Improved parameter identification algorithm for ship model based on nonlinear innovation decorated by sigmoid function

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Abstract

This paper investigates the problem of parameter identification for ship nonlinear Nomoto model with small test data, a nonlinear innovation-based identification algorithm is presented by embedding sigmoid function in the stochastic gradient algorithm. To demonstrate the validity of the algorithm, an identification test is carried out on the ship ‘SWAN’ with only 26 sets of test data. Furthermore, the identification effects of the least squares algorithm, original stochastic gradient algorithm and the improved stochastic gradient algorithm based on nonlinear innovation are compared. Generally, the stochastic gradient algorithm is not suitable for the condition of small test data. The simulation results indicate that the improved stochastic gradient algorithm with sigmoid function greatly increases its accuracy of parameter identification and has 14.2% up compared with the least squares algorithm. Then the effectiveness of the algorithm is verified by another identification test on the ship ‘Galaxy’, the accuracy of parameter identification can reach more than 95% which can be used in ship motion simulation and controller design. The proposed algorithm has advantages of the small test data, fast speed and high accuracy of identification, which can be extended to other parameter identification systems with less sample data.

Keywords: ship model; parameter identification; nonlinear innovation; sigmoid function; stochastic gradient

1. Introduction

As the importance of ships in the field of marine transportation, the parameter identification for ship models has received widespread attention from researchers all over the world. The mathematical model of ship is the basis of ship maneuverability prediction, ship motion simulation and ship motion controller design, in which high
accuracy and few parameters have always been the ultimate goal pursued by ship model identification [1, 2]. The complex Norrbin or MMG ship model with more parameters is usually used to marine simulation and the simple linear Nomoto model with two parameters is used to ship maneuverability prediction. The nonlinear Nomoto model with four parameters is paid more attention by ship motion control researchers because of its satisfactory accuracy and concise form. Generally, modeling techniques for ship maneuvers involve mechanism modeling and identification modeling. The mechanism modeling needs to calculate complex hydrodynamic derivatives, which requires a large amount of calculation, and the calculation of some parameters depends on empirical formulas, so the accuracy of the model is not high to some ships. Therefore, identification modeling has gradually become a common method to establish ship mathematical model. When a new ship leaves the shipyard, only full rudder turning tests and some zigzag tests can be done according to international standards. If parameters of ship mathematical model are identified by such small amount of test data, its accuracy is similar to that estimated by empirical formulas, only about 75%. It is not suitable for system simulation and controller design, which requires high accuracy for the mathematical model.

At present, the popular system identification algorithms mainly include least squares method, gradient identification method, and auxiliary model identification method and so on. Reference [3] presented a kind of non-parametric system identification algorithm for a surface ship, in which multi-output Gaussian processes could be accurately applied for non-parametric dynamic system identification. On the basis of the artificial bee colony algorithm (ABC), an optimized support vector machines (SVM) is developed to estimate the parameters of ship linear Nomoto model [4]. Hou et al. [5] gave a nonparametric identification method based on a combination of random decrement technique (RDT) and support vector regression (SVR) to identify the nonlinear damping and restoring moments in the ship model. Zhu et al. [6] identified a simplified model of large container ships using support vector machines and artificial bee colony algorithm. Luo et al. [7] proposed several measures to diminish the parameter drift in the parametric identification of ship maneuvering model. Park et al. [8] illustrated a numerical identification of excitation force and nonlinear restoring characteristics of ship roll motion. Ghorbani [9] used CIFER software to identify steering and roll dynamics of a container ship. Ghommam et al. [10] solved the problem of leader-follower formation control for a group of underactuated surface vessels with partially known control input functions. Its controller was developed within the framework of the backstepping technique, with the parametric uncertainties and the unknown gains being estimated by a novel structure identifier. In addition, some other identification methods such as Kalman filter [11], identification method based on model basin data [12], empirical algorithms and adaptive genetic algorithms [13], modified genetic algorithms [14] were also gradually being applied. The above studies focus on improving convergence speed, identification accuracy, which have achieved some research results. However, the identification effectiveness is not satisfactory in the case of small sample data. Ding [15] proposed the idea of multi-innovation, which focused on the operation of innovation. Zhang et al. [16-18] proposed the idea of nonlinear feedback to the control system, which processed the measured error with nonlinear function and received more satisfactory control results with energy saving.

Inspired by the idea of multi-innovation and nonlinear feedback, the main contributions of this paper are using a nonlinear sigmoid function to decorate the new identification information with mathematical analysis and identify the nonlinear Nomoto models of two marine ships. The identified results show that the improved algorithm has the advantages of fast identification and high accuracy in the case of small sample data.

2. System design

This paper is developed by following technical route as shown in Fig. 1.

3. The mathematical model of ship

Compared with the state space model, the ship motion response model has the advantages of fewer parameters and obvious physical significance, and ignores drift speed, focuses on the main line of the dynamic rudder angle, the yaw angular velocity and the heading angle ($\delta \rightarrow \psi \rightarrow \psi$), the obtained differential equation can retain the factors of nonlinear influence. It can even convert the disturbance of wind and wave into a disturbance rudder angle to form an input signal
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Stochastic gradient algorithm.

Process the innovation with sigmoid function.

Tuning simulations are carried out by the known nonlinear Nomoto model of ship “SWAN” with random disturbance.

Parameter identified by the less input-output test data produced by the tuning simulations.

Comparison results produced by the improved and original algorithm.

Conclusion: the identification accuracy of the improved algorithm is improved by 14.2%.

Verification of identification effect by ship “Galaxy”.

Conclusion: the identification accuracy of the improved algorithm is improved by 12.1%.

Advantages: small sample data is needed; identification effect is accurate and fast.

Fig. 1. Technical route of nonlinear innovation identification algorithm

together with the actual rudder angle, as shown in Fig. 2. In fact, this model is a generalization of linear Nomoto model [1].

In this paper, the nonlinear Nomoto model is used as the ship mathematical model [19]. The equation is shown as Equation (1).

\[ \ddot{\psi} + \frac{K}{T} (\alpha \dot{\psi} + \beta \dot{\psi}^3) = \frac{K}{T} \delta \]  

(1)

where \( \psi \) is heading angle, \( \dot{\psi} \) is yaw rate, \( \ddot{\psi} \) is angular acceleration, \( \delta \) is rudder angle, \( K \) and \( T \) are the ship maneuverability indices, \( \alpha \) and \( \beta \) are the nonlinear coefficients of yaw rate \( \dot{\psi} \). Generally, \( K \) and \( T \) can be easily obtained by theoretical calculation with ship parameters such as length, breadth and draft, but \( \alpha \) and \( \beta \) are difficult to obtain by calculation, which can be obtained by identification.

When the ship makes a steady turning test, the mathematical model of Equation (1) can be further simplified. where let \( r = \dot{\psi} \), \( \ddot{r} = \ddot{\psi} \) and \( \dot{r} = \dot{\psi} = 0 \) after the turning is stable [1], Equation (1) can be shown as:

\[ \delta = \alpha \dot{\psi} + \beta \dot{\psi}^3 = \alpha r + \beta r^3 = \begin{bmatrix} r \ r^3 \end{bmatrix} [\alpha \ \beta]^T \]  

(2)

Note here, the input and output of Equation (2) and Equation (1) are opposite. For Equation (1), \( \delta \) is input, and it is output for Equation (2). In this paper, Equation (2) is used as the ship mathematical model to identify the nonlinear coefficients \( \alpha \) and \( \beta \). In theory, Equation (2) can be calculated by two sets of ship turning test data, but the accuracy is low. Therefore, the accuracy of parameter identification can be improved by multiple sets of turning test data.

4. Nonlinear innovation stochastic gradient identification algorithm

For linear regression model

\[ y(t) = \psi^T \theta + v(t) \]  

(3)

where \( y(t) \) is output, for Equation (2), it is the same as \( \delta \); \( \psi(t) \) is regression information vector, for Equation (2), it is the same as \( [r \ r^3]^T \); \( \theta \) is parameter to be identified, for Equation (2), it is the same as \( [\alpha \ \beta]^T \); \( v(t) \) are zero mean value random noises. For identification system (3), the stochastic gradient (SG) is shown as:

\[ \hat{\theta}(t) = \hat{\theta}(t - 1) + \frac{\psi(t)}{r(t)} e(t) \]  

(4)
Fig. 2. Nonlinear ship model

\[ e(t) = y(t) - \varphi^T(t) \hat{\theta}(t - 1) \]  
(5)

\[ r(t) = r(t - 1) + \| \varphi(t) \|^2 \]  
(6)

where \( \hat{\theta}(t) \) and \( \hat{\theta}(t - 1) \) are estimates of \( \theta \) at current and last step, respectively. \( e(t) \) is the innovation, which means useful information that can improve the estimation accuracy. Compared with the least squares method, the stochastic gradient algorithm does not need to compute the covariance matrix and has less computational complexity, but its convergence speed is slower and identification accuracy is lower. Inspired by the nonlinear feedback algorithm [17, 18, 20] and multi-innovation identification algorithm [15], the innovation can be processed by the nonlinear sigmoid function. Then the improved stochastic gradient algorithm based on nonlinear innovation is shown as (NISG):

\[ \hat{\theta}(t) = \hat{\theta}(t - 1) + \frac{\varphi(t)}{r(t)} e'(t) \]  
(7)

\[ e'(t) = (1 - e^{-\omega t})/(1 + e^{-\omega t}) \]  
(8)

\[ r(t) = r(t - 1) + \| \varphi(t) \|^2 \]  
(9)

In Equation (8), \( \omega \) is the angular frequency and its value can be selected randomly between 0.5–2.0.

Next, the convergence performance of the algorithm is analyzed according to martingale convergence theorem and stochastic process theory [21]:

Let \( \{ v(t) \} \) be a martingale difference sequence defined in probability space \( \{ K, F, P \} \), where \( \{ F_t \} \) is an algebraic sequence generated by \( \{ v(t) \} \), and \( \{ v(t) \} \) satisfies the noise hypothesis:

1) \( \mathbb{E} [v(t) | F_{t-1}] = 0 \), a.s.;
2) \( \mathbb{E} [v^2(t) | F_{t-1}] = e_t^2(t) \leq e^2_t < \infty \), a.s.;
3) \( \limsup_{t \to \infty} \frac{1}{t} \sum_{i=1}^{t} v^2(i) \leq e^2_r < \infty \), a.s.

where ‘a.s.’ means ‘almost surely’.

**Lemma 1** For stochastic gradient algorithms (7) and (9), the following conclusions are valid:

\[ a) \lim_{t \to \infty} \sum_{i=1}^{t} \frac{\| \varphi(i) \|^2}{r(t-1) r(t)} < \infty, \text{ a.s.} \]
(11)

where,

\[ e(t) = y(t) - \varphi^T(t) \hat{\theta}(t) \]

\[ Z(t) = y(t) - \varphi^T(t) \hat{\theta}(t - 1) \]

**Lemma 2** For algorithms (7) and (9), if there are constants \( T_0, U \) and integer \( N \), which can make the following strong persistent excitation conditions established

\[ 4) T_0 \leq \frac{1}{N} \sum_{i=0}^{N-1} \varphi(t-i) \varphi^T(t-i) \leq U, \text{ a.s.} \]
(12)

Then, \( r(t) \) satisfies

\[ r(t - N) + nN T_0 \leq r(t) \leq r(t - N) + nNU; \]
\[ nT_0 (t - N) \leq r(t) \leq nU (t + N) + 1; \]
\[ 0 < nT_0 \leq \lim_{t \to \infty} \frac{r(t)}{r(t - 1)} \leq nU < \infty, \text{ a.s.} \]

If the noise hypothesis 1) – 3) and the strong persistent excitation condition 4) holds. Then, the estimated parameters given by the stochastic gradient algorithms (4) and (6) almost surely converge to the true parameters, i.e. \( \lim_{t \to \infty} \hat{\theta}(t) = \theta, \text{ a.s.} \), the proof process in detail can be found in Ref. [21].
Table 1. Particulars of ‘SWAN’

| Parameter                          | Value   |
|-----------------------------------|---------|
| Length between perpendiculars, L  | 114.0   |
| Breadth(moulded), B               | 20.5    |
| Designed draught, D               | 5.7     |
| Volume of displacement, V         | 7,286.0 |
| Block coefficient, C_b            | 0.547   |
| Trial speed, V                   | 11.0    |
| Rudder area, A_r                  | 9.36    |

Table 2. Ship mathematical model parameters of ‘SWAN’

| Parameter                          | Value   |
|-----------------------------------|---------|
| Turning ability index, K          | 0.24    |
| Following index, T                | 196.15  |
| α                                 | 14.23   |
| β                                 | 33 210.63 |

For the improved stochastic gradient algorithm based on nonlinear innovation, in Equation (8), \( \omega e(t) \) is generally small in marine practice, \( e'(t) = (1 - e^{-\omega e})/(1 + e^{-\omega e}) \) is expressed by Taylor series expansion:

\[
(1 - e^{-\omega e})/(1 + e^{-\omega e}) \approx \omega e/(2 - \omega e) \approx 0.5\omega e(t) \leq e(t)
\]

For Equation (13), \( r(t) \) becomes \( r'(t) = 0.5\omega r(t) \), Equations (10)–(12) still hold. Then the estimated parameters given by the improved stochastic gradient algorithms (7) and (8) almost surely converge to the true parameters.

5. Identification and results analysis

In this section, the new ship ‘SWAN’ is employed as the plant for identification. The ship mathematical model adopts the Nomoto model that shown in Equation (1), the ship parameters required for establishing Nomoto model of ‘SWAN’ are shown in Table 1. The computer simulation experiment is carried out by VB program.

According to the ship parameters of ‘SWAN’ given in Table 1, The true values of the Nomoto model parameters of ‘SWAN’ can be calculated by a VB program as shown in Table 2 [20, 22].

According to Table 2, the Nomoto model of ‘SWAN’ is known, a VB program is designed on the basis of the known model to carry out simulation experiments and produces identification data. In the simulation experiment, a random interference with amplitude 0.1 for \( \delta \) and a random interference with amplitude 0.5 for \( \psi \) are introduced under the consideration of marine practice. In the marine practice, turning test is one of the most common ship maneuvering experiments. In the simulation of this paper, the 26 sets of turning test data can be carried out from hard port (−35°) to hard starboard (35°), the step is 2.5° with the minimum rudder angle of ±5°.

Next, the identification effects of least square (LS) method, stochastic gradient (SG) algorithm and improved stochastic gradient (NISG) algorithm on nonlinear parameters \( \alpha \), \( \beta \) are compared in the case of only 26 sets of test data.

As shown in Figs. 3 and 4, the nonlinear parameters \( \alpha \), \( \beta \) of ship ‘SWAN’ are identified by LS and SG. The identification result of LS (red line): \( \alpha \) is 16.05, and \( \beta \) is 26 494.26, the error of \( \alpha \) is 12.82%, the error of \( \beta \) is 20.22%, and the mean error is 16.5%; The identification result of SG (blue line): \( \alpha \) is 26.04, and \( \beta \) is −3 748.78, the error of \( \alpha \) is 82.99%, the error of \( \beta \) is larger than 100%, the mean error is 97.1%.

![Fig. 3. Comparison of identification results (LS-red line & SG-blue line) for \( \alpha \) of ‘SWAN’](https://academic.oup.com/tse/advance-article/doi/10.1093/tse/tdab006/6302464)
Therefore, on the premise of 26 sets of test data, the error of SG is too large to be suitable for parameter identification, which has no practical significance; while the LS can still maintain a certain identification accuracy in the case of small sample data, and the identification effect is obviously better than the SG.

Then, the stochastic gradient algorithm is improved based on nonlinear innovation as follows:

\[
\hat{\alpha}(t) = \hat{\alpha}(t-1) + \frac{\psi(t)}{r(t)} (1 - e^{-0.95\alpha})/(1 + e^{-0.95\alpha}) \]

\[
\hat{\beta}(t) = \hat{\beta}(t-1) + \frac{\psi(t)}{r(t)} (1 - e^{-0.90\beta})/(1 + e^{-0.90\beta})
\]

As shown in Figs. 5 and 6, the nonlinear parameters \(\alpha, \beta\) of ship ‘SWAN’ are identified by LS and NISG. The identification result of LS (red line): \(\alpha\) is 16.05, \(\beta\) is 26 494.26, the error of \(\alpha\) is 12.28%, the error of \(\beta\) is 20.22%, and the mean error is 16.5%; The identification result of NISG (blue line): \(\alpha\) is 14.22, \(\beta\) is 31 720.64, the error of \(\alpha\) is 0.04%, the error of \(\beta\) is 4.49%, and the mean error is only 2.23%, the identification accuracy can reach 97.7%.

Therefore, on the premise of only 26 sets of test data, the NISG has higher identification accuracy, which is 14.2% higher than the LS. In addition, it is obvious that the curve is smooth according to Fig. 4, and the identification speed is faster than the LS.

To further test the identification effect of NISG, another ship ‘Galaxy’ can be used to verify the effect of the algorithm when the Equations (14) and (15) keep unchanged. The ship parameters of ‘Galaxy’ are shown in Tables 3 and 4.
Fig. 6. Comparison of identification results (LS-red line & NISG-blue line) for $\beta$ of ‘SWAN’

Table 3. Particulars of ‘GALAXY’

| Parameter                        | Value |
|----------------------------------|-------|
| Length between perpendiculars, L(m) | 160.0 |
| Breadth (moulded), B(m)          | 28.0  |
| Designed draught, D(m)          | 9.5   |
| Volume of displacement, V(m³)    | 28145 |
| Block coefficient, $C_b$         | 0.652 |
| Trial speed, V(kn)               | 18.1  |
| Rudder area, $A_r$ (m²)          | 36.86 |

Table 4. Ship mathematical model parameters of ‘GALAXY’

| Parameter                        | Value |
|----------------------------------|-------|
| Turning ability index, $K (1/s)$ | 0.48  |
| Following index, $T (s)$         | 186.82|
| $\alpha$                         | 8.87  |
| $\beta$                          | 8911.21|

Similarly, the nonlinear parameters $\alpha$, $\beta$ of ‘Galaxy’ are identified by LS and NISG. In which, the model (14) and (15) are adopted for NISG.

As shown in Figs. 7 and 8, for ship ‘Galaxy’, the nonlinear parameters $\alpha$, $\beta$ are identified by LS and NISG. The identification result of LS (red line): $\alpha$ is 10.06, $\beta$ is 7132.75, the error of $\alpha$ is 13.37%, the error of $\beta$ is 19.96%, and the mean error is 16.67%; The identification result of NISG (blue line): $\alpha$ is 9.06, $\beta$ is 8287.23, the error of $\alpha$ is 2.15%, the error of $\beta$ is 7.00%, and the mean error is only 4.58%, the identification accuracy can reach 95.4%.

As for ship ‘Galaxy’, the identification accuracy of NISG is still 12.1% higher than the LS in the case of small sample data, which proves the validity and universality of the algorithm.

6. Conclusions

This paper combines the essence of multi-innovation system identification and nonlinear feedback control and proposes a ship model parameter identification algorithm based on nonlinear innovation decorated by sigmoid function.

Fig. 7. Comparison of identification results (LS-red line & NISG-blue line) for ‘Galaxy’
Through comparison and analysis, the following conclusions are drawn:

(1) The algorithm requires small sample data for parameter identification. In the algorithm, only 26 sets of test data are used, and the identification accuracy of the algorithm can reach more than 95%, providing a reference for parameter identification in the case of small sample data.

(2) Through the parameter identification results of two ship models, the identification accuracy of the algorithm is improved about 94.8% compared with the original algorithm and improved about 12% compared with the least square method, which expanding the application of the stochastic gradient algorithm.

(3) The identification speed of this algorithm is faster. By observing the identification results, the identification curve of the algorithm is smooth, and the fluctuation is small, which can achieve the purpose of fast identification.

In this study, the parameters of the ship model have been established, so it is possible to verify the effectiveness and accuracy of the identification algorithm. In the future research, we only need to collect a small amount of real ship test data to identify the ship model directly according to the results of this study. This can help offset the typical requirements of other related theoretical methods for complex computation and low precision. In the future, multi innovation and nonlinear innovation can be combined to further expand the application scope of multi model and multi parameter method in ship model identification.

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Conflict of interest statement

None declared.

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