A New Method to Improve the Maneuver Capability of AUV Integrated Navigation Systems

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***Abstract*—The maneuver characteristic of the most commonly used AUV integrated navigation systems was investigated in this paper. After analyzing the error cause of conversional used Kalman filter of SINS/DVL integrated navigation systems in maneuver state, a novel method was proposed which is to use the output of complex navigation systems to revise the SINS in real-time, and an improved adaptive Kalman filter was discussed here to reach the seamless changing of the whole system. The measurement remnant method was introduced to judge whether the bearing change event happened or not. The whole design was aiming to reach the smooth transition between the different motion states and improve the maneuver capability of the AUV navigation system. The simulation results confirms the new approach could restrain the oscillation of Kalman filter in motion changing state and improve the accuracy of the AUV integrated navigation systems.**

***Index Terms*—maneuver, integrated navigation systems, adaptive Kalman filter, AUV**

I. INTRODUCTION

AUV has drawn a lot of attentions widely across the world because of its flexibility, small-dimension and multi-tasks characteristic which requires the navigation systems should have the long-term independently working capability and also provide accurate positioning information in the complicated marine environment. The precision of the navigation system can directly affect the quality of whole task because the most important factor for an AUV to successfully complete a typical survey mission is to follow a path specified by the operator as accurately as possible. Unlike the UAV (unmanned aerial vehicle), AUV presents a more challenging navigational problem, because it is always lack of the direct positioning signal from GPS (global positioning system) to revise the SINS positioning information when it is in submerging state and the normally used sensor DVL could only provide the velocity information. H. Stutters and H. Liu discussed different methods in different underwater environments of AUV and also addressed their current problems [1].

As is known to us all, the maneuver scenario is always an intractable and unavoidable problem not only for target tracking but also for navigation issue. As the conversional Kalman filter has limitation in such situation, a lot of researches have been made aiming to decrease the oscillation, speed up the convergence process with the help of GPS or an existing beacon to revise the position. The underwater maneuvering problem is still one of the most challenging scenarios of AUV, considering above requirements are hardly met during its mission.

One solution is to equip the AUV with more accurate acceleration and gyro sensors to somehow decrease the drift of SINS in long-term working range, but this always means higher cost and also limited by the mechanical technique.

The other solution is to use some methods to decrease the drift bias through rotation of SINS. S. Ishibashi, etc. proposed their method to improve the performance of INS which was put on a turntable with one rotational axis and rotated by it according to some rules [2].

The third solution is to redesign the integrated navigation system and improve the adaptive filtering algorithm to be adapted to the dynamic motion which is discussed later in this paper. B. Liu and J. Fang introduced a method to use the normalized observability of states as a factor to adaptively feedback the SINS with the estimated output value of Kalman filter [3]. But something should be done to improve the theory because the vehicle motion could improve the observability, it will also involve the short term oscillation of Kalman filter when switching between different state, such oscillation will even lead to the divergence of SINS if the estimated value is directly used to judge the SINS. Z. Guo and F. Sun proposed initial idea to adopt the dead reckoning algorithm using the heading information of the SINS and DVL to substitute the SINS/DVL integrated system [4] but without further investigation about the whole design of the changing method. The SINS/DVL integrated navigation system and the Compass/DVL dead reckoning system are the most common choice for AUV underwater working mode. Both systems have their own advantage in linear motion and curvilinear motion. SINS/DVL integrated navigation system normally uses

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Kalman filter which has a bad performance in maneuvering state; considering that the SINS' low frequency noise and the sensor bias will lead to poor accuracy in long term, the close loop feedback will even cause the divergence of the filtering process at the motion changing time. The Compass/DVL dead reckoning system depends on the DVL information and the accuracy in linear motion is not as good as the SINS/DVL integrated navigation system. How to take advantage of both systems and make seamless changing between them are quite meaningful in real application field.

The organization of this paper proceeds as follows. The next section outlines the structure of AUV navigation systems. Section III details the error of normal Kalman filter in maneuvering state, after explaining the traditional adaptive Kalman filter, the dynamic sliding window is introduced to be used in the improved adaptive Kalman filter. Section IV proposes the maneuver detect algorithm, and the improved adaptive Kalman filter proposed in previous session will be used for SINS/DVL maneuvering state, and then introduces the design of whole structure of the navigation systems and the seamless changing method. In Section V, simulation is made to verify the design. Finally, conclusions are drawn.

II. THE STRUCTURE OF AUV NAVIGATION SYSTEM

The AUV navigation system is composed of two sub systems namely SINS/DVL integrated navigation system and Compass/DVL dead reckoning system. They will be discussed respectively as they are the foundation of the seamless changing method.

A. SINS/DVL Integrated Navigation System

The SINS in a stand-alone mode provides the position, velocity, and attitude information, thus the relative error information including the gyro drift are chosen as the state vector representing the characteristic of SINS in long-time working state. The gyro drift's error model is regarded as a first-order Markov process. The random time-varying drift caused by accelerometer is taken into account as the system noise. The corresponding linear error equation of SINS can be referred to[1]. Considering the error model of DVL, the state vector of Kalman filter is augmented with the DVL velocity offset's error δV_d, log misalignment angle error $\delta\Delta$ and scale coefficient error δC. δV_d and $\delta\Delta$ are expressed by first-order Markov process, δC is random constant drift.

The discrete model of the integrated SINS/DVL system is as follows:

$$\left.\begin{aligned} X_k &= \Phi_{k,k-1} X_{k-1} + \Gamma_{k,k-1} W_{k-1} \\ Z_k &= H_k X_k + v_k \end{aligned}\right\} \quad k \geq 1 \tag{1}$$

where X_k and W_k denote system's state vector and noise vector; Z_k and V_k denote system's measurement vector and noise vector; $\Phi_{k,k-1}$ and H_k denote state vector's transition matrix and measurement matrix; Γ_{k-1} denotes system's noise matrix.

The state vector and noise vector of SINS/DVL integrated navigation system are given by

$$X = [\delta\varphi \quad \delta\lambda \quad \delta V_x \quad \delta V_y \quad \phi_x \quad \phi_y \quad \phi_z \quad \varepsilon_x \quad \varepsilon_y \quad \varepsilon_z \quad \delta V_d \quad \delta\Delta \quad \delta C]^T \tag{2}$$

$$W = [0 \quad 0 \quad a_x \quad a_y \quad 0 \quad 0 \quad 0 \quad w_x \quad w_y \quad w_z \quad w_d \quad w_\Delta \quad 0]^T \tag{3}$$

Where $\delta\varphi, \delta\lambda$ denote latitude error and longitude error; $\delta V_x, \delta V_y$ denote east and north velocity error; V_x, V_y denote east and north velocity; ϕ_x, ϕ_y, ϕ_z denote north , east level and azimuth misalignment angle; $\varepsilon_x, \varepsilon_y, \varepsilon_z$ denote gyro drift; a_x, a_y denote accelerometer random drift; $w_x, w_y, w_z, w_d, w_\Delta$ are stimulative white noise.

The difference between SINS velocity and DVL velocity compose the measurement vector.

$$Z = \begin{bmatrix} \delta V_x - \delta V_{dx} \\ \delta V_y - \delta V_{dy} \end{bmatrix} = HX + v \tag{4}$$

$$H = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & -V_y & 0 & 0 & 0 & -\sin K_d & -V_y & -V_x \\ 0 & 0 & 0 & 1 & 0 & 0 & V_x & 0 & 0 & 0 & -\cos K_d & V_x & -V_y \end{bmatrix} \tag{5}$$

B. Compass/DVL Navigation System

The Compass/DVL navigation system is somehow like a black box system, the dead reckoning working principle requires the outer sensors providing the initial position, and with the bearing information provided by compass and velocity information provided by DVL, the position will be calculated.

$$\varphi_{K(DR)} = \varphi_{K-1(DR)} + V_{dy} T / R_{yp} \tag{6}$$

$$\lambda_{K(DR)} = \lambda_{K-1(DR)} + V_{dx} T / (R_{xp} \cos(\varphi_{K(DR)})) \tag{7}$$

Where $\varphi_{K(DR)}$ and $\lambda_{K(DR)}$ denote latitude and longitude information of dead reckoning system; V_{dx}, V_{dy} denote DVL east and north velocity; R_{xp} and R_{yp} denote the curvature radiuses of the reference ellipsoid in north-south and east-west directions.

Although the dead reckoning system is not as accurate as SINS/DVL system in long-term linear course, it's not sensitive to the vehicle maneuver. Later, we'll have a look at the seamless changing method to combine the two navigation system.

III. IMPROVED ADAPTIVE KALMAN FILTER

The estimation accuracy of traditional Kalman filter depends on priory knowledge about the system model and noise statistics. From the state equation, we could intuitively find out the relationship of the position, velocity and accelerate. With the help of transition matrix $\Phi_{k,k-1}$, the system could predict the state vector in next time according to the current state vector, which is the main cause of the Kalman filter error in the maneuvering state. Let's take a look at the case when the

vehicle is going to change from curvilinear course to linear course. Theoretically, the predicted result is always based on the last state vector, so it is obvious the system would expect the vehicle turning a small arc again current position, while on the contrary, the real trajectory is the vehicle moving along the tangent direction of the last step. There's a disadvantageous factor that for the SINS/DVL integrated navigation system, there's no measurement like GPS signal to revise the position information, so the filtering result at the motion changing part is inevitably oscillating for a short period until the Kalman filter converging to its stable state. But for the close loop navigation system, it could be very dangerous that after a long-term working period, the SINS algorithm revised by the oscillating filtering information could cause the filter divergence at the motion changing state.

The solution for such problem is to minimize the effect of prediction part and maximize the effect of the innovation sequence in the maneuvering state. If we totally rely on the measurement of DVL velocity information, and drop the prediction part, then the calculation turns to the dead reckoning system. Then it comes to our next topic of seamless changing. However, for the SINS/DVL system, we enlarge the gain matrix according to the innovation sequence and adopt the improved adaptive Kalman filter for the maneuvering state shown in Fig. 1. Later, the traditional adaptive Kalman filter algorithm and improved adaptive Kalman filter will be discussed separately about the process noise unknown scenario.

A. Traditional adaptive Kalman filtering algorithm when Q is unknown

Let's take a look at the case of unknown precise information about covariance matrix of process noise covariance $Q = M[w_k w_k^T]$ is unknown, after rewriting the Kalman filter,

$$\hat{x}_k = \Phi_{k,k-1}\hat{x}_{k-1} + \Gamma_{k-1}\hat{w}_{k-1} \tag{8}$$

$$\hat{x}_k - \Phi_{k,k-1}\hat{x}_{k-1} = \Gamma_{k-1}\hat{w}_{k-1} \tag{9}$$

$$\hat{x}_k - \Phi_{k,k-1}\hat{x}_{k-1} = K_k v_k \tag{10}$$

$$\Gamma_{k-1}\hat{w}_{k-1} = K_k v_k \tag{11}$$

$$\Gamma_{k-1} M[\hat{w}_{k-1}\hat{w}_{k-1}^T]\Gamma_{k-1}{}^T = K_k M[v_k v_k^T]K_k^T \tag{12}$$

Where $v_k = Z_k - H\hat{X}_{k,k-1}$ denotes innovation sequence, and K_k denotes the gain matrix. Using the formula for the Gaussian probability density, the covariance matrix of innovation sequence can be defined as [5]:

$$\hat{C}_k = M[\hat{w}_{k-1}\hat{w}_{k-1}^T] = v_k v_k^T \tag{13}$$

$$\Gamma_{k-1}\hat{Q}_{k-1}\Gamma_{k-1}^T = K_{k-1}\hat{C}_k K_{k-1}^T \tag{14}$$

B. Improved Adaptive Kalman fitering algorithem when Q is unknown

Many researchers engage in the study of the adaptive Kalman filter. The covariance scaling algorithm was used to improve the stochastic modeling [7]. MMAE (Multiple Model Adaptive Estimation) algorithm using multiple Kalman filters running simultaneously to solve the uncertainty of the modeling problem was discussed [8] [9]. Fuzzy logic was used to tune the Kalman filter in the integrated navigation system [10]. Many algorithms basing on the IAE (Innovation Adaptive Estimator) were investigated [6] [11] [12] [14]. MMAE hasn't be widely used because of its complicated calculation. To estimate the process noise on-line, this paper proposes a new method basing on the innovation adaptive estimator: the sliding window length is adjusted by the measurement remnant value automatically, thus the measurement covariance could be tuned according to innovation message.

For a stationary system, one can determine the following estimate of C_k [5] [6]:

$$\hat{C}_k = \frac{1}{k}\sum_{i=1}^{k} v_i v_i^T \tag{15}$$

or in recurrent

$$\hat{C}_k = \frac{k-1}{k}\hat{C}_{k-1} + \frac{1}{k} v_i v_i^T \tag{16}$$

From (15)-(16), we could see that the traditional way to estimate C_k is the mean value of innovation sequence from the beginning to the current time K. Then with the time passing by, the effect of latest innovation method become smaller and smaller $\frac{1}{k} v_i v_i^T$, if the vehicle motion changing sharply at that time, the innovation sequence almost has no effect on the measurement covariance estimator.

Fading memory algorithm has been introduced to the AKF by some researchers, and the fixed length N (filtering window) to calculate covariance matrix of the innovation sequence has been used to increase the effect of the measurement value [12].

$$\hat{C}_k = \frac{1}{N}\sum_{i=k-N}^{k} v_i v_i^T \tag{17}$$

We could imagine that when the process noise has a sharp change due to vehicle maneuver, we would like to enhance the effect of the innovation sequence to evaluate the process noise online; while on the contrary, we would like to keep the stationary characteristic of the system.

After investigating the disadvantage of both Saga-Husa and fading memory algorithm, this paper proposes a method to adjust the window length automatically.

$$d = v_k^T C_k^{-1} v_k = (Z_k - H\hat{X}_{k,k-1})^T (H_k P_{k+1/k} H_k^T + R_k)^{-1} (Z_k - H\hat{X}_{k,k-1}) \tag{18}$$

Then the measurement remnant value d is used to adjust the window length which could be called "tuning factor". The sliding window length becomes smaller as the remnant value goes bigger, obviously, the minimum length of the sliding window is 1, and the maximum length of it is k, and the innovation sequence takes the biggest effect and smallest effect for above scenarios.

$$N = 1, \quad d > \alpha_{\max}$$

$$N = k, \quad d < \alpha_{\min}$$

$$N = Integer(k \times \lambda^{d-\alpha_{\min}}), \lambda < 1, N \geq 1, \quad \alpha_{\min} < d < \alpha_{\max} \tag{19}$$

Where, α is the given threshold, the value of λ decides the convergence speed of the length N by the remnant value. The sliding window length could be adjusted automatically according to (19). After substituting sliding window length N to (18) and the process noise could be calculated according to (14).

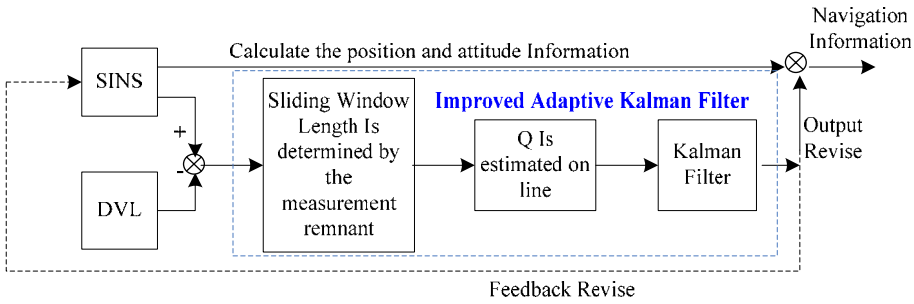

Figure 1. SINS/DVL Simple Structure with Improved Adaptive Kalman Filter

The improved adaptive Kalman filtering algorithm of SINS/DVL navigation system then comes as Fig.1.

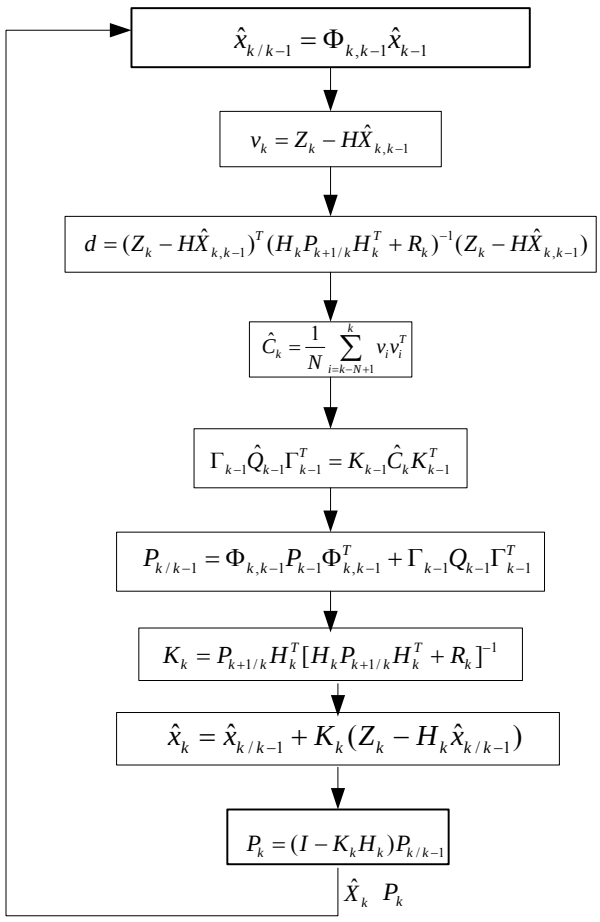

Figure 2. Improved Adaptive Kalman Filter Algorithm with Sliding Window

The advantage of above method is that the ratio of the prior innovation message depends on the latest measurement remnant value, the current innovation sequence could work effectively in this way, and when the remnant value is small enough, the sliding window length is extended to guarantee the stationary characteristic of the system. Thus the aim of adjusting the sliding window length is realized. The sliding window idea has been raised by author to estimate the measurement noise covariance on line [14]. However, there's still something to be done to separate the situation whether the process noise or the measurement noise is changed by some methods, e.g., judge the consistency of sensor information before it is used. Further research will be done in future. In next session, the improved adaptive Kalman filter algorithm will be used when maneuver event is detected to realize the smooth transition of AUV navigation.

IV. DESIGN OF SEAMLESS CHANGING METHOD

A. Maneuver Detection

Many discussions about maneuver detection have been made for Strong Target Tracking scenario in literature. The most commonly used method is the measure remnant χ^2 method [13]. However, this method could be disturbed by a fault instead of maneuver.

Let's take $D_k = H_k P_{k+1/k} H_k^T + R_k$, then we could rewrite (18)

$$d = v_k^T D_k^{-1} v_k \tag{20}$$

Compare it with the given threshold α, if

$$d > \alpha \tag{21}$$

The traditional method will assume the vehicle motion state as maneuver.

To avoid the misjudgment, the consistent detection of bearing information is used as supplement for maneuver detection. The heading sensor could record the bearing information of the last three steps: $\phi_{zK-2(DR)}$, $\phi_{zK-1(DR)}$, $\phi_{zK(DR)}$, considering the wavelet effect, we could assume that

$$\left|\phi_{zK-2(DR)} - \phi_{zK-1(DR)}\right| \approx \left|\phi_{zK(DR)} - \phi_{zK-1(DR)}\right| \approx \omega_{yaw} T \quad . (22)$$

Where ω_{yaw} is the yaw angular velocity against up axis caused by wave stimulation. When the first detection by (21) is given, and (22) is satisfied, we could assume the vehicle is in maneuver state. Otherwise, the (21) is caused by DVL fault, as the inertial sensor is normally taken to be reliable, and then the SINS/DVL should use prediction mode.

B. the Seamless Changing Method

Let's assume the AUV starts with linear course, then SINS/DVL is used to output navigation information.

Fig. 3 could help to understand the thorough design of AUV navigation systems.

SINS calculates position, velocity and attitude according to the output of the accelerator and gyro output. In order to realize the optimal filtering algorithm, when the AUV moves in straight line, the conversional Kalman Filter will be adopted for the SINS/DVL integrated navigation systems, and the estimated information will be used to revise relative information of SINS. When the maneuvering state is judged by the previous "maneuver detect" algorithm, the sliding window length will be determined by the measurement remnant, and the improved adaptive Kalman filtering algorithm will be used by the SINS/DVL integrated navigation systems. Please note that when maneuver is detected, the SINS/DVL uses adaptive Kalman filter, the last position of SINS/DVL is used to reset the compass/DVL dead reckoning system, and the DR system is adopted as the AUV navigation output resources which will be used as the feedback information to revise SINS.

When maneuver judgment tells us the vehicle is changing back to straight line, AUV keeps using DR (dead reckoning) system for several steps, after that, AUV adopts SINS/DVL as the output navigation system, and the SINS/DVL switches back to normal Kalman filtering process. The structure of AUV navigation system could be referred to Fig. 3 and Fig. 4.

The advantage of this design is that there's no extra cost on expensive high-level accuracy sensors, and the positioning accuracy will be improved in maneuvering state just with normal sensors. And the navigation method of SINS/DVL integrated navigation system combines the optimal Kalman filter in straight line and the dynamic adaptive Kalman filter in maneuver state fairly well, which could reduce the oscillation when switching between different modes.

V. COMPUTER SIMULATION

We now describe the application of the seamless changing method for navigation of Autonomous Underwater vehicles. In order to investigate the performance of the new approach, the medium precision's measurement sensors are simulated. The measurement sensors' errors and the initial navigation parameter's errors are given as (21). After fine alignment, the misalignment angle in three axes (pitch, roll, yaw

The whole system takes both advantage of SINS/DVL integrated navigation systems and the DR navigation systems. Thus, the AUV maneuver capability is improved with such seamless changing.

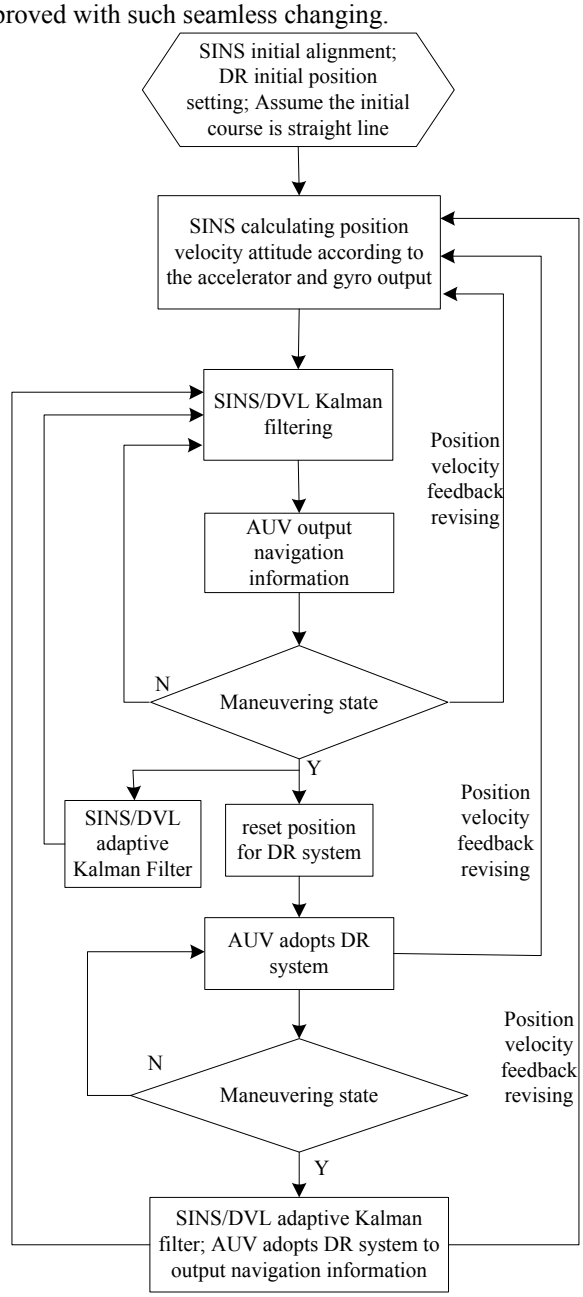

Figure 3. Diagram of the whole structure

error) is given as 0.0005°, 0.0005°, and 0.003° separately. The initial quaternion is calculated according to the misalignment angle so that the vehicle body frame is aligned with the local geographical frame. The gyro drift is chosen as $1\times10^{-3\circ}/h$. The accelerometer parameters are given by 10^{-4}g. The velocity offset's error δV_d and log misalignment angle error caused by the ocean current $\delta\Delta$ can be chosen as

$$\beta_i^{-1} = 2\text{h}(i = x, y, z), \beta_d^{-1} = 5\,\text{min}; \beta_\Delta^{-1} = 15\,\text{min}$$

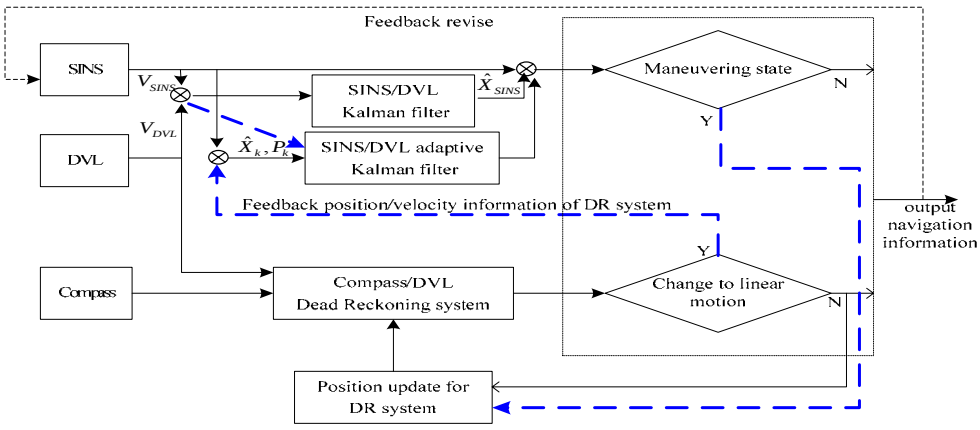

Figure 4. Structure of AUV navigation system

The vehicle trajectory is composed of several courses: straight forward with the bearing angle of 10°, velocity 10knots, lasting for 10 minutes; maneuver state, turning around a circle with 500m radius, at 10knots rate, 3.5 π arc; changing back to straight line, lasting for 10 minutes, velocity 10knots.

The sway motion model is represented as below:

$$\left.\begin{aligned} &\theta = \theta_m \sin(\omega_\theta t + \theta_0) \\ &r = r_m \sin(\omega_r t + r_0) \\ &\varphi = \varphi_m \sin(\omega_\varphi t + \varphi_0) \\ &V_x = V_{x0}, \quad V_y = V_{y0} \end{aligned}\right\} \tag{23}$$

where θ, r, φ are pitch, roll and yaw respectively; the sway magnitudes θ_m, r_m, φ_m are 5°, 6°, and 5° respectively. The sway period of pitch, roll and yaw is 10s, 10s, and 10s respectively. The initial phase angles θ_0, r_0 and φ_0 are set to 0°.

The trajectory of AUV is shown in Fig.5 and zoom in figure of the first motion changing trajectory is shown in Fig. 6. From which, we could see that the output of AUV navigation system is quite smooth without big gap during the motion change. The gyro output of three axes is shown in Fig.6.

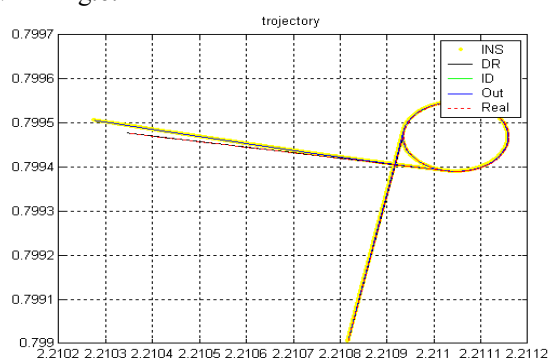

Figure 5. trajectory of AUV

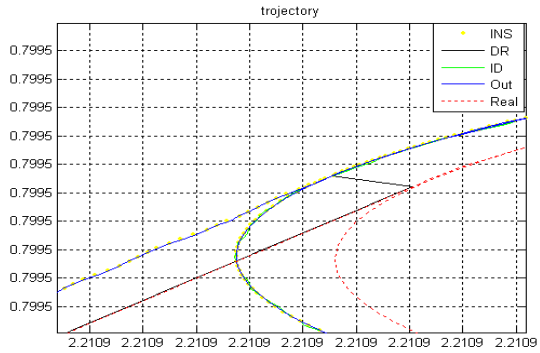

Figure 6. zoom in figure of the first motion change trajectory

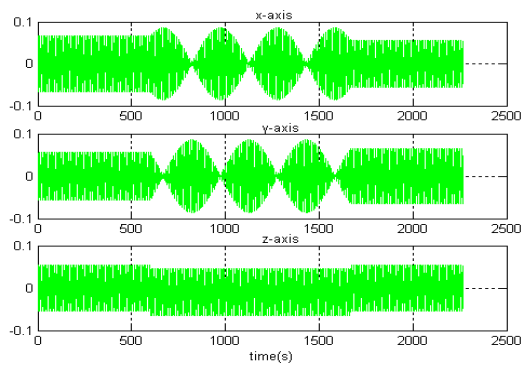

Figure 7. Gyro ouput of three axes

Fig.8 and Fig.9 reveal the longitude estimation error; Fig.10 and Fig.11 reveal the latitude estimation error. From these four figures, we could intuitively find out that the oscillation by the adaptive SINS/DVL Kalman filter is not as sharp as normal Kalman filter at the motion changing state, and the magnitude goes smaller during the maneuver period, while on the contrary, the general position output information by the method given in this paper is quite smooth due to the Compass/DVL dead reckoning system has a better performance in the maneuver state. Fig.12 and Fig.13 reveal the east and north velocity error of the system.

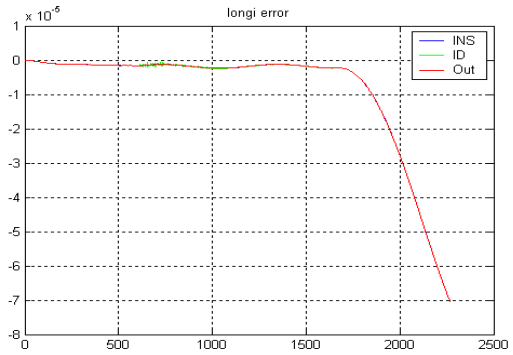

Figure 8. longitude error for maneuvering state

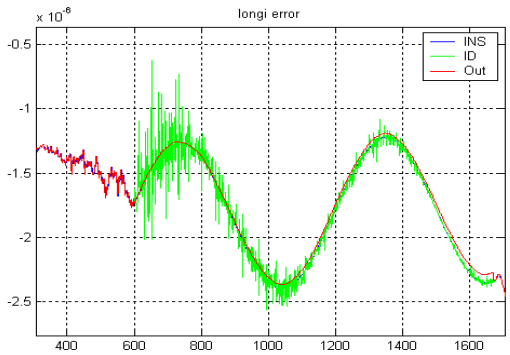

Figure 9. zoom in plot of longitude error

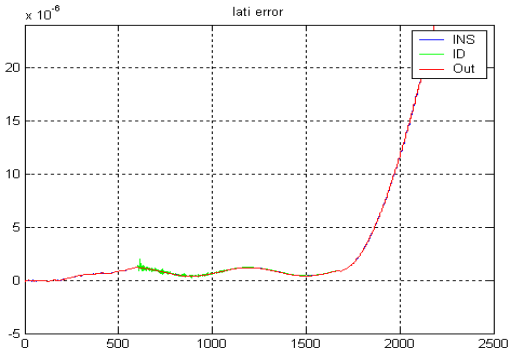

Figure 10. latitude error for maneuvering state

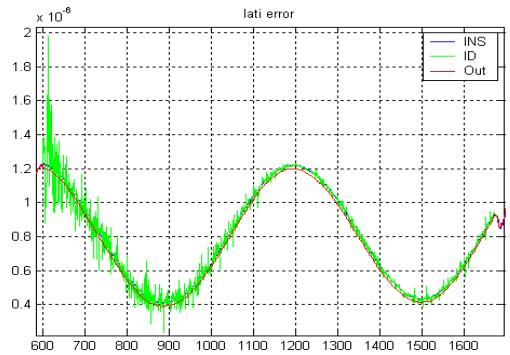

Figure 11. zoom in plot of latitude error

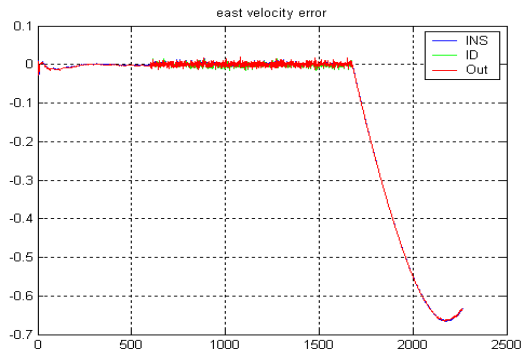

Figure 12. east velocity error

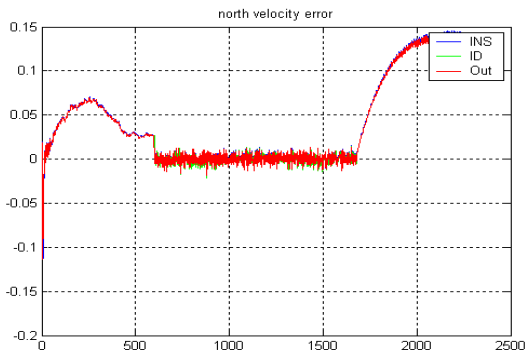

Figure 13. north velocity error

VI. CONCLUSION

As AUV faces a serious problem of maneuvering state in marine environment, this paper proposes a new method to improve the maneuver capability of the AUV integrated navigation systems. The main target is to reduce the oscillation of traditional Kalman filter in motion changing state and improve the positioning accuracy. The whole design is based on the normal sensor without extra cost.

It is founded that the bearing consistent check combining with the measure remnant χ^2 method could avoid the misjudgment of maneuver. The dynamic sliding window tuned by measurement remnant is proposed here to judge the process noise on line, and thus is the main idea of the improved adaptive Kalman filter which could help the SINS/DVL system to reduce oscillation when the AUV is in motion changing state. The whole structure of the AUV navigation systems is introduced with a thorough diagram. The most important of all is that after adopting the seamless changing method, the AUV output navigation information is much smoother than before. The simulation result proves that such design with improved adaptive Kalman filter is efficient and could be used in the application field.

ACKNOWLEDGMENT

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