An Applied navigation arithmetic used in “SY-1” AUV

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Abstract: Since little information can be used in underwater navigation, the paper presents a navigation method based on dead reckoning of automatics underwater vehicle (AUV).The paper introduces the constitutes of system and describes the arithmetic in detail. After applying dead reckoning using the sensors' outputs, Singer dynamical model is made and an adaptive Kalman filter algorithm is used to improve the system's precision and reliability. GPS data are used to revise the result. Song Hua Lake's test has proved the system's practicability.
Key Words: automatic underwater vehicle; dead reckoning; adaptive Kalman filter;

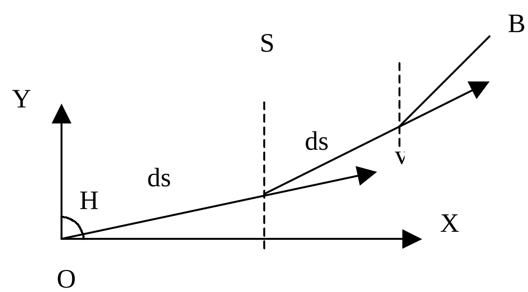
1. Introduction

How to improve the precision of underwater navigation is a key problem of AUV technology. Since the Hertzian waves attenuates rapidly in water, little information can be used for AUV navigation. It is the precondition and guarantee for a applied AUV to realize the minitype but high precision. “SY-1”AUV is a new vehicle developed and researched at vehicle and AUV lab of HEU. To test this navigation system is one of its tasks, whose sensors include Doppler Velocity Log (DVL), fiber optic gyrocompass, GPS and sonar. The paper introduces “SY-1” AUV's navigation arithmetic based on the dead reckoning, and strong tracking Kalman filter is used to improve the precision of location. Before the error accretes too large to endure, GPS data is used to relocate.

2. Dead Reckoning Theory

Dead reckoning is a basic navigation method. Especially in underwater navigation field, tow unique advantages build its status. Firstly, it can locate at any moment. Secondly, it can get not only the present but the future location of vehicle approximately.

Supposing $A(\varphi_1, \lambda_1)$ is the jumping-off point, and $B(\varphi_1, \lambda_1)$ is the end point. The length of loxodrome AB equals the voyage S, and H is the course. We may arrive at the opinion from figure 1. If we get the length of each section, the sum of the all voyage's length can be gotten approximately. As we all know, DVL provides three dimensions velocity vector of vehicle coordinates $\begin{bmatrix} v_x & v_y & v_z \end{bmatrix}$, and gyrocompass outputs vehicle's course and pose angles. Then we can easily get the vehicle's velocity vector in terrestrial coordinates $\begin{bmatrix} v_\xi & v_\eta & v_\zeta \end{bmatrix}$ and the voyage S by the formula (1).



B

A

Fig.1 dead reckoning theory

$$\begin{bmatrix} v_\xi \\ v_\eta \\ v_\zeta \end{bmatrix} = \begin{bmatrix} \cos\varphi\cos\theta & -\cos\gamma\sin\varphi + \sin\gamma\sin\theta\cos\varphi & \sin\gamma\sin\varphi + \cos\gamma\sin\theta\cos\varphi \\ \sin\varphi\cos\theta & \cos\gamma cso\varphi + \sin\gamma\sin\theta\sin\varphi & \cos\gamma\sin\theta\sin\varphi - \sin\gamma\cos\varphi \\ -\sin\theta & \cos\theta\sin\gamma & \cos\gamma\cos\theta \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ v_z \end{bmatrix}$$

(1)

where φ is the latitude of the vehicle , and θ is the longitude. By all appearance, the more accurate of the samples, the more accurate of the reckoning result.

3. First-order time correlation Singer model

Usually, there are tow methods to elevate the precision of dead reckoning result. One is to improve the sensors' output dependability by filter, the other is to increase the precision of dead reckoning result by optimum estimate theory. The paper builds a strong tracking Kalman filter to estimate the result of reckoning in order to amend the system precision.

Since the sonar has been fixed on the "SY-1" AUV, only planar kinematics model has been considered. The movements between east-west and north-south have serious coupling, it is too complex to analyze here, we consider movements respectively. The paper builds the transmeridional system equation. Considering the basic characters of general continuous time random process, we express the auto correlation function of mobile acceleration $\ddot{X}_e(t)$ as the following attenuating exponential expression.

$$R(\tau) = E[\ddot{X}_e(t)\ddot{X}_e(t+\tau)] = \sigma_A^2 e^{-\alpha\tau},$$

(2)

where o_A^2 is the mobile acceleration error of root-mean-square, and α is the reciprocal of mobile time const. They are fixed value by measuring the real status. Therefore, mobile acceleration $\ddot{X}_e(t)$ can be put with first-order time correlation model which is driven by white noise, that is

$$\dddot{X}_e(t) = -\alpha\ddot{X}_e(t) + W'(t),$$

(3)

where $\{W'(t)\}$ is the white noise whose mean is zero and root-mean-square error is $2\alpha\sigma_A^2$. Then we get Singer model. The Lake Test has proved the tractability of model.

$$\begin{bmatrix} \dot{X}_e(t) \\ \ddot{X}_e(t) \\ \dddot{X}_e(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -\alpha \end{bmatrix} \begin{bmatrix} X_e(t) \\ \dot{X}_e(t) \\ \ddot{X}_e(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} W'(t)$$

(4)

If we disperse the upper function, we will get the corresponding discrete model.

$$\begin{bmatrix} X_e(t) \\ \dot{X}_e(t) \\ \ddot{X}_e(t) \end{bmatrix} = \begin{bmatrix} 1 & h & \frac{1}{\alpha}(-1+\alpha h+e^{-\alpha h}) \\ 0 & 1 & \frac{1}{\alpha}(1-e^{-\alpha h}) \\ 0 & 0 & e^{-\alpha h} \end{bmatrix} \begin{bmatrix} X_e(t) \\ \dot{X}_e(t) \\ \ddot{X}_e(t) \end{bmatrix} + \begin{bmatrix} \frac{1}{\alpha}(-h+\frac{\alpha h^2}{2}+\frac{1-e^{-\alpha h}}{\alpha}) \\ h-\frac{1-e^{-\alpha h}}{\alpha} \\ 1-e^{\alpha h} \end{bmatrix} W'(k) \quad (5)$$

Since the vehicle's velocity is slow, we take the sampling period 0.5 second. The paper overlooks the other terms whose order exceeds second-order, and get the linear system equation.

$$\begin{bmatrix} X_e(k) \\ \dot{X}_e(k) \\ \ddot{X}_e(k) \end{bmatrix} = \begin{bmatrix} 1 & h & \frac{h^2}{2} \\ 0 & 1 & (1-\frac{\alpha h}{2}h) \\ 0 & 0 & (1-\alpha h+\frac{\alpha^2 h^2}{2}) \end{bmatrix} \begin{bmatrix} X_e(k-1) \\ \dot{X}_e(k-1) \\ \ddot{X}_e(k-1) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{\alpha h^2}{2} \\ \alpha(1-\frac{\alpha h}{2})h \end{bmatrix} W'(k), \qquad (6)$$

where $\{W'(k)\}$ is the white noise whose mean is zero and root-mean-square error is $2\alpha\sigma_A^2/h$. Tell its own story; the north-south equation has the same form. Now we get the whole system equation, and the system variable vector is $\vec{X} = [x_e \quad x_n \quad \dot{x}_e \quad \dot{x}_n \quad \ddot{x}_e \quad \ddot{x}_n]$.

How to choose the observation variables depends on the equipment of the navigation sensors. Here we select the vehicle's longitude $\lambda(k)$, latitude $\varphi(k)$, eastward velocity $v_e(k)$, and northward velocity $v_n(k)$ as the observation variables. Easily, we can get the observation equation,

$$\begin{bmatrix} z_{xe}(k) \\ z_{ve}(k) \\ z_{xn}(k) \\ z_{xn}(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_e(k) \\ \dot{x}_e(k) \\ \ddot{x}_e(k) \\ x_n(k) \\ \dot{x}_n(k) \\ \ddot{x}_n(k) \end{bmatrix} + \begin{bmatrix} V_{xe}(k) \\ V_{ve}(k) \\ V_{xn}(k) \\ V_{vn}(k) \end{bmatrix} \qquad (7)$$

the corresponding vector form is,

$$\vec{Z}(k) = H \cdot \vec{X}(k) + V(k) \qquad (8)$$

where $Z(k)$ and $V(k)$ are respectively measuring vector and observation noise matrix. Thus, the system model equation can be described as

$$\vec{X}(k) = \Phi \cdot \vec{X}(k-1) + W(k)$$
$$\vec{Z}(k) = H \cdot \vec{X}(k) + V(k)$$

(9)

4. Strong Tracking Kalman filter

Kalman filter is an effective method to apply to Gauss process data. When the model is exact enough, the system variables and the parameters do not change. It has excellent performance. But if there is any inexactness of model or the system variables and parameters move, the forepassed measuring data will harm the present estimating result, even diverge the system. Then Kalman filter do not get any plus. In order to process the case, the paper build a discrete strong tracking Kalman filter based the upper system model.

$$\vec{X}(k+1/k) = \Phi(k+1/k)\hat{\vec{X}}(k) \qquad (10•$$

$$\vec{X}(k+1) = \hat{\vec{X}}(k+1/k) + K(k+1)[\vec{Z}(k+1) - H(k+1)\hat{\vec{X}}(k+1/k)] \qquad (11•$$

$$K(k+1) = P(k+1/k)H^T(k+1)[H(k+1)P(k+1)H^T(k+1) + R(k+1)]^{-1} \qquad (12•$$

$$P(k+1/k) = \lambda(k+1)\Phi(k+1/k)P(k)\Phi^T(k+1/k) + Q(k) \qquad (13•$$

$$P(k+1) = [I - K(k+1)H(k+1)]P(k+1/k) \qquad (14)$$

where $\beta(k+1) \geq 1$ is the adaptive fading gene importing here in order to restrict the length of forepassed data, and adjust the covariance matrix of forecasting error and relevant plus matrix. The method can amend the dynamic capability and fetch up the error that is caused by the uncertainty of system model. The expression of gene $\beta(k+1)$ has been expounded detail in literature [1]. Here we give a one-step approximate arithmetic of $\beta(k+1)$, and then it becomes a hypo-optimum fading gene.

$$\beta(k+1) = \begin{cases} \beta_0, & \beta_0 \geq 1 \\ 1, & \beta_0 < 1 \end{cases} ,$$

(15)

where $$\beta_0 = \frac{tr[N(k+1)]}{tr[M(k+1)]}$$

(16)

$$M(k+1) = H(k+1)\Phi(k+1/k)P(k)\Phi^T(k+1/k)H^T(k+1) \qquad (17)$$

$$N(k+1) = V_0(k+1) - H(k+1)Q(k+1)H^T(k+1) - R(k+1) \qquad (18)$$

We can get the matrix $V_0(k+1)$ by the following expression.

$$V_0(k+1)=\begin{cases}\dfrac{1}{2}v(1)v^T(1) & k=0\\ \dfrac{\lambda(k)v(k+1)v^T(k+1)}{1+\lambda(k)}, & k\geq 1\end{cases} \tag{19}$$

where $0\leq\rho\leq 1$ is a oblivious gene. Here we can conclude the physical meanings of oblivious gene. When the system variables change, covariance matrix $V_0(k+1)$ rises for the accretion of estimating errors, $\beta(k+1)$ also rises, the tracking ability increases, and the dynamical performance of filter boosts up. But actually, the adaptive fading gene is also small in using and can not satisfy the vehicle's dynamical performance. Consequently, here we induct the adjusting coefficient $\beta(k+1)=\max\{1,\alpha\cdot tr[N(k+1)]/tr[M(k+1)]\}$, where α is the adjusting coefficient. We can modulate the value of adjusting coefficient to influence the tracking performance of filter. It has been approved in the lake test of "SY-1" AUV that the value is between 1.0 and 2.0. The filter ability weakens when minishing the value of α, and the tracking ability boosts up when the value of α augments.

5. Pretreatment of GPS Data

When a AUV voyages for a long sail, the navigation error will become too large to endure. There must be revised by the outer information. "SY-1" vehicle installs a GPS receiver to revise the dead reckoning results by its data. But in the practical data of Lake Test, there are a few invalid data for the influence of environment and the receiver itself. Firstly, the paper processes the GPS data by the arithmetic based on the changing rate of data which has been expounded detail in reference [2]. The paper sets the data after processing as the default benchmarks to evaluate the performance of the strong tracking filter.

The principle of arithmetic based on the changing rate of data is setting the changing rate of samples' amplitude as the criterion to judge whether the samples is a valid datum or not. We restrict the changing rate of valid data within a bandwidth that adjusts by the real-time samples' variety. When the changing rate of new sample excesses the bandwidth, we believe that it is a invalid sample and replace it by a extrapolative value. The paper only give the result of experiment data here in figure (2).

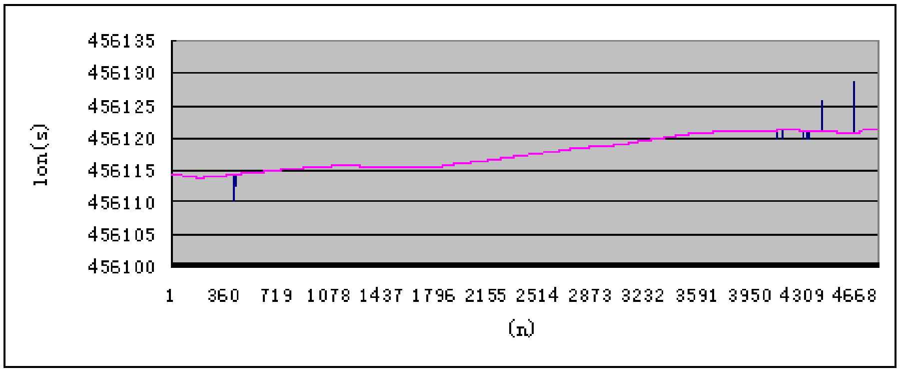


Fig 2-a longitude data

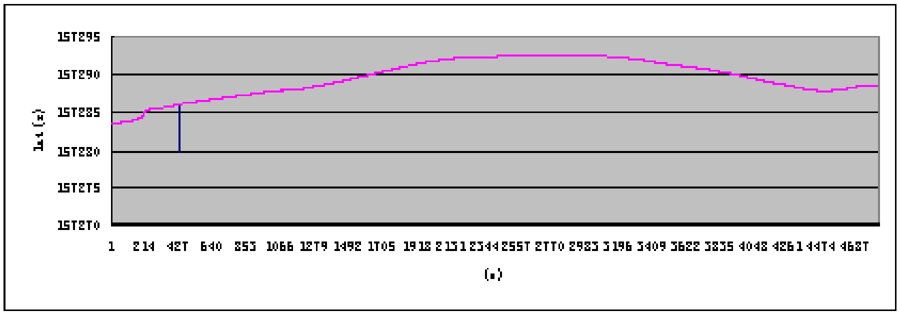


Fig 2-b latitude data

6. Lake Test Result of "SY-1" AUV

The navigation system of "SY-1" vehicle, which is designed and manufactured by the vehicle and AUV lab HEU, has been tested in Oct, 2002. The upper arithmetic has been validated to a degree and the farther researches are carrying through now.

The sampling period of the sensors is 0.5 second, and the GPS data, Doppler velocity log and the gyrocompass outputs are received at the same time. Since the strong tracking Kalman filter has been used, the outputs' stability becomes strong, and the influence of model parameters' varieties has been weaken. The preliminary values are listed, $\varphi(0)=\varphi_0, \dot{\varphi}(0)=0, \ddot{\varphi}(0)=0,\ \lambda(0)=\lambda_0$, $\dot{\lambda}(0)=0$ • $\ddot{\lambda}(0)=0$ •where φ_0 and λ_0 is the preliminary location gotten by the GPS outputs. When the adjusting coefficient $\alpha \geq 1.2$, the system's tracking ability is strong enough. While if $\alpha \leq 1.1$, the system's filter performance becomes good enough. Here we set the value $\rho = 0.95$. The result has been described in Fig (3).

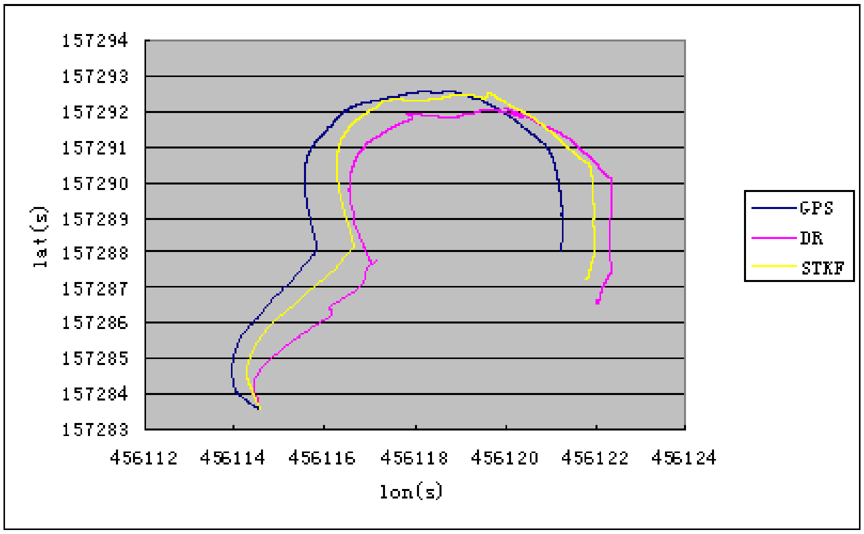


fig 3-a track of circle voyage

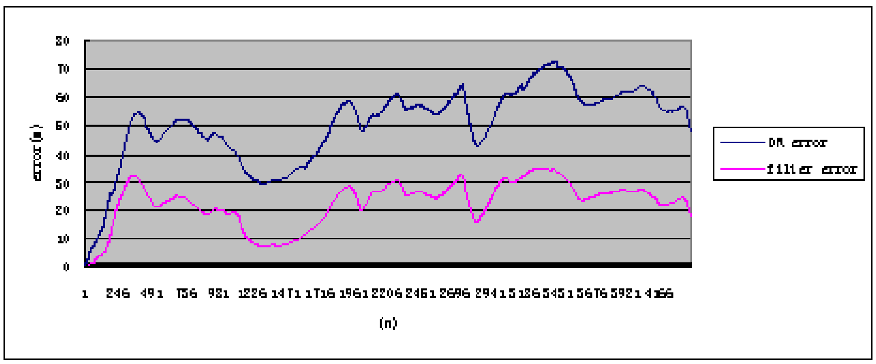


fig 3-b error

From the test result we can draw the conclusion that the reckoning error has been decreed about fifty percents compared with the result before filter. But, there is also much dissatisfaction to the experiment results and further more researches will continue to do.

7. Conclusion

The paper adopts the strong tracking Kalman filter arithmetic based on the dead reckoning to the “SY-1” AUV, and estimates the reckoning outputs in real-time. GPS is used to revise the locating error. The whole system is simple in hardware and applied in software. It especially fits to the minitype AUV system and the Lake Test has been proved the validity of the arithmetic.

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