Integrated Navigation System for Unmanned Surface Vehicles via GPS/INS with Particle Filter

Xin Yan, Xiaofei Yang, Wei Liu, Hongwei She, Xiangbing Hu and Weibo Zhong

June 22, 2022

Integrated Navigation System for Unmanned Surface Vehicles via GPS/INS with Particle Filter

1st Xin Yan*
School of Electronics and Information
Jiangsu University of Science and Technology
Zhenjiang, China
yanxin029029@163.com

2nd Xiaofei Yang *
School of Electronics and Information
Jiangsu University of Science and Technology
Zhenjiang, China
yxfei_0809@just.edu.cn

3rd Wei Liu
School of Electronics and Information
Jiangsu University of Science and Technology
Zhenjiang, China
cherub200711@163.com

4th Hongwei She
School of Electronics and Information
Jiangsu University of Science and Technology
Zhenjiang, China
202030053@stu.just.edu.cn

5th Xiangbing Hu
School of Electronics and Information
Jiangsu University of Science and Technology
Zhenjiang, China
hxbing97@163.com

6th Weibo Zhong
School of Electronics and Information
Jiangsu University of Science and Technology
Zhenjiang, China
vebo@just.edu.cn

***Abstract*—This paper is about the implementation of integrated GPS/INS navigation for unmanned surface vessels (USVs) and the improvement of the accuracy of inertial navigation system (INS) navigation alone using the power model of a dual-thruster USV. Using the power model of the dual-thruster USV as an event-triggered switch for effective acceleration integration allows the INS of the USV to maintain high positioning accuracy for longer periods of time when the Global Positioning System (GPS) signal is disconnected or vulnerable. When GPS signals are available, the particle filter algorithm is used as the data fusion algorithm for the GPS/INS integrated navigation system, thus improving the positioning accuracy. This approach solves the problem that the INS navigation system composed of economical inertial navigation units (IMUs) has low positioning accuracy and only a short validity time.**

Keywords—GPS/INS integrated navigation system, power model, particle filter, USV

I. Introduction

As countries are operating more and more frequently in reconnaissance, detection and intelligence gathering of marine resources, more and more attention has been paid to the research and development of unmanned surface vehicles (USVs). As the most important part of the USV, the navigation system determines the accuracy and effectiveness of the USV operation. An integrated navigation system consisting of the Global Positioning System (GPS) and the Inertial Navigation System (INS) can provide more accurate navigation information (position, velocity, and attitude) [1] and is widely used in maritime missions around the world. In an integrated navigation system, high-precision position and velocity information for USVs can be provided by GPS, while accurate and reliable attitude information can be provided by INS in the short time. Obviously, combining both GPS and INS can not only overcome the shortcomings of each system individually, but also give full play to the advantages of each system and improve the accuracy and reliability of the system.

GPS/INS integrated navigation system is a solution where the navigation information from INS prevails and GPS information is the auxiliary correction. For some cases with harsh environments or severe interference, GPS satellite signals are not available and it is difficult to achieve continuous and effective positioning. Without providing external auxiliary sources, the navigation accuracy of INS decreases rapidly over time [2]. So this will inevitably lead to a rapid degradation of the integrated GPS/INS navigation system during the time when GPS is not available. There are three ways to solve this problem, using higher accuracy INS, adding auxiliary devices such as velocity loggers and using algorithms and techniques. In this paper, the third approach will be investigated to improve the accuracy of the GPS/INS integrated navigation system. Low-cost inertial measurement units (IMUs) are the preferred choice for integrated navigation systems for USVs. These IMUs also have other advantages such as small size, light weight and low power consumption. The data between the sensors of the integrated navigation system are independent of each other and do not achieve mutual correction. Therefore, information fusion algorithms are needed for combined navigation system design, and common methods include kalman filter (KF) [3], extended kalman filter (EKF) [4], unscented kalman filter (UKF) [5], and federal kalman filter (FKF) [6]. These KF-based navigation solutions suffer from divergence during GPS unavailability on account of approximations during the linearization process and system mismodeling.

KF estimates the error of the navigation states rather than the states themselves, so the system model used by KF is a dynamic error model. The method used in the particle filter (PF) is a total state method rather than an error state method. PF is a nonlinear estimation technique that is not restricted to model characteristics. It can combine a priori knowledge and observation information and can deal with nonlinear problems more effectively under the condition of Monte Carlo simulation. Recently, PF has been explored using different approaches to improve the performance of IMU/GPS integration [7-12].

In this paper, we combine the use of PF filters and Alternative Thruster Models[13] to achieve integrated navigation of USVs and to improve the accuracy of combined navigation. In this paper, a loosely coupled integration scheme is used, as shown in Fig. 1 And experiments with USVs were conducted to verify the feasibility of the method.

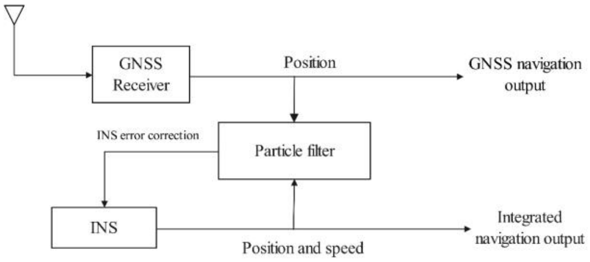

Fig. 1. Loosely coupled integrated navigation structure

II. THEORY AND MTHODS

A. Coordinate System

The body-fixed frame and Earth-fixed inertial frame are two common coordinate systems for ship motion control modeling, as shown in Fig.1. The specific meaning of each symbol in Fig. 2 is given in Table I.

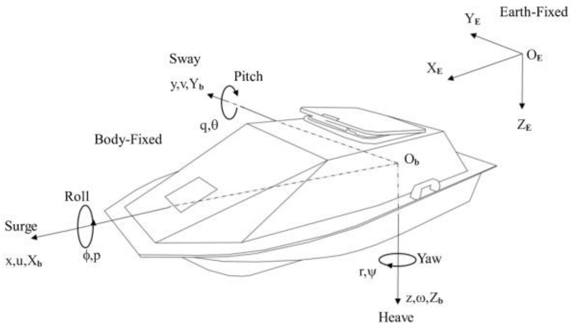

Fig. 2. Coordinate system of the USVs

TABLE I. MEANING OF THE SYMBOLS RELATED TO THE SHIP'S SIX-DEGREE-OF-FREEDOM MOTION STATE

Name of the motion state	Linear velocity and angular rate	Location and Euler angle
Surge	u	x
Sway	v	y
Heave	w	z
Roll	p	ϕ
Pitch	q	θ
Yaw	r	ψ

B. INS Navigation Principle

The basic block diagram of a Strap-down INS is shown in Fig. 3. Strap-down means that the gyroscope and accelerometer are firmly fixed to the navigation platform. The angular velocity measured by the gyroscope is used to track the rotation relationship between the body-fixed frame of the navigation platform and the Earth-fixed inertial frame. This information is used to convert the specific force measured by the accelerometer in the body-fixed frame to the Earth-fixed inertial frame, and the acceleration of the navigation platform in the Earth-fixed inertial frame is obtained after eliminating the local gravitational acceleration obtained according to the gravitational acceleration model. The position of the navigation platform can be obtained by integrating the acceleration twice with respect to time.

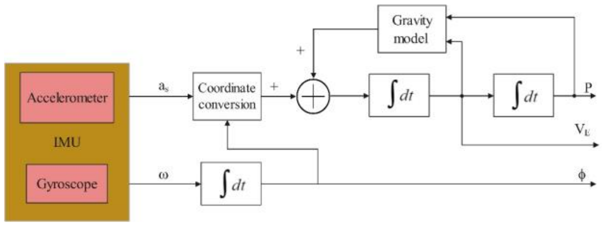

Fig. 3. Schematic diagram of INS basic principle

where a_s is the measured specific force, $\omega = [p,q,r]$ is the angular acceleration of the gyroscope output, $P = [x, y, z]$ is the position information, $V_E = [u_E, v_E, w_E]$ is the velocity information, and $q = [\varphi, \theta, \psi]$ is the angle information.

In this paper, we do not consider the variation of vertical velocity of the USV, but only the variation of horizontal velocity. As shown in Fig. 2, only the velocity variation of the USV in the x-axis direction and y-axis direction in the earth-fixed inertial frame is considered. So the equation for the change in longitude λ and latitude L in INS is

$$\lambda = \lambda_0 + \int \frac{\sec L}{R_N + h} v_E dt \quad (1)$$

$$L = L_0 + \int \frac{1}{R_M + h} u_E dt \quad (2)$$

Where

$$R_M = R_N (1-e^2) / (1-e^2 \sin^2 L) \quad (3)$$

$$R_N = R_e / (1-e^2 \sin^2 L)^{1/2} \quad (4)$$

R_e is the long semi-axis of the meridian ellipse, e is the elliptical eccentricity and h is the local elevation.

C. Power Model of Dual Thruster USV

The steering control of the USV is as follows,

$$\tau_u = F_L + F_R \quad (5)$$

$$\tau_r = (F_L - F_R) \cdot l \quad (6)$$

where, F_L and F_R denote the thrust force of the left and right thruster, respectively, and l denotes the distance between the thruster and shafts. τ_u and τ_r are the thrust and yaw moments, respectively.

The data related to the USV platform are obtained by doing experiments. The method of Alternative Thruster Models is used to obtain the relationship equation $f(s)$ between the power F of the individual thrusters of the USV and the controller signal s. The change of the real-time thrust of the USV can then be obtained using $f(s)$ while the USV is traveling. Since the relationship equation $f(s)$ is the same for the left and right thrusters, the change of the combined force of the USV can be known according to equations (5) and (6), and thus the change of the acceleration of the USV can be known.

III. INS Navigation Structure and Integrated Navigation Scheme Design

The accuracy of integrated navigation has a great relationship with the accuracy of INS navigation system, so improving the accuracy of INS navigation system is beneficial to the accuracy improvement of integrated navigation. In the following, we first describe the INS navigation system designed to improve the accuracy of the INS navigation system. Then, the integrated navigation system with particle filter algorithm as data fusion algorithm is described.

A. INS Navigation Structure Design

Considering that there are external factors such as wind, waves and currents in the process of actual navigation and internal factors such as the performance of IMU, the actual effective speed of the USV cannot be accurately obtained. Therefore, it is difficult to obtain more accurate position information directly by the methods shown in equations (1) and (2). The analysis of the data obtained through the experiment shows that the data measured by the low-performance IMU are more affected by the external factors during the USV's travel. Therefore, the velocity information obtained by integrating the acceleration data is inaccurate, which leads to the low accuracy of the position information. However, the analysis of the experimental data shows that the acceleration data measured by the IMU is more accurate during the time when the combined force generated by the thrusters of the USV has a significant change. Therefore, this paper designs the structure of INS navigation system that selectively integrates the effective acceleration data to obtain velocity and position information, and uses the relation τ_u as the switch for event triggering. From equation (5), we can see that

$$\tau_u = f(s_L) + f(s_R) \tag{7}$$

So comparing τ_u at the previous moment with τ_u at the current moment, if there is a change, it triggers the integration of the acceleration data, and on the contrary, it stops the integration. The designed INS navigation structure diagram is shown in Fig. 4.

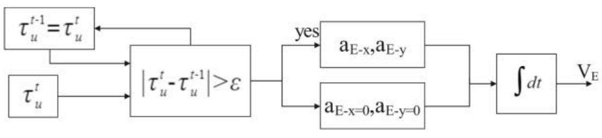

Fig. 4. INS navigation structure diagram

where τ_u^{t-1} is the state of τ_u at the previous moment, ε is the range parameter of the event trigger. a_{E-x} and a_{E-y} are the x-axis acceleration and y-axis acceleration in the earth-fixed inertial frame, respectively. For convenient description, let $a_E = [a_{E-x}, a_{E-y}]$.

By using the power model of the dual-thruster USV as a switch for event triggering of the effective acceleration integral, it allows USV's INS navigation system to maintain high positioning accuracy for longer periods of time when the GPS signal is disconnected or vulnerable. This is because the speed of the USV can be considered to remain constant in practice if the combined force generated by the dual thrusters remains constant while the USV is underway. When the combined force changes, the effective acceleration is then integrated to obtain the corresponding velocity.

B. Particle Filter

Typically for integrated navigation systems, the discrete nonlinear, non-Gaussian white noise dynamic system can be described as

$$\begin{cases} X_k = f(X_{k-1}, U_{k-1}, \sigma, \zeta_{k-1}) \\ Y_k = H(X_k, U_{k-1}, N_{k-1}) \end{cases} \tag{8}$$

Where X is the state vector, U is the known input vector, σ is the unknown parameter, ζ is the process noise, N is the observation noise, Y is the observation vector with noise, k is the discrete time step.

The real-time filtering of the integrated navigation system is how to sequentially estimate the system state and the unknown parameters when new observations are obtained. According to the Bayesian minimum variance estimation, the goal of estimation is how to obtain the observation sequence $\chi_k = \{Y_1, Y_2, \cdots, Y_k\}$, after seeking the posterior probability density function (PDF) with estimates, such as $P(X_k \mid \chi_k)$, $P(\sigma \mid \chi_k)$, the system state and parameters of the estimated value of the equation is

$$\begin{cases} X_k = E[X_k \mid \chi_k] = \int X_k P(X_k \mid \chi_k) dX_k \\ \sigma_k = E[\theta_k \mid \chi_k] = \int \theta_k P(\theta_k \mid \chi_k) dX_k \end{cases} \tag{9}$$

To be able to recursively calculate the PDF of the unknown quantity, using Bayes' formula, the following derivation can be made

$$P(X_k \mid \chi_k) = \frac{P(\chi_k \mid X_k) P(X_k)}{P(\chi_k)} = \frac{P(Y_k \mid X_k) P(X_k \mid \chi_{k-1})}{P(Y_k \mid \chi_{k-1})} \tag{10}$$

Where the prior probability density is

$$P(X_k \mid \chi_{k-1}) = \int P(X_k \mid X_{k-1}) P(X_{k-1} \mid \chi_{k-1}) dX_{k-1} \tag{11}$$

The recursive expression of PDF is formed by equations (9) , (10) and (11).

The particle filtering algorithm uses n discrete samples with weights $\{X_{0:k}^i, \rho_k^i\}_{i=1}^n$ to approximate the PDF , and as the number of samples increases, the particle filter algorithm approaches the Bayesian optimal estimate. The specific steps of the algorithm are as follows.

1) Initialization. $t = 0$, sample $\{X_0^i, \rho_0^i\} \sim P(X_0)$, where $P(X_0)$ is the prior probability of the initial state. X_0^i, ρ_0^i are the i-th sampling point and the weight of the point, respectively, and have $\rho_0^i = 1/n$, so that $k = 1$.

2) Prediction.

$$X_k^i = f(X_{k-1}^i, \zeta_{k-1}) \tag{12}$$

3) Weighted.

$$\rho_k^i = \rho_{k-1}^i \times \frac{P(Y_k \mid X_k^i) P(X_k^i \mid X_{k-1}^i)}{Q(X_k^i \mid X_{0:k-1}^i, Y_{1:k})} \tag{13}$$

$$Q(X_{0:k} \mid y_{1:k}) = Q(X_{0:k-1} \mid Y_{1:k-1}) Q(X_k \mid X_{0:k-1}, Y_{1:k}) \quad (14)$$

4) Weight normalization

$$\rho_k^i = \rho_k^i / \sum_{i=1}^{n} \rho_k^i \quad (15)$$

5) Resampling. Each normalizes the weight ρ_k^i, retains or discards the sample X_k^i, and then makes $\rho_k^i = 1/n$ to obtain n distribution samples that approximately obey the posterior probability density function $P(X_k \mid \chi_k)$.

$$P(X_{0:k} \mid \chi_k) \approx \sum_{i=1}^{n} \rho_k^i \Delta(X_{0:k} - X_{0:k}^i) \quad (16)$$

6) Estimation. Use equation (15) to calculate the filtering value. Let $k = k+1$, return 2); if $k = T_{end}$, then terminate.

C. GPS / INS Integrated Navigation System

According to the designed INS navigation system, the structure of the designed GPS/INS integrated navigation system is shown in Fig. 5, combined with the method of data fusion by particle filter.

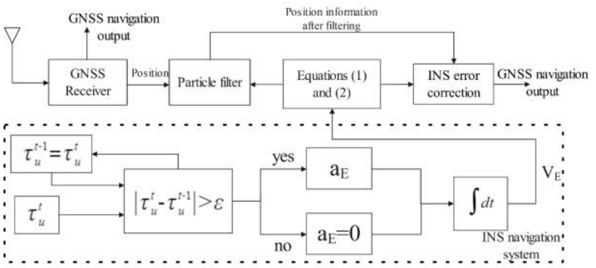

Fig. 5. GPS/INS integrated navigation system

When the USV is navigating on the surface, the accelerometer error has a much greater impact on the accuracy of the integrated navigation system compared to the gyroscope error. Therefore, in order to reduce the computational effort and ensure the real-time of the solution, only the main error sources are filtered in this paper. The state transfer equation is established only for the accelerometer data. The northward velocity v_E and eastward velocity u_E in the earth-fixed inertial frame can be expressed as

$$v_E = \int a_{E-y} dt \quad (17)$$

$$u_E = \int a_{E-x} dt \quad (18)$$

According to equations (1) and (2), the position state transfer equation in the earth-fixed inertial frame can be expressed as

$$\begin{bmatrix} \dot{L}(t) \\ \dot{\lambda}(t) \end{bmatrix} = \begin{bmatrix} \dfrac{1}{R_M + h} u_E \\ \dfrac{\sec L}{R_N + h} v_E \end{bmatrix} + \begin{bmatrix} \delta_L \\ \delta_\lambda \end{bmatrix} \quad (19)$$

Where $\delta = [\delta_L, \delta_\lambda]^T$ is the process noise.

Direct use of GPS-measured position information as observation information for integrated navigation systems. The observation equation is

$$\begin{bmatrix} Y_L \\ Y_\lambda \end{bmatrix} = \begin{bmatrix} L_{GPS}(t) \\ \lambda_{GPS}(t) \end{bmatrix} + \begin{bmatrix} e_L \\ e_\lambda \end{bmatrix} \quad (20)$$

Where $e = [e_L, e_\lambda]^T$ is the measurement noise.

IV. VERIFICATION

In order to verify the effectiveness of our integrated navigation algorithm proposed in the paper, a real ship experiment is carried out in the "haiyun" lake of Jiangsu University of Science and Technology.

A. Experimental Platform

The real-time heading angle of the USV is measured by the miniature micro-electromechanical system IMU (Inertial Measurement Unit) ADIS16505, which is made by Analog Devices Corporation and includes a triaxial gyroscope and a triaxial accelerometer. The model number of the GPS module is UBLOX NEO-M8N, which is a more economical GPS module. True position measured and given by the differential GPS, which includes mobile station in USV and base station in land.

Fig. 6. Experimental platform of the USV

Through the analysis of the experimental data, the relationship between the control signal s of this experimental platform and the power F of a single thruster is obtained as

$$F = -0.00009275 P_{thr}^2 + 0.1762 P_{thr} + 15.07 \quad (21)$$

$$P_{thr} = 0.0008923 s^2 - 0.07909 s - 0.2835 \quad (22)$$

where P_{thr} is the power of a single thruster. The range of s is $[100, 1000]$.

B. Analysis of INS Navigation Experimental Data

Before implementing the integrated navigation, the navigation performance of the INS designed in this paper is examined. Experimental data of the USV navigating along a straight line in the direction of 80 degrees east of north for a fixed power case are shown below.

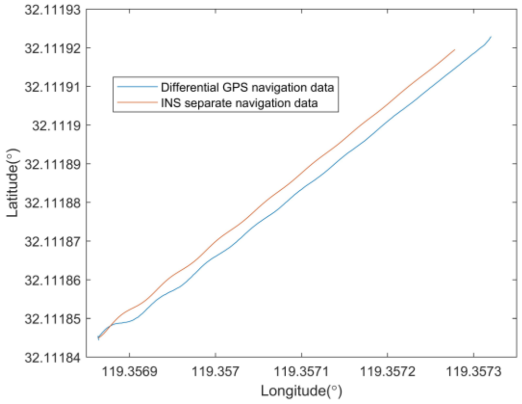

Fig. 7. Route data for INS and differential GPS

In this paper, the route data of differential GPS is taken as the real route of the actual USV voyage and it is used as the standard for comparison. From Fig. 7, we can know that the route of INS deviates from the route of differential GPS. The maximum distance between the two routes is 3.58 m, and it can be seen that the maximum distance keeps increasing as time goes by. The distance between the start and the end point is 46 m in the differential GPS route, while it is 39.41 m in the INS route.

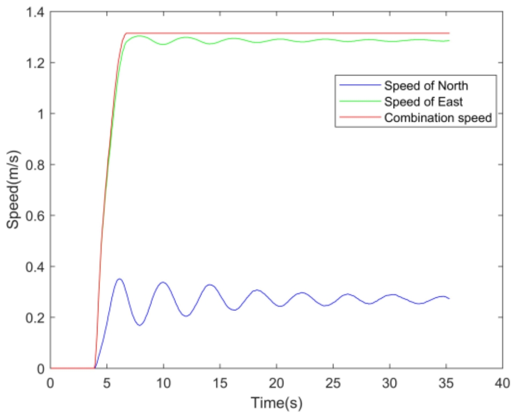

Fig. 8. Source of speed data from INS

0~4s is the time for system initialization of USV.

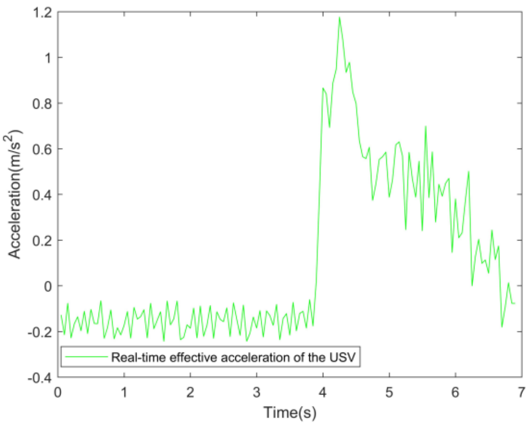

Fig. 9. Valid acceleration data from INS

The integration time of effective acceleration is 4 s~7 s.

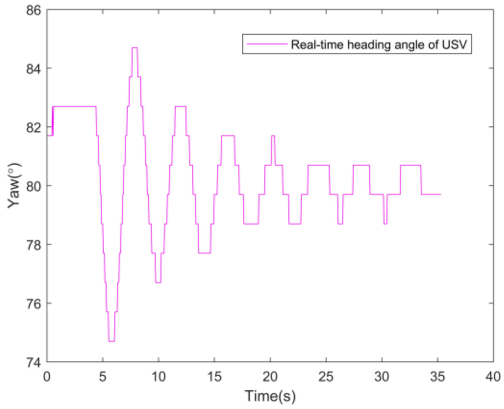

Fig. 10. Real-time heading angle of USV

C. *Integrated Navigation System Experimental Data Analysis*

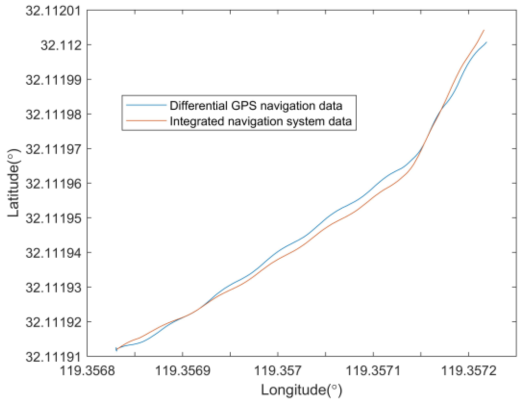

Fig. 11. Route data for integrated navigation system and differential GPS

From Fig. 11 we can know that the integrated navigation system has better navigation effect compared to INS. The straight line distance between the start and the end of the route of the differential GPS is 37.89 meters, and the straight line distance between the start and the end of the route of the integrated navigation system is 37.69 meters. The maximum distance between the two routes is 0.73 m.

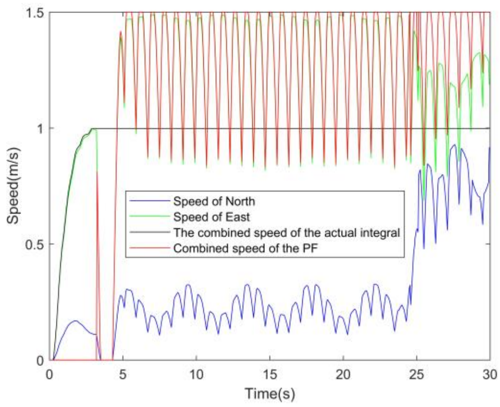

Fig. 12. Source of speed data from integrated navigation system

From the data in Fig. 12, we can see that the black line shows the original velocity data obtained by integration and the red line shows the velocity data obtained by PF. It is known that the velocity data of PF is time-varying and is constantly adjusted to obtain a more accurate velocity. It is better than the original velocity data which remains unchanged after the effective integration is completed.

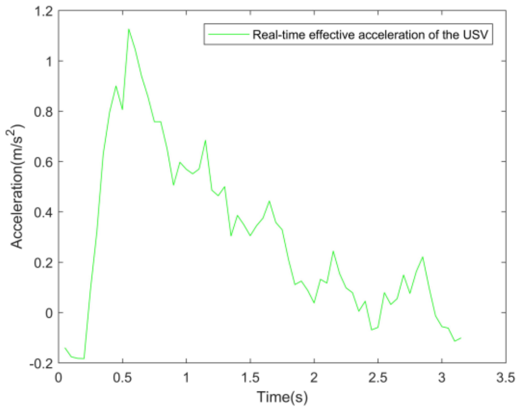

Fig. 12. Valid acceleration data from integrated navigation system

The integration time of effective acceleration is 0.2 s~3.2 s.

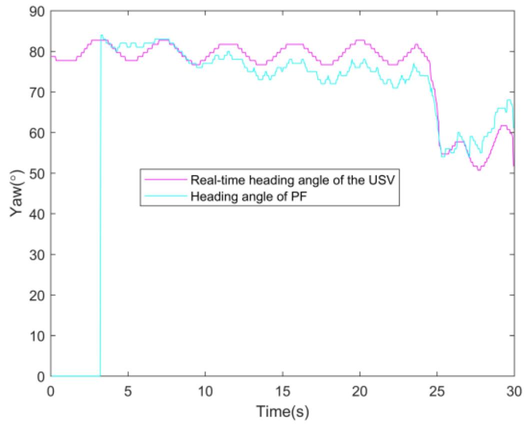

Fig. 13. Real-time heading angle of USV

The PF output heading angle corrects the real-time heading angle.

V. Conclusion

The integrated navigation method for USV proposed in this paper focuses on improving the accuracy of INS independent navigation first, and then using the data from PF fused GPS to further improve the performance of navigation. The proposed integrated navigation method can be applied to inexpensive IMUs to achieve more accurate navigation and positioning functions for USVs. The method has good practicality, and the experimental data prove that the method has high navigation accuracy. The shortcoming of the method is the large computational effort in the case of a large number of particles in the PF algorithm, which leads to poor real-time data solving and affects the navigation accuracy.

Acknowledgment

This work was in part supported by research startup foundation of Jiangsu University of Science and Technology under Grant 1032932006, part by the National Natural Science Foundation of China under Grant 61903163, and the Postgraduate Research & Practice Innovation Program of Jiangsu Province under Grant SJCX21-1748.

References

[1] Mostafa M Z, Khater H A, Rizk M R, et al. A novel GPS/RAVO/MEMS-INS smartphone-sensor-integrated method to enhance USV navigation systems during GPS outages[J]. Measurement Science and Technology, 2019, 30(9): 095103..

[2] Choi B S, Yoo W J, Kim L, et al. Tightly-Coupled GPS/INS/Ultrasonic-Speedometer/Barometer Integrated Positioning for GPS-Denied Environments[J]. Journal of Positioning, Navigation, and Timing, 2020, 9(4): 387-395.

[3] Choi W, Kang H, Lee J. Robust Localization of Unmanned Surface Vehicle Using DDQN-AM[J]. International Journal of Control, Automation and Systems, 2021, 19(5): 1920-1930.

[4] Fossen S, Fossen T I. Five-state extended Kalman filter for estimation of speed over ground (SOG), course over ground (COG), and course rate of unmanned surface vehicles (USVs): experimental results[J]. Sensors, 2021, 21(23): 7910.

[5] Liu W, Liu Y, Bucknall R. Filtering based multi-sensor data fusion algorithm for a reliable unmanned surface vehicle navigation[J]. Journal of Marine Engineering & Technology, 2022: 1-17.

[6] Liao J, Wang Y, Yin J, et al. An integrated navigation method based on an adaptive federal Kalman filter for a rice transplanter[J]. Transactions of the ASABE, 2021, 64(2): 389-399.

[7] Xia G, Wang G. INS/GNSS tightly-coupled integration using quaternion-based AUPF for USV[J]. Sensors, 2016, 16(8): 1215.

[8] Zhang X, Liu D, Lei B, et al. An intelligent particle filter with resampling of multi-population cooperation[J]. Digital Signal Processing, 2021, 115: 103084.

[9] Vouch O, Minetto A, Falco G, et al. On the Adaptivity of Unscented Particle Filter for GNSS/INS Tightly-Integrated Navigation Unit in Urban Environment[J]. IEEE Access, 2021, 9: 144157-144170.

[10] Xia G, Wang G. INS/GNSS tightly-coupled integration using quaternion-based AUPF for USV[J]. Sensors, 2016, 16(8): 1215.

[11] Zhang C, Guo C, Zhang D. Ship navigation via GPS/IMU/LOG integration using adaptive fission particle filter[J]. Ocean Engineering, 2018, 156: 435-445.

[12] Jung J, Park J, Choi J, et al. Navigation of unmanned surface vehicles using underwater geophysical sensing[J]. IEEE Access, 2020, 8: 208707-208717.

[13] Klinger W B, Bertaska I R, von Ellenrieder K D, et al. Control of an unmanned surface vehicle with uncertain displacement and drag[J]. IEEE Journal of Oceanic Engineering, 2016, 42(2): 458-476.