4119	0.3749	−1.1588	0.9324	10.9319	13.8855	2.2003	−1.2222	−4.2381
95858	−2.4251	1.3151	−9.4401	−0.3111	1.6133	0.6589	0.3743	−1.1611	0.9294	10.9369	13.8855	2.2019	−1.2219	−4.2375
95878	−2.4203	1.3199	−9.4426	−0.5411	1.6322	1.3059	0.3722	−1.1619	0.9309	10.9419	13.8855	2.2036	−1.2213	−4.2369
95898	−2.3593	1.3074	−9.4206	−0.1633	1.1276	0.9705	0.3704	−1.1631	0.9314	10.9369	13.8855	2.2055	−1.2217	−4.2362
95918	−2.3958	1.2566	−9.4415	−0.3494	0.7471	1.4077	0.3701	−1.1674	0.9305	10.9319	13.8855	2.2066	−1.2225	−4.2358
95938	−2.4276	1.3126	−9.4643	−0.4363	1.4516	1.6526	0.3694	−1.1635	0.9286	10.9268	13.8855	2.2074	−1.2232	−4.2358
95958	−2.3619	1.3973	−9.4029	0.1593	0.8070	0.9403	0.3688	−1.1639	0.9320	10.9369	13.8855	2.2087	−1.2225	−4.2349
95978	−2.3424	1.3947	−9.4150	−0.2972	0.9458	0.4372	0.3688	−1.1635	0.9297	10.9319	13.8855	2.2108	−1.2207	−4.2340
95998	−2.3497	1.3412	−9.4456	−0.2364	0.6253	0.6216	0.3680	−1.1634	0.9310	10.9369	13.8855	2.2119	−1.2203	−4.2340
96018	−2.4081	1.2759	−9.4855	−0.0536	0.5968	0.8360	0.3670	−1.1641	0.9297	10.9319	13.8855	2.2125	−1.2206	−4.2344
96038	−2.3253	1.3582	−9.4216	−0.6855	−0.2139	0.5288	0.3675	−1.1608	0.9303	10.9319	13.8855	2.2127	−1.2197	−4.2351
96058	−2.4179	1.2906	−9.4834	−0.6950	0.6022	0.8157	0.3680	−1.1616	0.9297	10.9369	13.8855	2.2127	−1.2195	−4.2360
96078	−2.4131	1.3343	−9.4696	−0.6736	0.4542	0.8841	0.3680	−1.1651	0.9277	10.9419	13.8855	2.2126	−1.2189	−4.2368
96098	−2.3351	1.3849	−9.4221	−0.4068	0.1128	0.5533	0.3655	−1.1634	0.9299	10.9369	13.8855	2.2135	−1.2173	−4.2368
96118	−2.4009	1.3317	−9.4769	−0.7776	0.4172	0.8385	0.3653	−1.1638	0.9327	10.9369	13.8855	2.2134	−1.2165	−4.2376

Fig. 7. experimental data

By using Matlab, making data input to the mathematical model, We obtain a series of optimal estimates of the position information, the output error in the process of solving the situation, Fig. 8 to Fig. 11.

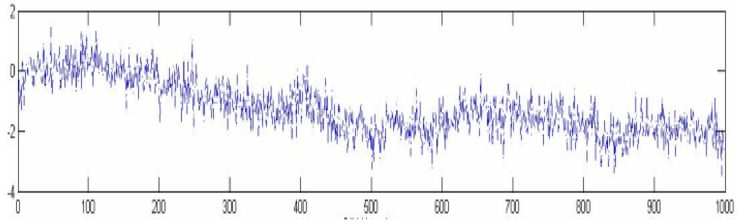


Fig. 8. error before the position information filtering

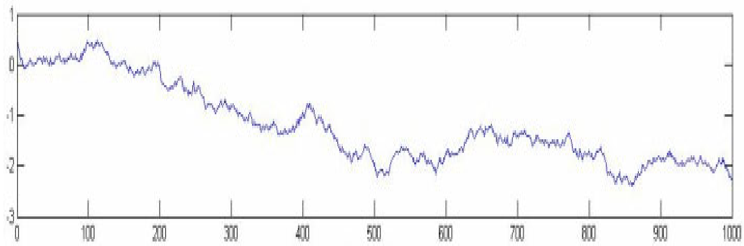


Fig. 9. error of position information after filtering

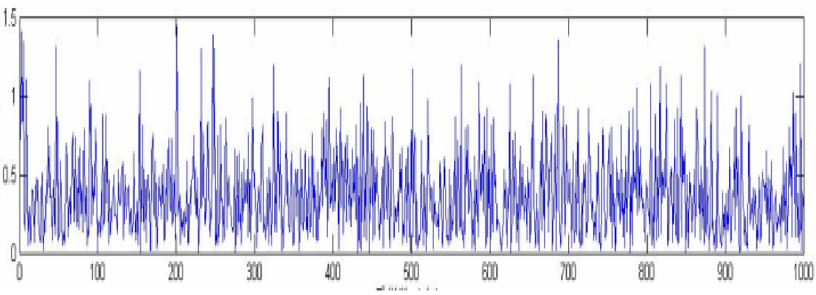


Fig. 10. correction of position error

Description: in Fig. 8 to Fig. 10, X axis direction for the cumulative distance traveled, Y axis direction for the error size, the units are meters

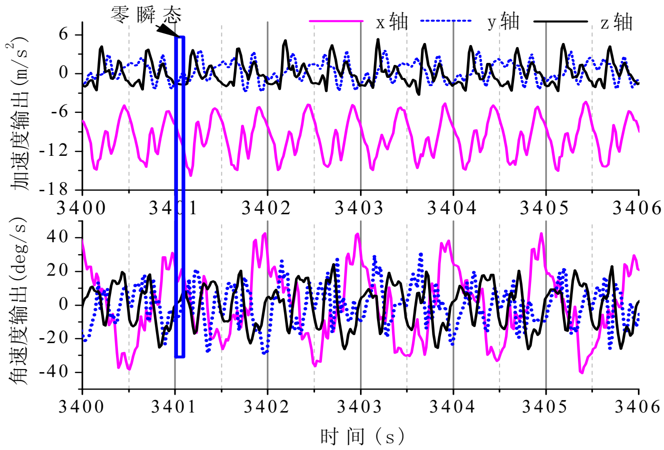


Fig. 11. the result of zero transient

Finally, the positioning results are compared with the calculated results (shown in Fig. 12). The results show that the model has high prediction accuracy.

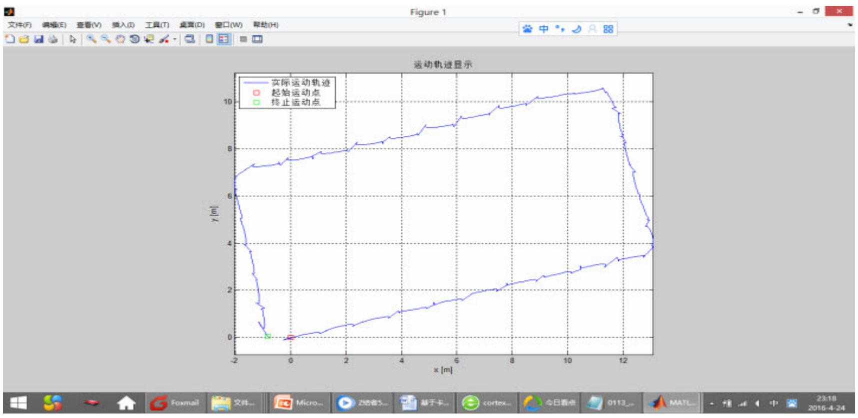


Fig. 12. The results of self localization test after correction

4 Conclusion

The core problem of intelligent integrated navigation system is the multi sensor information fusion. Multi sensor information fusion method is a function of the human brain complex problem simulation by for a variety of sensor observation information reasonable allocate and use, the various sensors in space and time complementary and redundant information according to some optimization criteria combined, to observe the environment consistency interpretation and description. This topic will be comprehensive analysis of ultrasonic ranging and gyro navigation information processing, through information fusion to form complementary local information derived more accurate positioning results, improve the dead reckoning positioning precision and efficiency. Inertial navigation system is a kind of passive navigation equipment, relative to other navigation systems, it has the characteristics of strong autonomy, and has a huge application value in the military or civil. In this paper, focused on the requirements of cumulative error correction for inertial navigation in wearable navigation, based on ultrasonic distance estimate zero transient for inertial navigation devices, realize the zero calibration of the output of the inertial navigation system. The experimental results show that the algorithm can effectively reduce the error and improve the precision of the autonomous positioning.

Acknowledgements

This work is supported by Scientific Research Project of Beijing Educational Committee (Grant No. KM201711232012); The National Natural Science Foundation of China (Grant NO. 61603047); The Qin Xin Talents Cultivation Program of BISTU. (Grant No. QXTCPC201704)

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