Parametric Identification of Ship's Maneuvering Motion Based on Improved Least Square Method

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Abstract—In order to solve the problem of parameter identification of ship's Maneuvering Motion, a fast convergent iterative least squares algorithm is presented considering nonlinear and non-stationary characteristics of ship motion in time domain. The speed and precision of parameter identification have been improved using this algorithm. Firstly, the models of ship's first-order and second-order nonlinear response motion were established and made discrete. Then, parameters identification were made using new least squares algorithm which was improved by using iterative learning and introducing p-type learning rate. And the convergence of the algorithm was also analyzed. A Z-Type simulation experiment of first and second order non-linear model of a certain type of ship was conducted using the numerical methods above. At last, the results were compared with the experimental data from the free running model test carried out in Hamburg, Germany pool (HSVA). The experimental results demonstrate that the algorithm is feasible and effective.

Keywords- least square method; parameter identification; interactive learning; ship maneuvering; response model

I. INTRODUCTION

Ship maneuverability is one of the focus in the study of ship hydrodynamic performance, and it is related to the ship navigation safety. After nearly 30 years' development, the study on ship maneuverability has received more and more attention and obtained major achievements represented by the "provisional standards of ship maneuvering" and the "official standards". These standards are promulgated successively in 1993 and 2002 by the International Maritime Organization (IMO) after consulting the advice of each member states [1]. Putting forward clear quantitative requirements for ship maneuverability forecast in the design phase and maneuverability index, these standards have greatly promote the study of ship maneuverability forecast. The method of ship maneuverability forecast by establishing the maneuvering motion simulation system in the design phase is the most practical and effective one [2]. This method asks for a mathematical modeling of ship motion model, while to determine the hydrodynamic derivatives of the mathematical model is the key to modeling.

At present, using the method of system identification to determine the hydrodynamic derivatives is one of the most simple and effective method. The least square method is the most basic one in system identification [3]. It has the advantages of low system prior statistical knowledge, simple algorithm, less amount of calculation and good convergence, especially the recursive least squares method which can avoid matrix inversion calculation and realize parameter online identification. But the recursive least squares method needs further improved on the identification precision and speed. By adopting the tactics of "learning in duplicate", the iterative learning method has the memory system and empirical correction mechanism [4]. And when applied in the recursive least squares algorithm, it can make the latter have some kind of intelligence [5]. The iterative learning method can obtain additional information from the system input and output as well as parameter estimation of the past. Through constant training of identification, it provides a possibility to improve the parameter estimation and makes the identification effect better.

In this paper, the idea of iterative learning was adopted on the base of the least square method, and at the same time the vector P type was added in the process of iterative learning to improve the convergence speed and precision of the algorithm. The online identification of nonlinear ship maneuvering parameters based on the fast convergent iterative learning least squares algorithm was completed, and the effectiveness of the proposed method was verified.

II. THE ESTABLISHMENT OF SHIP MANEUVERING MOTION MODEL

At present, there are mainly two kinds of ship maneuvering motion models that has gone through theoretical analysis and practical test: one is the hydrodynamic model and another kind is the response model [6-8]. In this paper, the classic KT equation was adopted considering its fewer ship maneuvering parameters and good observability. This model contains maneuverability indices such as K, T, and these indices can be obtained by some linear hydrodynamic derivatives.

The first order nonlinear response model is described in equation (1):

$$T\dot{r} + r + \alpha r^3 = K\delta \quad (1)$$

Where r is the turn bow angular velocity, δ is the rudder Angle, K and T are the maneuverability indices, α is the nonlinear coefficient.

The second order nonlinear response model is described in equation (2):

$$T_1T_2\ddot{r} + (T_1 + T_2)\dot{r} + r + \alpha r^3 = K\delta + KT_3\dot{\delta} \quad (2)$$

Where K, T_1, T_2 and T_3 are the maneuverability indices, α is the nonlinear coefficient.

By conducting forward difference discretization on equation (1), we get equation (3):

$$r(t+1) = a_1 r(t) + a_2 r^3(t) + b_1\delta(t) + \varepsilon(t) \quad (3)$$

Where t is the time stamp, $\varepsilon(t)$ is the Gaussian white noise, a_1, a_2 and b_1 are coefficients to be identified, their relationship with the first order nonlinear ship maneuverability indices is as follows:

$$\begin{cases} T = (1-a_1)/\Delta t \\ \alpha = -a_2 T/\Delta t \\ K = b_1 T/\Delta t \end{cases} \quad (4)$$

Where Δt is the Sampling interval.

We make $T_1T_2 = h$, $T_1 + T_2 = g$, and conduct forward difference discretization on equation (2), thus we get the following equation:

$$\begin{aligned} r(t+1) &= a_1 r(t) + a_2 r(t-1) + a_3 r^3(t-1) \\ &+ b_1\delta(t) + b_2\delta(t-1) + \varepsilon(t) \end{aligned} \quad (5)$$

Where a_1, a_2, a_3, b_1 and b_2 are coefficients to be identified, their relationship with the second order nonlinear ship maneuverability indices is as follows:

$$\begin{cases} h = \Delta t^2/(1-a_1-a_2) \\ g = (2-a_1)h/\Delta t \\ \alpha = -a_3 h \\ K = (b_2+b_1)h/\Delta t^2 \\ T_3 = b_1 h/(K\Delta t) \end{cases} \quad (6)$$

The problem of ship maneuverability parameter identification can be summed up as follows: the ship motion sequences $r(t)$ and $\delta(t)$ are known, we need to solve a_1, a_2, a_3, b_1 and b_2 and then calculate the nonlinear ship maneuverability indices like K, T, T_1, T_2, T_3 and α.

We Make $\varphi^{\mathrm{I}}(t) = [r(t), r^3(t), \delta(t)]^T$, $\theta^{\mathrm{I}} = [a_1, a_2, b_1]^T$

So that equation (3) becomes as following:

$$y^{\mathrm{I}}(t) = \varphi^{\mathrm{I}T}(t)\theta^{\mathrm{I}} + \varepsilon(t) \quad (7)$$

Then we make $y^{\mathrm{II}}(t) = r(t+1)$,

$\varphi^{\mathrm{II}}(t) = [r(t), r(t-1), r^3(t-1), \delta(t), \delta(t-1)]^T$,

And equation (5) is converted into the following form:

$$y^{\mathrm{II}}(t) = \varphi^{\mathrm{II}T}(t)\theta^{\mathrm{II}} + \varepsilon(t) \quad (8)$$

III. A FAST CONVERGENT ITERATIVE LEARNING LEAST SQUARES ALGORITHM

A. Standard recursive least squares method

We use the following model to express the two systems in equation (7) and equation (8):

$$y(t) = \varphi^T(t)\theta + \varepsilon(t) \quad (9)$$

The principle of the least square method is seeking the estimate $\hat{\theta}(t)$ for the unknown vector θ to make the residual sum of square to the minimum. Equation (10) is the expression for the residual sum of square:

$$J = \sum_{t=1}^{N} e^2(t) \quad (10)$$

Where $e(t) = y(t) - \varphi^T(t)\hat{\theta}(t)$.

We make $Y(t) = [y(1), y(2), \ldots, y(t)]^T$,

$\Phi(t) = [\varphi(1), \varphi(2), \ldots, \varphi(t)]^T$,

So that the performance indicator J can be written as the following form:

$$J = [Y(t) - \Phi^T(t)\hat{\theta}(t)]^T[Y(t) - \Phi^T(t)\hat{\theta}(t)] \quad (11)$$

The non-recursive least squares estimate of the observation θ base on time t can be obtained as following:

$$\hat{\theta}(t) = [\Phi(t)^T\Phi(t)]^{-1}\Phi^T(t)Y(t) \quad (12)$$

In order to eliminate the situation of zero denominator and avoid matrix inversion, the recursive gain least squares estimate is written as the following form:

$$\hat{\theta}(t+1) = \hat{\theta}(t) + \frac{P(t)\varphi(t+1)[y(t+1) - \varphi^T(t+1)\hat{\theta}(t)]}{1 + \varphi^T(t+1)P(t)\varphi(t+1)} \quad (13)$$

$$P(t+1) = P(t) + \frac{[P(t)\varphi(t+1)][P(t)\varphi(t+1)]^T}{1 + \varphi^T(t+1)P(t)\varphi(t+1)} \quad (14)$$

In the above equations, the initial values $\hat{\theta}(0) = 0$, $P(0) = \gamma I$, γ is a very large positive number, and we define $r(t) = 0, \delta(t) = 0, t \le 0$.

B. Fast convergent iterative learning least squares algorithm

From equation (9) we get the form at time t:

$$y(t) = \varphi^T(t)\hat{\theta}(t) + e(t) \quad (15)$$

After k times iterations, the above formula evolves into the following form:

$$y_k(t) = \varphi_k{}^T(t)\hat{\theta}_k(t) + e_k(t) \quad (16)$$

We make $e_k(t) = y_k(t) - \varphi_k{}^T(t)\hat{\theta}_k(t)$,

$Y_k(t) = [y_1(t), y_2(t), \cdots, y_k(t)]^T$,

$\Phi_k(t) = [\varphi_1(t), \varphi_2(t), \cdots, \varphi_k(t)]^T$,

then we get the form:

$$Y_k(t) = \Phi_k{}^T(t)\hat{\theta}_k(t) + \Omega_k(t) \quad (17)$$

Considering the following index function:

$$J_k(\hat{\theta}_k(t)) = \frac{1}{2}[Y_k(t) - \Phi_k(t)\hat{\theta}_k(t)]^T [Y_k(t) - \Phi_k(t)\hat{\theta}_k(t)] \quad (18)$$

Similarly, the least squares algorithm is derived as:

$$\hat{\theta}_k^{LS}(t) = \hat{\theta}_{k-1}(t) + \frac{P_{k-1}(t)\varphi_k(t)}{1+\varphi_k{}^T(t)P_{k-1}(t)\varphi_k(t)} e_k(t) \quad (19)$$

Where

$$P_k(t) = P_{k-1}(t) - \frac{P_{k-1}(t)\varphi_k(t)\varphi_k{}^T(t)P^T{}_{k-1}(t)}{1+\varphi_k{}^T(t)P_{k-1}(t)\varphi_k(t)} \quad (20)$$

The initial values are given in equation (21):

$$\begin{cases} P_0(t) = P(t-1) \\ \hat{\theta}_0(t) = \hat{\theta}(t-1) \end{cases} \quad (21)$$

After N times iterations when the iterative termination condition is satisfied, we can get the form:

$$\begin{cases} P(t) = P_N(t) \\ \hat{\theta}(t) = \hat{\theta}_N(t) \end{cases} \quad (22)$$

The iterative termination conditions are generally as follows:

$$\begin{cases} \|\hat{\theta}_{k+1}(t) - \hat{\theta}_k(t)\| < \sigma \\ else \\ k = N\max \end{cases} \quad (23)$$

Where σ is a small positive number, $N\max$ is the pre-set largest number of iterations.

In order to accelerate the convergence speed, the P-type iterative item is added as follows:

$$\hat{\theta}_k(t) = \hat{\theta}_k^{LS}(t) + \beta\varphi_k(t)\hat{e}_k(t) \quad (24)$$

Where β is the p-type iterative coefficient, $\hat{e}_k(t) = y_k(t) - \varphi_k{}^T(t)\hat{\theta}_k^{LS}(t)$.

From the foregoing, the basic steps of fast convergent iterative learning least squares algorithm can be summarized as follows:

- Determine initial values $P_0(t)$ and $\hat{\theta}_0(t)$ for time t according to formula (21), and make $k = 0$.
- Update $P_k(t)$ and $\hat{\theta}_k(t)$ according to formula (20) and (24) when the kth rerun.
- Check the termination conditions of iterative learning according to formula (23).If the condition is met, go to step 4, if not, make $k = k+1$ and go to step 2.
- Update $\hat{\theta}(t)$ and $P(t)$ according to formula (22), then make $t = t+1$ and go to step 1.

C. Convergence analysisw

Making $\tilde{\theta}_k(t) = \hat{\theta}_k(t) - \theta$, we can get the follow form:

$$\tilde{\theta}_k(t) - \tilde{\theta}_{k-1}(t) = \hat{\theta}_k(t) - \hat{\theta}_{k-1}(t) = \frac{P_{k-1}(t)\varphi_k(t)}{1+\varphi_k{}^T(t)P_{k-1}(t)\varphi_k(t)} e_k(t) + \beta\varphi_k(t)\hat{e}_k(t) \quad (25)$$

We define $\chi(t) = \frac{1}{1+\varphi_k{}^T(t)P_{k-1}(t)\varphi_k(t)}$, the following formula is obtained from equation (19):

$$P_k(t)\varphi_k(t) = \chi_k(t)P_{k-1}(t)\varphi_k(t) \quad (26)$$

While A and B take the following expression forms:

$$e_k(t) = y_k(t) - \varphi_k{}^T(t)\hat{\theta}_{k-1}(t) = -\varphi_k{}^T(t)\tilde{\theta}_{k-1}(t) \quad (27)$$

$$\hat{e}_k(t) = -\chi_k(t)\varphi_k^T(t)\tilde{\theta}_{k-1}(t) \quad (28)$$

After substituting equation (27) and equation (28) into equation (25), we can get:

$$\tilde{\theta}_k(t) = P_k(t)P_{k-1}^{-1}(t)\tilde{\theta}_{k-1}(t) - \beta\chi_k(t)\varphi_k(t)\varphi_k{}^T(t)\tilde{\theta}_{k-1}(t) \quad (29)$$

The Lyapunov function is defined as following:

$$V_k(t) = \tilde{\theta}_k^T(t)P_k^{-1}(t)\tilde{\theta}_k(t) \quad (30)$$

Then we can get

$$V_k(t) - V_{k-1}(t) = \tilde{\theta}_k^T(t)P_k^{-1}(t)\tilde{\theta}_k(t) - \tilde{\theta}_{k-1}^T(t)P_{k-1}^{-1}(t)\tilde{\theta}_{k-1}(t) = A + B \quad (31)$$

Where

$$A = -\chi_k(t)\tilde{\theta}_{k-1}^T(t)\varphi_k(t)\varphi_k{}^T(t)\tilde{\theta}_{k-1}(t) \quad (32)$$

$$B = -\beta\chi_k^2(t)\tilde{\theta}_{k-1}^T(t)\varphi_k(t)\varphi_k{}^T(t)\{2P_{k-1}^{-1}(t) + [2I - \beta P_k^{-1}(t)]\varphi_k(t)\varphi_k{}^T(t)\}\tilde{\theta}_{k-1}(t) \quad (33)$$

We can know $A \le 0$ by formula (32), and as long as $B \le 0$, the convergence of the algorithm can be proved according to Lyapunov's law. From formula (20) we know that:

$$0 < \lambda_{(P_k(t))} < \lambda_{(P_{k-1}(t))} < \cdots < \lambda_{(P_0(t))} < \lambda_{(P(0))} = \gamma \quad (34)$$

Where λ is the largest eigenvalue of $P_k(t)$, then we get:

$$B < -\beta\chi_k^2(t)\tilde{\theta}_{k-1}^T(t)\varphi_k(t)\varphi_k{}^T(t)\{2P_{k-1}^{-1}(t) + [2 - \beta\gamma^{-1}]\varphi_k(t)\varphi_k{}^T(t)\}\tilde{\theta}_{k-1}(t) \quad (35)$$

If $\beta \le 2\gamma$, then $B < 0$, that is:

$$V_k(t) - V_{k-1}(t) = A + B < 0 \quad (36)$$

For γ is a very large positive number, the condition of $0 < \beta \le 2\gamma$ is easy to be satisfied, so the inequality (36) is true, and the convergence of iterative learning least squares is proved.

IV. SIMULATION EXPERIMENT

This simulation experiment described in this paper is mainly about the numerical simulation of a certain type of ship according to reference [10]. The Z-type simulation experiments of $5^\circ/10^\circ$ was carried out respectively for the first and the second order nonlinear model. In the simulation experiments, the four order runge kutta method was used in integral for the response model and the sampling interval was 0.1 s. In order to simulate the real situation, the

Gaussian white noise was added into the model, its mean value is 0 and the variance is 0.05. The initial values for the first order nonlinear response model are $K=0$, $T=0$ and $\alpha=0$, while the initial values for the second order nonlinear model are $K=1$, $g=0.2$, $h=0.01$, $T_3=0$ and $\alpha=0$ .The recursive least squares method and the fast convergent iterative least squares algorithm were respectively adopted for identification of unknown parameters. In the fast convergent iterative least squares algorithm, the biggest iteration step. $N\max=200$, $\beta=0.005$, the minimum is $\sigma=0.001$, $\gamma=10^6$.

The simulation experimental results are shown in table 1 and table 2, the course curves of each identification parameters are given in Fig. 1 and table1.

Table I data of the first order nonlinear simulation experiment

	Set value	The basic least square method		The fast convergent iterative least squares algorithm	
		Identification value	***error***	***Identification value***	***error***
K	0.216	0.2182	0.0022	0.2175	0.0015
T	13.514	13.647	0.133	13.598	0.084
α	258.405	260.394	1.989	256.738	-1.667

Figure 1a error curve for K

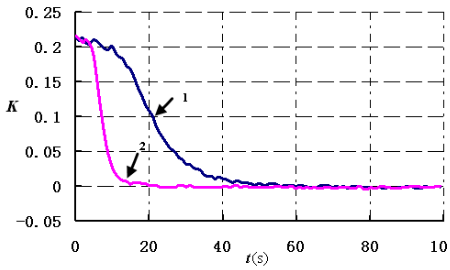

Figure 1b error curve for T

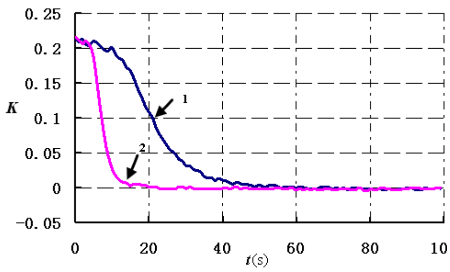

Figure 1c error curve for α

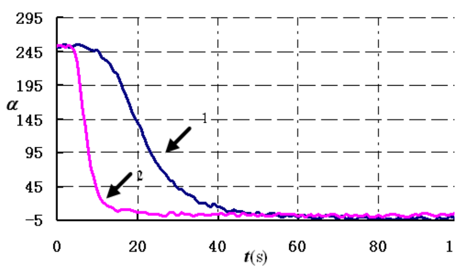

Figure 1 error curves for the first order nonlinear model parameters

Table 1 shows that the basic least square method and the fast convergent iterative least square method can both identify the first order nonlinear motion parameters. The identification errors for K are 0.002 and 0.0015, almost the same. But there is a big difference between the identification errors for T and α gained by the two methods, and the fast convergent iterative least square method is slightly better than the basic least square method. From Fig.1 1 we can see that it takes 60s to converge to the real value when using the basic least square method, while less than 20s is taken when using the fast convergent iterative least square method, thus the rapidity of convergence of the latter is prove.

Table II data of the second order nonlinear simulation experiment

	Set value	The basic least square method		The fast convergent iterative least squares algorithm	
		Identification value	***error***	***Identification value***	***error***
h	8.045	8.483	-0.438	8.065	-0.02
g	16.136	16.527	-0.391	15.838	0.298
α	98.14	98.65	-0.51	98.12	0.02
T_3	0.312	0.323	-0.011	0.304	0.008
K	0.201	0.216	-0.014	0.213	-0.012

Figure 2a error curve for h

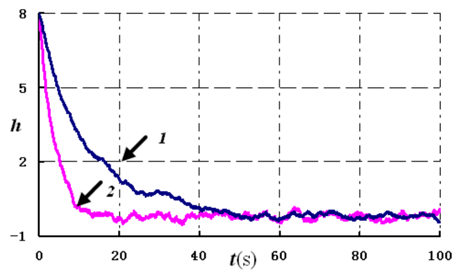

Figure 2b error curve for g

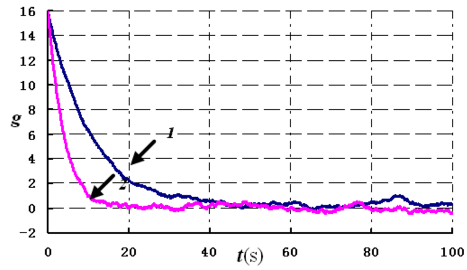

Figure 2c error curve for α

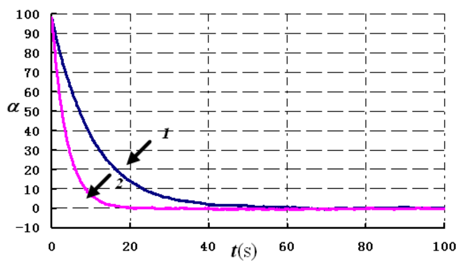

Figure 2d error curve for T_3

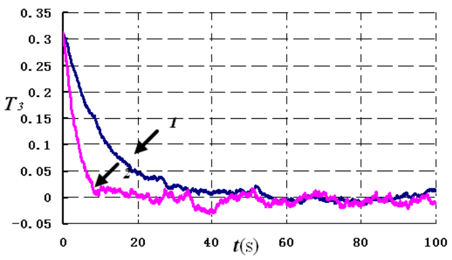

Figure 2e error curve for K

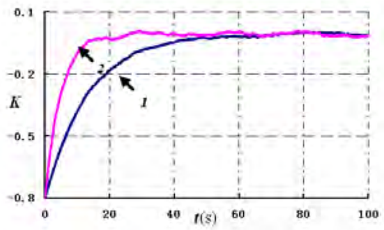

Figure 2 error curves for the first order nonlinear model parameters

For identification of the second order nonlinear maneuvering motion parameters, these two methods both work. Table 2 shows that the identification errors for K and T_3 are almost the same, differences exist in identification errors for g , h and α , and the fast convergent iterative least square method is proved much better than the basic least square method. We can learn from Fig. 2 that, it takes more than 60s for the identification values of the second order nonlinear parameters to convergence to their corresponding real values by using the basic least square method, while about 20s is used when taking the fast convergent iterative least square method, thus the rapidity of convergence of the latter is proved.

V. Water-tank experiment

KVLCC1 has been adopted as the benchmark ship form for inspection of ship maneuverability forecast method. In this paper, the experimental data are from the free running model test carried out in Hamburg, Germany pool (HSVA). In the experiment the ship model was dragged in static and deep water. Reference [11] has introduced the basic parameters of the model. The direct test speed $U_0 = 1.179 m/s$, the propeller speed $n = 10.23(1/s)$, the steering rate $\dot{\delta}_R = 15.8^{\circ}/s$ and there is no trim between stem and stern.

Z-type test of 15°/5° was carried out and the fast convergent iterative least square method was used in identification for the first order nonlinear response model. The initial values $K = 0$, $T = 0$ and $\alpha = 0$, the biggest iteration step $N\max = 200$, $\beta = 0.005$, the minimum $\sigma = 0.001$, $\gamma = 10^3$

Course curves of corresponding parameters are shown in the figures below:

Figure 3a change curve of T

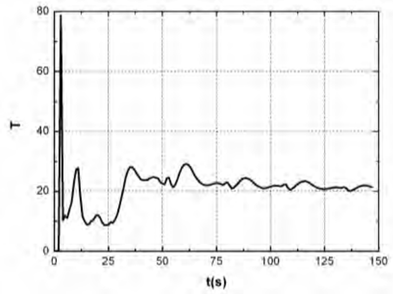

Figure 3b change curve of α

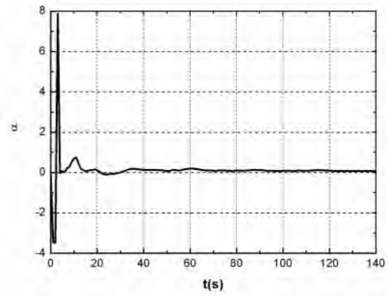

Figure 3c change curve of K

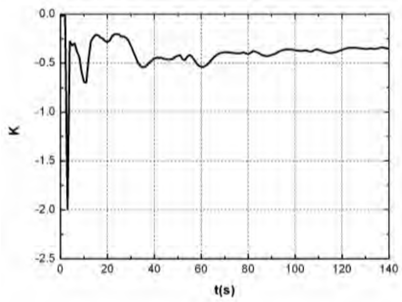

Figure 3 Course curves of parameter identification

After finishing the parameter identification, Z-type test of 25°/5°was carried out and the results are shown in Fig. 4:

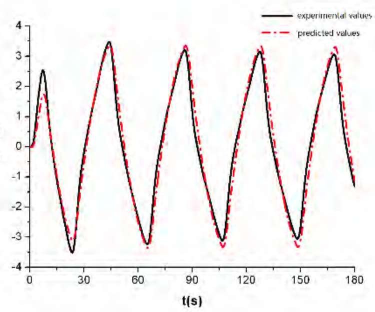

Figure 4 forecast of the heading angular velocity

From the above figures we know that the identification of related maneuvering parameters via this algorithm can be a good prediction of the ship maneuvering performance.

To sum up, the fast convergent iterative least square method has been improved in terms of convergence speed and identification precision relative to the basic least square method, and the former works better than the later in identification of nonlinear control motion parameters. Due to the introduction of the idea of the iterative learning, the amount of calculation increases. When the biggest iteration steps is set to 200, the existing computer is be able to complete the calculation in a limited time. At the same time, the effectiveness of the algorithm has been proved through contrast between the forecast value and the actual experimental value.

VI. CONCLUSION

In this paper, a fast convergent iterative least square algorithm is proposed and used to solve the problem of parameter identification of ship maneuverability. Introduction of the iterative learning method has ensured the algorithm's efficiency and make the basic least square method have some kind of intelligence. Simulation and practical experiments show that fast convergent iterative least square algorithm's convergence speed and precision are improved, the algorithm is feasible and effective and it is of great significance on the ship parameter online identification.

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