THE FUSION FOR COMPOSED NAVIGATION INFORMATION AND ACCURACY ESTIMATION IN FLIGHT TEST

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Abstract

In traditional flight tests for navigation systems appraisal, the output parameters accuracy of tested sub-systems were generally estimated relying on more accurate reference navigation sensors' parameters and outputs. If the reference sensors' accuracy declines or larger disturbing error occurs, the accuracy estimation confidence gotten from the tested sub-systems would lower, and even the flight test results could not be approved. Moreover in the present flight tests, the output accuracy of tested navigation equipment becomes higher and higher, so it is very difficult to meet with the present appraisal flight tests' requirement based upon the traditional navigation reference sensors measurement.

At present major navigation equipment installed in aircraft includes inertial navigator, GPS, Tacon, air-data-computer, JIDS, then plus terrain assistant navigator, SAR radar imaging navigation system which increase the navigation parameters and reliability margin of aircraft. This paper proposed the structure of navigation information fusion and accuracy estimation based upon multi-navigation sensors' output signals, building a high accurate navigation reference platform according to multi-navigation sensors' data fusion[1].

1 Navigation information fusion module

The navigation information fusion and accuracy estimation about flight tests consist of the following function modules:

1.1 Characteristic analysis of navigation system output errors in flight

Automatically divide the flight into several stages according to the flight test data, determine each flight stage, maneuver feature, sensors working condition[2]. The relative statistics analysis is made about each navigation sensor error distribution according to flight stages and different maneuver feature, and then the parameters in information fusion are determined to select chief navigation sensors for fusion processing.

1.2 Initial flight test navigation data fusion

The forward fusion[3], which consists of two steps, variable measurement information fusion and optimum filtering estimation, is made about each flight navigation sensor's output signals:

- According to each sensor's error distribution analysis, successive, high accurate position and velocity measurement fusion are created.
- The inertial navigator output and measured fusion measurement are through Kalman filtering by means of optimum filtering estimation, resulting in the forward fusion optimum navigation parameters.

1.3 Whole procedure information optimization about flight test

By means of flight test data and known flight conditions, the whole procedure optimization

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fusion is made based upon initial information fusion results. The fixed interval optimum smoothing algorithm is applied to the whole procedure optimization fusion, by which an inverse smoothing is exert to the state estimation and filtering covariance matrix derived from initial fusion so as to upgrade the fusion result accuracy[4].

1.4 Fusion accuracy estimation of flight test data based upon theory analysis

The prerequisite for the fusion result as a navigation system estimation reference is that the fusion navigation is much more accurate than any other single sensor, such as inertia navigator, GPS, air digital computer, Tacon, JIDS (joined information distribution system), such that the fusion result is useful to navigation flight accuracy estimation in engineering application. So how to estimate the navigation fusion accuracy is a key problem to navigation flight test information fusion estimation[5], and the estimation method procedure is as follows:

- Based the two step fusion of navigation flight test information, the covariance matrix derived from the forward Kalman filtering and fixed interval optimized smoothing is the theory estimation index for the data fusion accuracy, which is as an estimation criterion for information fusion results.
- The most accurate navigation sensor is selected as the estimation criterion of data fusion while processing flight test data. GPS, for example, is used as an estimation criterion for the information fusion of inertial navigator, air digital computer, Tacon, JIDS, and etc. Then the error between the fusion result and real reference is gotten to verify the error concordance between the information fusion covariance and real reference[6].
- The error concordance between the information fusion covariance and real fusion result is verified through theory simulation and real flight test data, which may verify the practicability of information fusion covariance as an estimation index for fusion accuracy[7].

So the final information fusion may simultaneously result in the accuracy estimation index verified by real flight tests.

2 Navigation information fusion algorithm

Because an inertial navigator is the most primary and principal sensor, and also the sensory system whose signals output is most frequent and navigation information is most plentiful among multi-redundancy navigation sensors, its output data are certainly the most principal data sources about the navigation flight test information fusion and estimation system. The relative data fusion processing algorithms are mostly based upon its output data[8].

To improve data fusion accuracy an overall data fusion algorithm is used in course of test[9], and the Kalman filtering is combined with fixed interval optimized smoothing so as to upgrade the fusion accuracy concerning the output data of multi-redundancy navigation sensors. The main procedure is that the Kalman filtering optimized estimation is done according to time sequence, in which relative information is memorized. The fixed interval optimized smoothing is made in accordance with adverse time sequence after finishing Kalman filtering, then the data after fusion are gotten. The navigation data fusion algorithm mainly consists of the following two parts:

- Primary fusion concerning navigation flight test data based upon concentrative Kalman filtering.
- The overall information optimization fusion by means of the fixed interval optimized smoothing based upon Kalman.

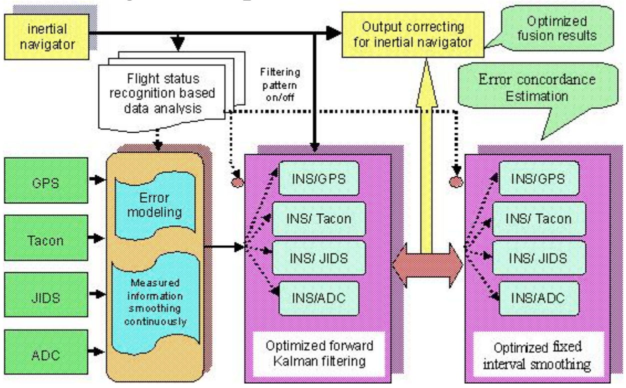

Fig.1 The core of navigation information fusion

The core of navigation information fusion is shown in Fig.1.

To meet with a large amount of data flow and high rate of data transfer for multi-navigation sensors, an information fusion processing system based a distributed network configuration is used as showed in Fig.2[10]. The system consists of five sub-systems: a data pre-processing and fusion procedure management system, an attitude recognition and measuring fusion system, an overall filtering fusion for navigation information system, a control system for flight test information fusion, a monitor/control and display system.

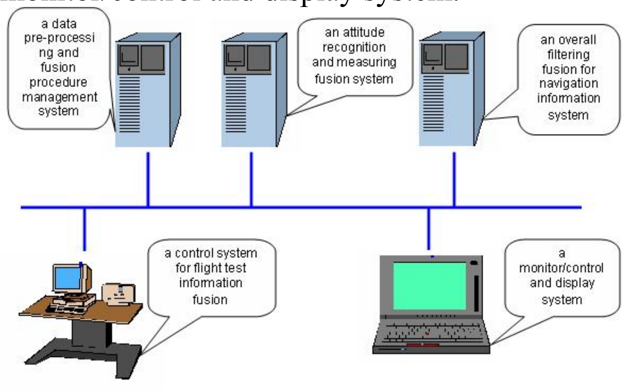

Fig.2 The information fusion processing system based a distributed network configuration

It is mainly for failure checking and revising about inertial navigator data in the pre-processing stage of navigation flight test data, and for failure checking, large error rejecting, revising and smoothing about assistant navigation sensors data. The data pre-processing algorithm procedure is showed in Fig.3.

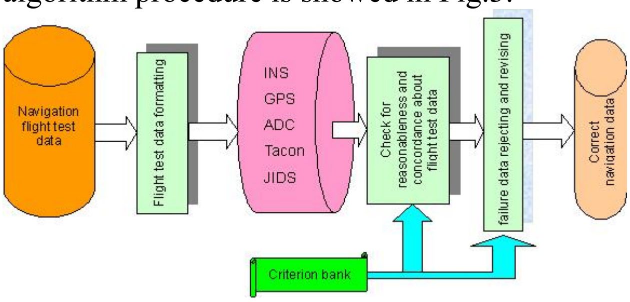

Fig.3 The pre-processing algorithm for navigation flight test data

Data reasonableness is checked against relative navigation parameter thresholds. Failure data rejecting and revising are completed by use of inner interpolation to pad the data after rejecting the data beyond the thresholds[11]. The failure checking equations on inertial navigator data are defined as follows:

Longitude: $|\lambda| > \lambda_{\max}$

Latitude: $|L| > L_{\max}$

East velocity: $|v_e| > v_{e\max}$

North velocity: $|v_n| > v_{n\max}$

Platform aspect angle: $|\psi| > \psi_{\max}$

Longitude variable: $|\lambda_i - \lambda_{i-1}| > \Delta\lambda_{\max}$

Latitude variable: $|L_i - L_{i-1}| > \Delta L_{\max}$

East velocity variable: $|v_{e_i} - v_{e_{i-1}}| > \Delta v_{e\max}$

North velocity variable: $|v_{n_i} - v_{n_{i-1}}| > \Delta v_{n\max}$

Platform aspect variable: $|\psi_i - \psi_{i-1}| > \Delta\psi_{\max}$

The threshold method is applied with the same threshold method in the inertial navigator data for the failure checking and isolating of assistant sensors according to their outputs.

The smoothness and continuity of each navigation sensor's outputs are changed under maneuverable flight so as to cause sudden changes at each navigation sensor's outputs. So it is necessary to recognize maneuverable attitudes and abrupt changing status about aircraft to determine the relationship between maneuverable flying conditions and the special time periods. According to flight status or attitudes and actual flight status indication, it is estimated whether the navigation information concerning inertial navigators, ADC, Tacon, JIDS and etc. is continuous, and their random errors are stable during the special flight periods.

The interval data mirror method is mainly applied to maneuverable flight status recognition, in which the data supplied by INS, position information supplied by GPS, Tacon and JIDS, atmosphere height and rising/descending velocity supplied by ADC are there and back cut off in a period of time to form a contrast table on maneuverable flight status against flight conditions, and the recognition function on flight status is designed. In the processing steps, the first step begins from a stable flight stage to scan the flight test data several times, in which the scanning period depends on the maneuver characteristic period of a test airplane. Flight status could be determined in terms of flight status recognition functions and maneuver conditions classification, as showed in Fig.4[12].

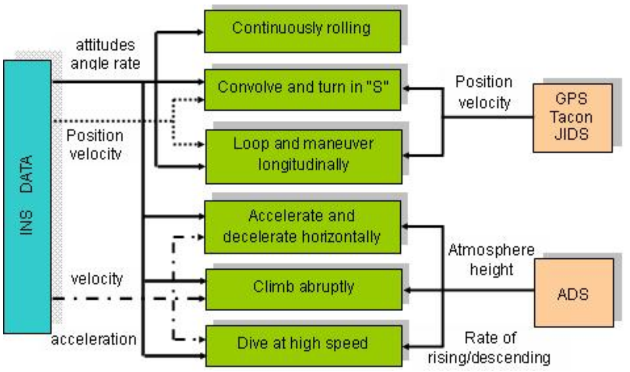

Fig.4 The configuration of functions on navigation flight test data and maneuver flight status

2.1 INS-GPS integrated algorithm model

For the integrated INS-GPS algorithm model, it is here given an optimized integrated Kalman filtering processing algorithm[13] as an example. The navigation error equations of a basic INS and inertial instruments are as follows:

$$\dot{X}(t)_{18\times 1} = A(t)_{18\times 18}X(t) + G(t)_{18\times 9}W(t)_{9\times 1} \quad (1)$$

where the system state vectors are three dimension of platform angle errors, three dimension of velocity errors, three dimension of position errors, three dimension of random constant errors for a gyro and their first order Markov process errors, and the first order Markov process errors of an accelerometer.

$$X = [\phi_n \quad \phi_e \quad \phi_d \quad \delta V_n \quad \delta V_e \quad \delta V_d \quad \delta L \quad \delta\lambda \quad \delta h \quad \varepsilon_{bx} \quad \varepsilon_{by} \quad \varepsilon_{bz} \quad \varepsilon_{rx} \quad \varepsilon_{ry} \quad \varepsilon_{rz} \quad \nabla_{rx} \quad \nabla_{ry} \quad \nabla_{rz}]^T \quad (2)$$

The white noise vector of a system consists of white noises of a gyroscope, exciting white noises of the first order Markov process about a gyroscope and exciting white noises of the first order Markov process about an accelerometer, showed in eq.(3).

$$W = [\omega_{gx} \quad \omega_{gy} \quad \omega_{gz} \quad \omega_{rx} \quad \omega_{ry} \quad \omega_{rz} \quad \omega_{ax} \quad \omega_{ay} \quad \omega_{az}]^T \quad (3)$$

The system measuring equations may classified two types, position-velocity composed measuring and positions composed measuring. A position-velocity composed measuring equation is in accordance with eq.(4), and positions composed measuring is the subset of a composed position-velocity set.

$$Z(t) = \begin{bmatrix} v_{nI} - v_{nG} \\ v_{eI} - v_{eG} \\ v_{dI} - v_{dG} \\ (L_I - L_G)R_n \\ (\lambda_I - \lambda_G)R_e \cos L \\ h_I - h_G \end{bmatrix} = \begin{bmatrix} \delta v_n + M_n \\ \delta v_e + M_e \\ \delta v_d + M_d \\ R_n \delta L + N_n \\ R_e \cos L \delta\lambda + N_e \\ \delta h + N_h \end{bmatrix} = \begin{bmatrix} H_v(t) \\ H_p(t) \end{bmatrix} X(t) + N(t) \quad (4)$$

2.2 INS-TACON integrated algorithm model

The INS-Tacon integrated algorithm model, which is the same with INS-GPS integrated measuring equations in fusion algorithm, is a kind of position composition. The distinction between them is that the former needs to add a measuring information solution and errors compensation[14], as is illustrated in Fig.5.

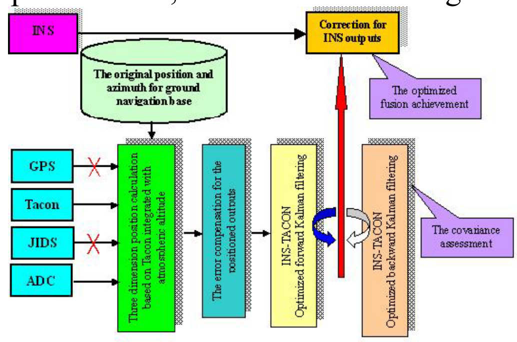

Fig.5 INS/TACON integrated system

2.3 INS-JIDS integrated algorithm model

The INS-JIDS integrated navigation belonging to a position composed navigation, is similar to GPS in the positioning system, and locates the geometrical position of aircraft by relative multi-elements positioning. From the fusion algorithm model, the measuring error is equivalent to the measuring error of the INS-GPS integrated system. The algorithm frame of the INS-JIDS integrated system is showed in Fig.6.

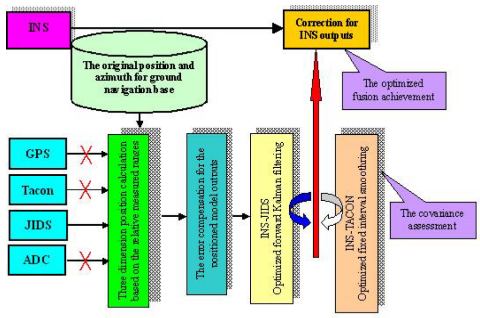

Fig.6 INS-JIDS integrated algorithm frame

2.4 INS-ADC integrated algorithm model

The INS-ADC integrated navigation fusion, a kind of navigation information fusion, is the adoption of velocities combination + altitude damping combination. The error introduced by atmosphere disturbance is the primary error in this integrated algorithm model. So it is necessary to take account of wind velocity compensation before the measured information feeding to filtering, as is showed in Fig.7.

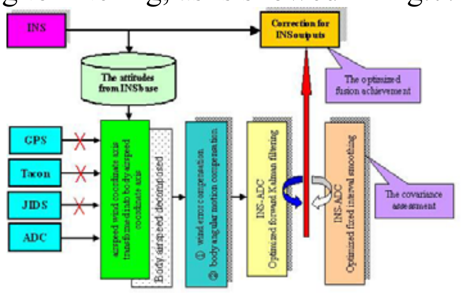

Fig.7 INS-ADC integrated information fusion frame

2.5 INS-ADC-TACON (or JIDS) integrated algorithm model

For full application of more information in flight test information fusion, usually more sensor outputs are used in fusion processing. The INS-ADC-TACON integrated navigation is adopted where ADC and TACON work simultaneously for the combination of positions and velocities at the same time. And others involve INS-ADC-JIDS combination model.

2.6 Filtering algorithm flow

For integrated Kalman filtering, the integrated open Kalman filter equations[15] are derived as follows:

$$\begin{cases} \hat{X}(k/k-1) = \Phi(k,k-1)\hat{X}(k-1/k-1) \\ \hat{X}(k/k) = \hat{X}(k/k-1) + K(k)[Z(k) - H(k)\hat{X}(k/k-1)] \\ K(k) = P(k/k-1)H^T(k)[H(k)P(k/k-1)H^T(k) + R(k)]^{-1} \\ P(k/k-1) = \Phi(k,k-1)P(k-1/k-1)\Phi^T(k,k-1) + \Gamma(k,k-1)Q(k-1)\Gamma^T(k,k-1) \\ P(k/k) = [I - K(k)H(k)]P(k/k-1)[I - K(k)H(k)]^T + K(k)R(k)K^T(k) \end{cases} \tag{5}$$

where the above variables are described as follows:

$\hat{X}(k/k)$	The real time state estimation at k time.
$\hat{X}(k/k-1)$	The state forecasted from k-1 to k.
$K(k)$	Filtering gain array at k.
$P(k/k-1)$	Error covariance array estimated from k-1 to k.
$P(k/k)$	Error covariance array estimated at k.
$Q(k-1)$	System noise variance array.
$R(k)$	Noise variance array for an observed system.

The calculation flow referring to the above Kalman filtering algorithm is illustrated in Fig.8.

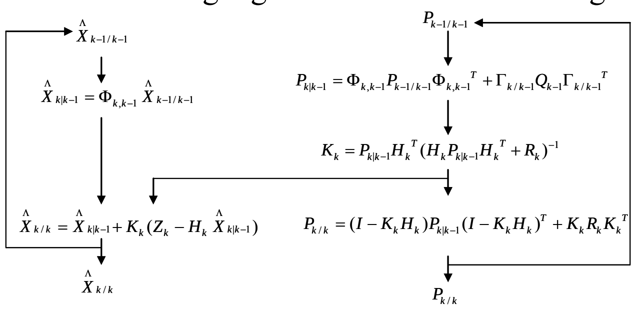

Fig.8 Kalman filtering flow diagram

In the above information fusion algorithm flow the measured D-values between INS outputs and the outputs of GPS or other sensors is used as the measuring values, and then the errors of INS are estimated by use of integrated Kalman filtering so as to correct the open outputs of INS. The whole processing flow is illustrated in Fig.9.

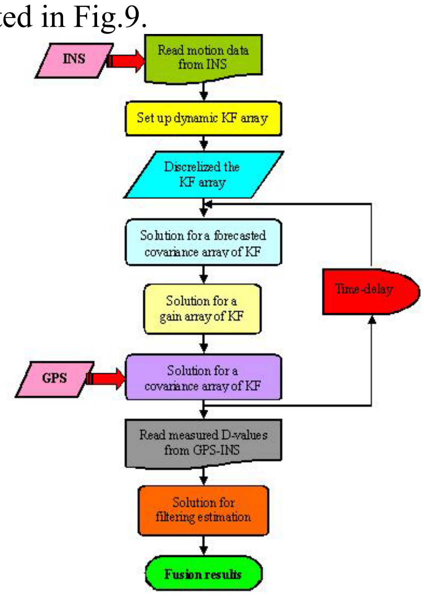

Fig.9 GPS-INS integrated algorithm flow

2.7 The realization for the optimized fixed interval smoothing algorithm

From engineering practice the Rauch-Tung-Striebel(R-T-S) fixed interval smoothing algorithm may be utilized in flight navigation test information fusion, which is simple to calculate, easy to be realized in engineering, and has been verified to be effective for post-processing of flight test data.

Supposing discrelized state equations and observing equations are as follows,

$$\begin{cases} X_k = \Phi_{k,k-1} X_{k-1} + \Gamma_{k-1} W_{k-1} \\ Z_k = H_k X_k + V_k \end{cases} \tag{6}$$

Before the optimized R-T-S interval smoothing the above discrelized system is firstly processed by use of Kalman filtering in time interval [0,…,N]. In the course of Kalman filtering the estimated state $\hat{X}_F(k/k)$ (the subscript F stands for Kalman filtering variables, and the same for following), predicted state $\hat{X}_F(k/k-1)$, estimated error covariance array $P_F(k/k)$, and predicted error covariance array $P_F(k/k-1)$ are all memorized real time.

After finishing Kalman filtering the optimized R-T-S fixed interval smoothing is taken against the data memorized during filtering. Before smoothing the smoother is firstly initialized. Take K=N, then

$$\begin{cases} \hat{X}_S(N/N) = \hat{X}_F(N/N) \\ P_S(N/N) = P_F(N/N) \end{cases} \tag{7}$$

where the subscript S indicates optimized fixed interval smoothing, and the same for the following. In the time interval [N-1,…,0] the recursive R-T-S fixed interval smoothing formula is as follows,

The smoothing gain is

$$K_S(k) = P_F(k/k)\Phi^T_{k+1,k} P_F^{-1}(k+1/k) \tag{8}$$

The recursive smoothed state vectors and their variance array are as follows,

$$\begin{cases} \hat{X}_S(k/N) = \hat{X}_F(k/k) + K_S(k)(\hat{X}_S(k+1/N) - \hat{X}_F(k+1/k)) \\ P_S(k/N) = P_F(k/k) + K_S(k)(P_S(k+1/N) - P_F(k+1/k))K_S^T \end{cases} \tag{9}$$

From the above, the recursive R-T-S fixed interval smoothing formula[16] is an inverted derivation from K=N-1to K=0. $\hat{X}_S(k/N)$ is a result smoothed. Because it is necessary to use $\hat{X}_F(k/k)$, $\hat{X}_F(k/k-1)$, $P_F(k/k)$, $P_F(k/k-1)$ in recursive smoothing, the R-T-S algorithm should be based upon Kalman filtering. The fixed interval smoothing is illustrated in Fig.10.

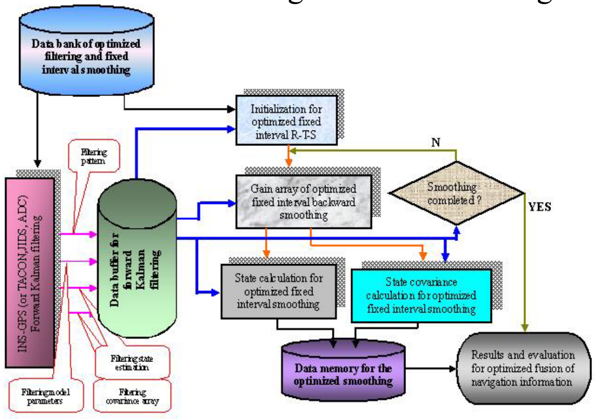

Fig.10 Fixed interval smoothing

3 Demonstration Tests

3.1 Static composed navigation fusion tests

The test data originate from

- a static IMU (inertia measurement unit) and atmosphere pressure altimeters installed in a biaxial rotating platform in the laboratory.
- GPS data are acquired from number 002 reference mark then translated to the biaxial rotating platform site by matrixing.
- Static TACAN data are simulated by a computer.

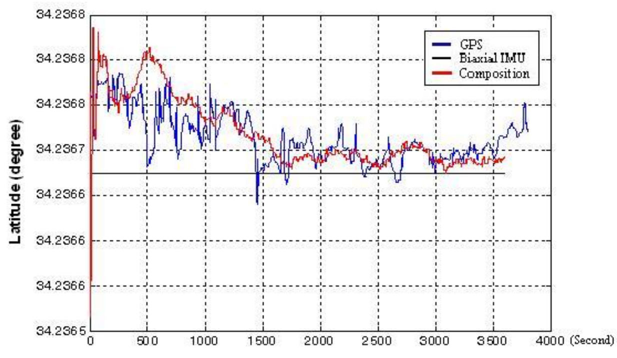

Fig.11 Latitudes of static tests for GPS-Composition-Biaxial IMU

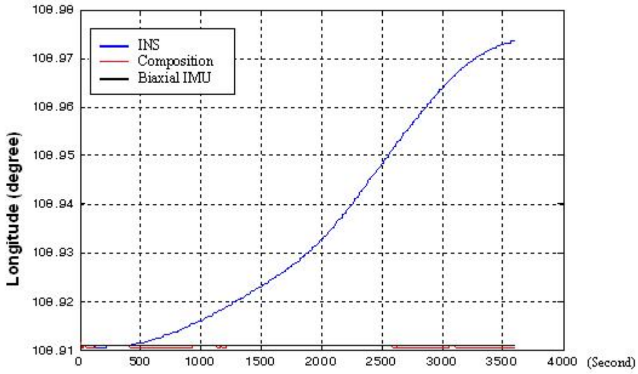

Fig.12 Longitudes of static tests for INS-Composition-Biaxial IMU

Fig.13 shows the velocity curves of a composition and biaxial IMU along the geocentric x axis at static condition. Fig.8 shows the velocity curves of a composition and GPS along the geocentric x axis at static condition.

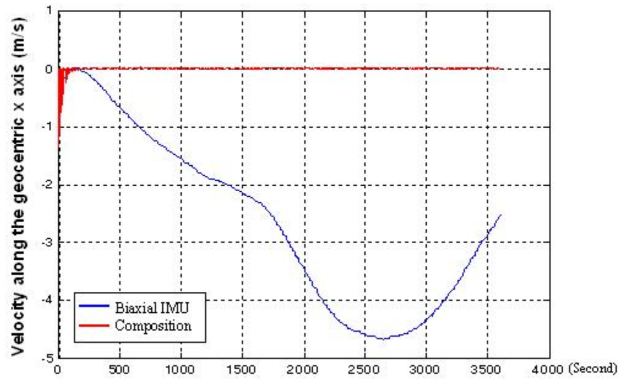

Fig.13 The velocity curves of a composition and biaxial IMU along the geocentric x axis at static condition

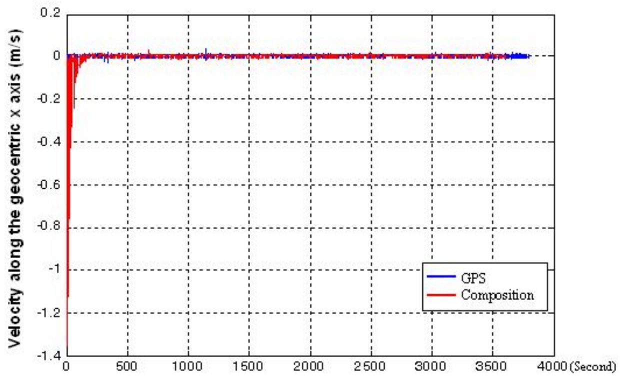

Fig.14 The velocity curves of a composition and GPS along the geocentric x axis at static condition

The accuracy of static tests about composed navigation is listed in table 1.

Table 1 The static accuracy about integrated navigation systems

	Composed	Inertial navigation	GPS	TACAN
Horizontal location errors (CEP)	5.3 m	5.16 nmile/h	6.3 m	200 m
Horizontal velocity measured error (RMS)	0.005 m/s	9.3 m/s	0.01 m/s	——

3.2 Dynamic composed navigation fusion tests

The dynamic test data originate from outputs of INS, atmosphere pressure altimeter and GPS in flight. Fig.15 shows the flight test tracks about INS, GPS, and composed navigation. Fig.10 shows the respective velocity curves about INS, GPS, and composed navigation along the geocentric x axis in flight.

The test accuracy of integrated navigation systems at dynamic condition is listed in table 2.

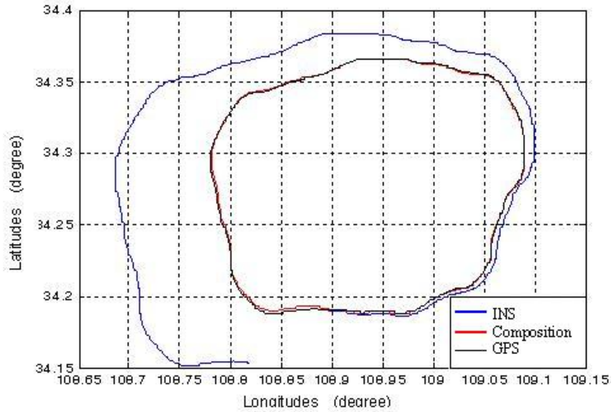

Fig.15 The flight test tracks about INS, GPS, and integrated navigation

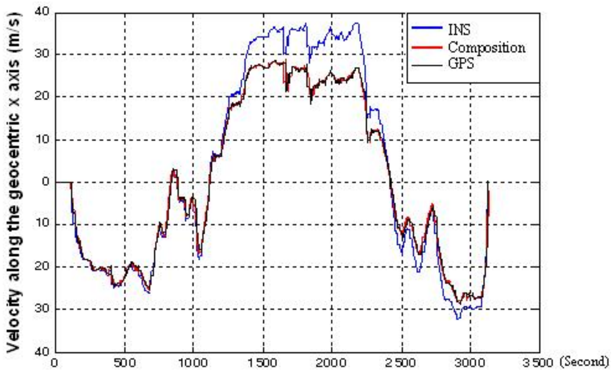

Fig.16 The velocity curves about INS, GPS, and integrated navigation along the geocentric x axis in flight

Table 2 The dynamic accuracy about integrated navigation systems

	Composed	Inertial navigation	GPS
Horizontal location errors (CEP)	15.9 m	6.25 nmile/h	20 m
Horizontal velocity measured error (RMS)	1.2 m/s	9.5 m/s	0.5 m/s

4 Demonstration Test and Result Analysis

a) It can be seen, from Fig.11 and Fig.12, that for INS its latitude outputs hardly change but its longitudes drift quickly. When the GPS and biaxial IMU are integrated, their composed navigation outputs after fusion processing nearly tend to be consistent with GPS.

b) It can be seen from Fig.13 that the static velocity of the biaxial IMU along x axis deviates heavily. But the velocities along x axis about the composition and GPS basically tend to be consistent, showed in Fig.14.

c) From the static test results, the horizontal location errors (CEP) and horizontal velocity measured error (RMS) are far better than any other single locating owing to the fusion processing algorithm applied to composed navigation systems.

d) It can be seen, from the flight track test results concerning INS, GPS and composed navigation illustrated in Fig.15, that their outputs behave consistently at initial stage, but the location output of the INS drifts heavily especially in longitudinal direction. From the velocity test results along the geocentric x axis in flight about INS, GPS and composed navigation, their velocities vary consistently. However the velocity amplitude about the INS outputs fluctuates more than the other two modes in the meddle of test course because of in-flight maneuver in the period.

e) From the average results of the composed navigation system accuracy after a fusion processing, the horizontal location errors (CEP) is better than INS's and GPS's, but the horizontal velocity measured error (RMS) is better than INS's and poorer than GPS's.

References

[1] Shesheng Gao, Yongmin Zhong, Xueyuan Zhang, Bijan Shirinzadeh. Multi-sensor optimal data fusion for INS/GPS/SAR integrated navigation system. *Aerospace Science and Technology*. 2009, 13(4-5): pp 232-237.

[2] Jin X B, Sun Y X. Optimal centralized state fusion estimation for multi-sensor system with correlated measurement noise. *Proc.2003 IEEE Conference on Control Applications*. Istanbul, Turkey:IEEE,2003. pp 770-772.

[3] Yan-ling Hao, Ming-hui Chen, Liang-jun Li , Bo Xu. Comparison of robust H_∞ filter and Kalman filter for initial alignment of inertial navigation system. *Journal of Marine Science and Application*. 2008, 7(2): pp 116-121.

[4] Fitzgerald R J. Analytic track solutions with range-dependent errors. *IEEE Transactions on Aerospace and Electronic Systems*, 2000, 36(1): pp 343-348.

[5] David J. Allerton,Huamin Jia. A Review of Multisensor Fusion Methodologies for Aircraft Navigation Systems. *The Journal of Navigation*. 2005, 58: pp 405-417.

[6] M.J.Hall, S.A.Hall, and T.Tate. Removing the HCI bottleneck: how the human computer interface (HCI) affects the performance of data fusion systems, *Proc. 2000 Meeting of the MSS, Nat. Symp. Sensor and Data Fusion*, pp 89-104, 2000.

[7] Niehsen, W. Information fusion based on fast covariance intersection filtering. *Information Fusion*. 2002, vol.2: pp 901 – 904.

[8] Duan Z S,Han C Z,Tao T F. Optimal multi-sensor fusion target tracking with correlated measurement noises. *Proceedings of the 2004 IEEE International Conference on Systems, Man and Cybernetics*. New York,United States:IEEE,2004. pp 1272-1278.

[9] Li X Rong. Optimal linear estimation fusion – part Ⅶ: dynamic systems. *Proc.2003 International Conf. on Information Fusion*. USA:IEEE,2003. pp 455-462.

[10] Mirjalily G, Luo Zhi-Quan, Davidson T N, Bosse E. Blind adaptive decision fusion for distributed detection. *IEEE Trans. On Aerospace and Elect. Syst.*,2003,39(1): pp 34-52.

[11] Xiaojing J. Kong. Setting the Response Time Threshold Parameter to Differentiate Solution Behavior From Rapid-Guessing Behavior. *Educational and Psychological Measurement*. 2007, 67(4): pp 606-619.

[12] Juha Jylhä, Marja Ruotsalainen, Tuomo Salonen, Harri Janhunen, Tomi Viitanen, Juho Vihonen, Ari Visa. Towards Automated Flight-Maneuver-Specific Fatigue Analysis. *ICAF 2009, Bridging the Gap between Theory and Operational Practice Part 7*[M]. 2009, pp 1121-1134.

[13] M. Mottaghi-Kashtiban, A. Khoei, Kh. Hadidi. Optimization of rational-powered membership functions using extended Kalman filter. *Fuzzy Sets and Systems*. 2008, 159(23): pp 3232-3244.

[14] Yu. G. Bulychev, A. P. Lapsar. Method of compensation for systematic errors in goniometric systems. *Optoelectronics, Instrumentation and Data Processing*. 2009, 45(1): pp 30-36.

[15] John Bagterp Jørgensen, Morten Rode Kristensen, Per Grove Thomsen, Henrik Madsen. New Extended Kaiman Filter Algorithms for Stochastic Differential Algebraic Equations. *Lecture Notes in Control and Information Sciences*. 2007, Vol. 358, pp 359-366.
[16] Sarkka Simo. Unscented Rauch-Tung-Striebel Smoother. IEEE Transactions on Automatic Control. 2008, 53 (3) : pp 845-849.

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