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RESEARCH ARTICLE

An improved nonlinear innovation-based parameter identification algorithm for ship models

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Abstract

To solve the problem of identifying ship model parameters quickly and accurately with the least test data, this paper proposes a nonlinear innovation parameter identification algorithm for ship models. This is based on a nonlinear arc tangent function that can process innovations on the basis of an original stochastic gradient algorithm. A simulation was carried out on the ship *Yu Peng* using 26 sets of test data to compare the parameter identification capability of a least square algorithm, the original stochastic gradient algorithm and the improved stochastic gradient algorithm. The results indicate that the improved algorithm enhances the accuracy of the parameter identification by about 12% when compared with the least squares algorithm. The effectiveness of the algorithm was further verified by a simulation of the ship *Yu Kun*. The results confirm the algorithm's capacity to rapidly produce highly accurate parameter identification on the basis of relatively small datasets. The approach can be extended to other parameter identification systems where only a small amount of test data is available.

1. Introduction

Manoeuvrability is one of the most important aspects of a ship's performance. It is key to the safety and effectiveness of ship navigation. The 'Standards for Ship Manoeuvrability' formulated by the International Maritime Organization recommends that ship manoeuvrability be predicted at the design stage. The current approach of combining ship mathematical models and computer simulations is effective at predicting ship manoeuvrability. The first step in accomplishing it is to establish the ship mathematical model. Determining the best parameters for this model is key (Zhang, 2012). Generally, modelling techniques for ship manoeuvres involve first principles modelling and identification modelling (Bai et al., 2019). First principles modelling involves the extensive calculation of complex hydrodynamic derivatives. The calculation of some parameters depends on empirical formulas. As a result, the accuracy of such models is variable. In view of its capacity to determine high-precision parameters, identification modelling has therefore become the more common approach. However, when a new ship leaves the shipyard, only full rudder turning tests and some zigzag tests can be done according to international standards. If this small amount of ship test data is used to identify the model parameters, its accuracy is no better than that estimated by empirical formulas (typically, about 75%). This is not sufficiently good for system simulation and controller design, where accuracy is essential.

Identification modelling techniques include parametric modelling and nonparametric modelling. For parametric modelling it is necessary to know the structure of the ship's motion system first. The hydrodynamic derivatives are then estimated by a variety of identification methods, such as the least squares method (Nagumo and Noda, 1967), the maximum likelihood method (Astrom and Källström, 1976), the recursive prediction error method (Zhou and Blanke, 1989) and the genetic algorithm (Sutulo and

Soares, 2014). A number of novel ideas and strategies for system identification algorithms have appeared in the relevant literature. For example, Qin et al. (2016) proposed a kind of fast convergent iterative learning least squares algorithm. This incorporated P-type learning rates into the iterative learning process to improve its convergence speed and identification accuracy. Xie et al. (2017) introduced multiple innovations into the least squares method. Zhang et al. (2015) proposed a multi-innovation auto-constructed least squares identification. These, too, improved the convergence speed and identification accuracy. Zhang (2017), by contrast, proposed using a stochastic gradient genetic algorithm. This increased the target identification speed according to the number of iterations. Bai et al. (2018) also presented a gradient iteration method with multiple innovations. Wang (2012) proposed a stochastic gradient identification algorithm that was based on work originally undertaken by Aitken, and Cheng and Li (2019) also proposed an Aitken-based stochastic gradient algorithm. All of these approaches have improved identification accuracy. Zhu et al. (2017) used a support vector machine-based approach, which was optimised by an artificial bee colony algorithm. This was able to estimate the parameters for a Nomoto linear ship model. The above studies have focused on improving convergence speed and identification accuracy, with some measure of success. However, identification effectiveness can be severely constrained if there is a lack of test data. Ding has therefore proposed the notion of multi-innovation (Ding, 2013), which focuses on design innovation itself. In relation to this, Zhang and colleagues have proposed using nonlinear feedback (Zhang and Zhang, 2016; Zhang et al., 2018), which enables innovations to be processed by nonlinear functions. This has led to superior simulation results and a saving of energy. This paper draws upon these notions of multi-innovation and nonlinear feedback and finds that innovation can be processed using nonlinear functions to provide for more effective identification algorithms. The results of a simulation conducted using the improved algorithm presented here show that it can offer both rapid identification and high levels of accuracy without the need for large amounts of test data.

2. Nonlinear ship model

Ship motion can be described by a state space model or an input-output model (Zhang et al., 2020a, 2020b, 2020c). The former can deal with the multiple variables associated with ship motion. Thus, introducing wind, waves and current disturbances can generate more accurate and direct results. However, it comes at the price of greater computational complexity. The latter approach is also known as a response model (Deng and Zhang, 2020). It ignores drift speed and focuses on the main line of the dynamic rudder angle, the yaw angular velocity and the heading angle ($\delta \rightarrow \dot{\psi} \rightarrow \psi$). The resulting differential equations can retain factors of nonlinear influence. This approach can even convert the disturbances arising from the wind and waves into a disturbance rudder angle, which can then form an input signal together with the actual rudder angle (see Figure 1). This model is a generalisation of the linear Nomoto model (Nomoto et al., 1957; Zhang and Jin, 2013).

This paper adopts a response ship mathematical model as shown in Figure 1, which is composed of a first-order Nomoto model and a nonlinear feedback compensating item. According to marine practice, a set of rudder servo system is considered, angle limiter and revolution rate limiter. Rudder angle $\delta \in [-35°, 35°]$. The first-order Nomoto model from δ to yaw rate r is presented as

$$G_{r\delta}(s) = \frac{K}{Ts+1} \tag{1}$$

where the nonlinear feedback compensating item $f(u)$ is expressed as

$$f(u) = (\alpha - 1/K)\dot{\psi} + \beta\dot{\psi}^3 \tag{2}$$

The nonlinear Nomoto model is then used as the ship mathematical model (Zhang and Jin, 2013). The relevant equation is:

$$\ddot{\psi} + \frac{K}{T}(\alpha\,\dot{\psi} + \beta\dot{\psi}^3) = \frac{K}{T}\delta \tag{3}$$

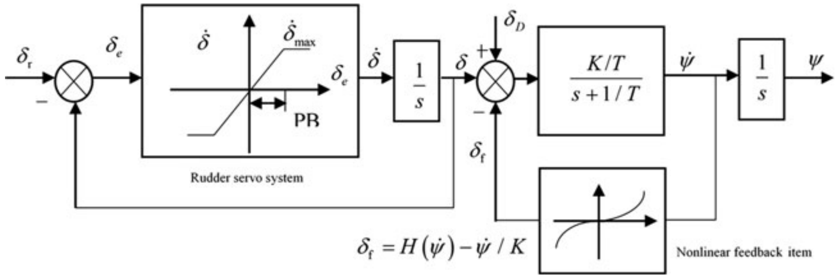

Figure 1. *Nonlinear ship model.*

where ψ is the heading angle; $\dot{\psi}$ is the yaw rate; $\ddot{\psi}$ is the angular acceleration;δ is the rudder angle; K and T are ship manoeuvrability indices; and α and β are the nonlinear coefficients of the yaw rate $\dot{\psi}$.

When the ship makes a steady turning test, the mathematical model shown in Equation (3) can be further simplified. If we let $r = \dot{\psi}$, $\dot{r} = \ddot{\psi}$ and $\dot{r} = \ddot{\psi} = 0$ after the turning is stable (Jia and Zhang, 2001), the equation can be rewritten as:

$$\delta = \alpha\dot{\psi} + \beta\dot{\psi}^3 = \alpha r + \beta r^3 = \begin{bmatrix} r & r^3 \end{bmatrix} \begin{bmatrix} \alpha & \beta \end{bmatrix}^{\mathrm{T}} \tag{4}$$

Note, here, that the input and output of Equation (4) and Equation (3) are opposite. For Equation (3), δ is the input, but it is the output for Equation (4). In this paper, Equation (4) is used as the mathematical ship model so as to be able to identify the nonlinear coefficients α, β.

3. Nonlinear innovation stochastic gradient identification algorithm

The linear regression model is:

$$y(t) = \varphi^{\mathrm{T}}\theta + v(t) \tag{5}$$

where $y(t)$ is the output. In Equation (2), this is δ. $\varphi(t)$ is the regression information vector. In Equation (4), it is $\begin{bmatrix} r & r^3 \end{bmatrix}^{\mathrm{T}}$. θ relates to the parameters to be identified. In Equation (5), they are $\begin{bmatrix} \alpha & \beta \end{bmatrix}^{\mathrm{T}}$.$v(t)$ is zero-mean-value random noise. For the identification system described by Equation (5), the stochastic gradient (SG) will be

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \frac{\varphi(t)}{r(t)}e(t) \tag{6}$$

$$e(t) = y(t) - \varphi^{\mathrm{T}}(t)\hat{\theta}(t-1) \tag{7}$$

$$r(t) = r(t-1) + ||\varphi(t)||^2 \tag{8}$$

where $\hat{\theta}(t)$ and $\hat{\theta}(t-1)$ are estimates for θ at the current and previous moment, respectively. $e(t)$ is innovation, which means useful information that can improve the accuracy of the parameter estimation or state estimation. Unlike the least squares method, the SG algorithm does not need to compute a covariance matrix and has less computational complexity. However, its convergence speed is slower and its identification is less accurate. Drawing upon the nonlinear feedback algorithm of Zhang et al. (2016, 2018) and the multi-innovation identification algorithm of Ding (2013), the innovation can be processed by a nonlinear arc tangent function. The improved SG algorithm based on nonlinear innovation (NISG)

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can therefore be written as follows:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \frac{\varphi(t)}{r(t)} \mathrm{e}'(t) \tag{9}$$

$$\mathrm{e}'(t) = A \arctan(\omega e(t)) = \arctan(\omega(y(t) - \varphi^{\mathrm{T}}(t)\hat{\theta}(t-1))) \tag{10}$$

$$r(t) = r(t-1) + ||\varphi(t)||^2 \tag{11}$$

In Equation (10), the value of A, ω is a nonlinear parameter, generally 0.5–2.0.

The performance of this algorithm can be analysed using the Martingale convergence theorem and stochastic process theory (Ding and Yang, 1999). Let $\{v(t)\}$ be a Martingale difference sequence defined in the probability space $\{K,F,P\}$, where $\{F_t\}$ is an algebraic sequence generated by $\{v(t)\}$, and $\{v(t)\}$ satisfies the following noise hypothesis:

$$\begin{aligned} &1)\ E[v(t)|F_{t-1}] = 0, a.s.; \\ &2)\ E[v^2(t)|F_{t-1}] = e_v^2(t) \leq e_v^2 < \infty, a.s.; \\ &3)\ \limsup_{t\to\infty} \frac{1}{t} \sum_{t=1}^{t} v^2(i) \leq e_v^2 < \infty, a.s.. \end{aligned} \tag{12}$$

Note that *a.s.* here means 'almost surely'.

Lemma 1: For the SG algorithms (9) and (11), indicates that the following conclusions are valid:

$$\begin{aligned} &\text{a) } \lim_{t\to\infty} \sum_{i=0}^{t} \frac{||\varphi(i)||^2}{r(i-1)r(i)} < \infty, a.s.; \\ &\text{b) } e(t) = \frac{r(t-1)}{r(t)} Z(t). \end{aligned} \tag{13}$$

where

$$e(t) = y(t) - \varphi^{\mathrm{T}}(t)\hat{\theta}(t)$$
$$Z(t) = y(t) - \varphi^{\mathrm{T}}(t)\hat{\theta}(t-1)$$

Lemma 2: For the same algorithms states that, if there are constants T_0, U and the integer N, that can establish the following strong persistent excitation conditions:

$$\begin{aligned} &4)\ T_0 I \leq \frac{1}{N} \sum_{I=0}^{N-1} \varphi(t-i)\varphi^{\mathrm{T}}(t-i) \leq UI, a.s. \\ &0 < T_0 \leq U < \infty, N \geq n. \end{aligned} \tag{14}$$

then, $r(t)$ satisfies:

$$r(t-N) + nNT_0 \leq r(t) \leq r(t-N) + nNU;$$
$$nT_0(t-N) \leq r(t) \leq nU(t+N) + 1;$$
$$0 < nT_0 \leq \lim_{t\to\infty} \frac{r(t)}{t} \leq nU < \infty, a.s..$$

If the noise hypotheses 1)–3) in Equation (12) and the strong persistent excitation condition 4) in Equation (14) hold, then the estimated parameters given by the SG algorithms Equations (6) and (8) almost surely converge to the true parameters, i.e., $\lim_{t\to\infty} \hat{\theta}(t) = \theta, a.s.$. The specific proof process for this can be found in Ding and Yang (1999).

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Table 1. *Particulars of Yu Peng.*

Length between perpendiculars L(m)	189.0
Breadth (moulded) B(m)	27.8
Designed draught D(m)	11.0
Volume of displacement ∇(m^3)	42,293.0
Block coefficient C_b	0.72
Trial speed V(kn)	17.3
Rudder area A_R(m^2)	38
Longitudinal centre of gravity x_c(m)	−1.8

Table 2. *Mathematical model parameters for Yu Peng.*

Turning ability index K(1/s)	0.38
Following index T(s)	297.75
α	11.95
β	23,928.91

For the improved SG algorithm based on nonlinear innovation, $\mathrm{e}'(t) = \arctan(\omega e(t))$ in Equation (8) can be expressed by a Taylor series expansion:

$$\arctan(\omega e(t)) \approx \omega e(t) - \frac{(\omega e(t))^3}{3} + \frac{(\omega e(t))^5}{5} - \frac{(\omega e(t))^7}{7} \ldots \tag{15}$$

$\omega e(t)$ in Equation (15) is generally small in marine practice. So, $\arctan(\omega e(t)) \approx \omega e(t)$. In the above equations, $r(t)$ then becomes $r'(t) = A\omega r(t)$ and Equations (12)–(14) still hold. Thus, the estimated parameters given by the improved SG algorithms (9) and (10) almost surely converge to the true parameters.

4. Simulation and results

This paper uses Dalian Maritime University's new teaching and training ship *Yu Peng* to test an application of the ship mathematical model. *Yu Peng* made its first voyage in 2017, so its test data are relatively complete. This helps with the verification of the identification of the ship model parameters. The ship mathematical model is based on the Nomoto model presented in Equation (1). The ship parameters required for establishing the Nomoto model are shown in Table 1. The experimental simulation was carried out using Visual Basic.

According to the particulars of *Yu Peng* given in Table 1, the true values of the Nomoto model parameters for *Yu Peng* were calculated in Visual Basic, as shown in Table 2 (Nomoto et al., 1957; Zhang and Zhang, 2019). On the basis of Table 2, a Visual Basic program was designed to carry out experimental simulations and produce identification data. In the simulations, random interference with an amplitude of 0.1 for δ and random interference with an amplitude of 0.5 for ψ were introduced, according to marine practice. Twenty-six sets of turning test data were then generated, from hard port ($-35°$) to hard starboard ($35°$) in steps of $2.5°$.

Next, the identification capacity of the least squares (LS) method, SG algorithm, and the NISG algorithm were compared for the nonlinear parameters, α,β, across just the 26 sets of test data. The identification error for parameters α,β means the ratio of the difference (identification value and true value) and the true value.

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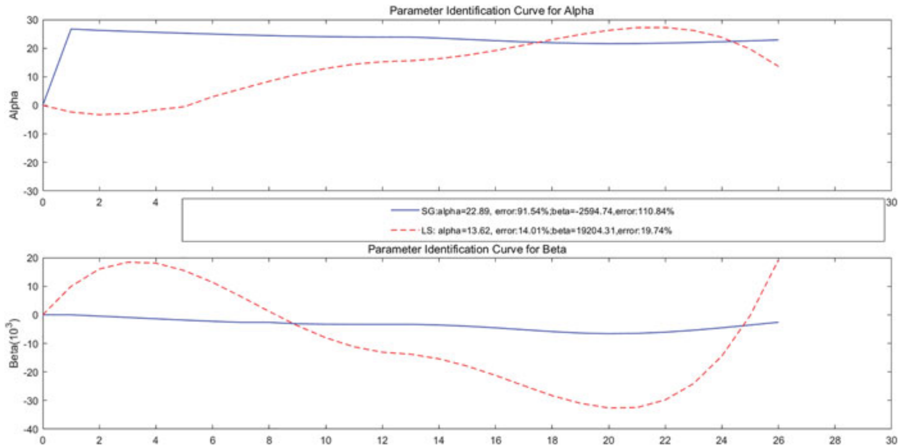

Figure 2. *Comparison of the identification results (LS and SG) for Yu Peng.*

As shown in Figure 2, the nonlinear parameters α,β were identified by LS and SG. The identification result for LS is the solid line and indicates an error of 14.01% for α and an error of 19.74% for β, with the mean error being 16.86%. The identification result for SG (the dashed line) indicates an error of 91.54% for α and an error of over 100% for β. So, on the basis of only 26 sets of test data, the error for SG is too large to be suitable for parameter identification, which means it has no practical significance. LS still maintains some level of identification accuracy when there is less test data and it is obviously better than SG.

For the improved SG algorithm based on nonlinear innovation, the refined models for identifying α and β are as follows:

$$\hat{\alpha}(t) = \hat{\alpha}(t-1) + \frac{\varphi(t)}{r(t)} \arctan(0.5 * ((y(t) - \varphi^{\mathrm{T}}(t)\hat{\alpha}(t-1))) \tag{16}$$

$$\hat{\beta}(t) = \hat{\beta}(t-1) + \frac{\varphi(t)}{r(t)} \arctan 1.2*(0.9 * ((y(t) - \varphi^{\mathrm{T}}(t)\hat{\beta}(t-1))) \tag{17}$$

As can be seen in Figure 3, the nonlinear parameters α and β were also identified by NISG. The identification result for LS (the solid line) is reproduced for easier comparison. As previously stated, the error for α was 14.01% and the error for β was 19.74%, with a mean error of 16.86%. The identification result for NISG (the dashed line) indicates an error of 0.23% for α and an error of 9.19% for β, with a mean error of only 4.71%. So, the identification accuracy for NISG can reach 95.3%.

Based on just 26 sets of test data, the results suggest that the NISG method has a 12.2% higher identification accuracy than the LS method. It can also be seen in Figure 4 that the curve is smooth, with less fluctuation, and the identification speed is faster than LS.

To further verify the effectiveness of the NISG method, another of Dalian Maritime University's teaching and training ships, the *Yu Kun*, was also used as the basis of an experimental simulation. The parameters of the *Yu Kun* are shown in Tables 3 and 4.

Again, the nonlinear parameters α and β of the *Yu Kun* were identified by LS and NISG. The models described by Equations (14) and (15) were used once more for NISG.

As shown in Figure 4, the identification results for LS (the solid line) indicate an error of 12.08% for α and an error for β of 23.27%, with a mean error of 17.68%. The results for NISG (the dashed line) show that the error for α was 9.44% and the error for β was 3.08%, with a mean error of only 6.26%. So, it achieved an identification accuracy of about 93.7%.

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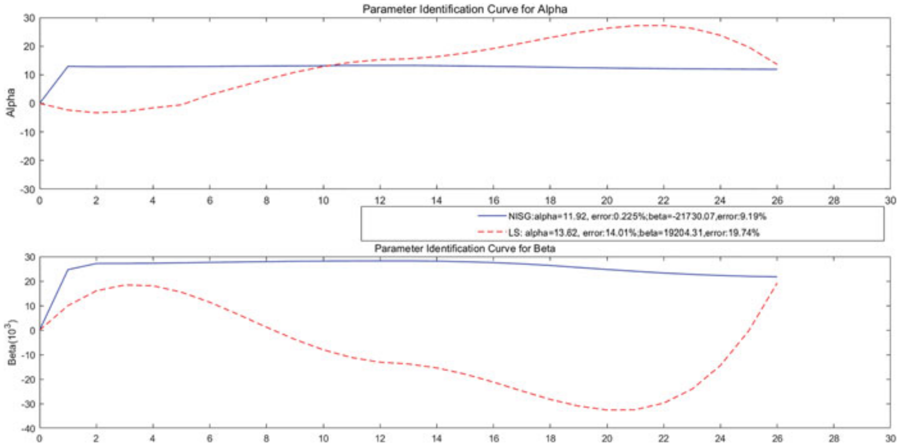

Figure 3. *Comparison of the identification results (LS and NISG) for Yu Peng.*

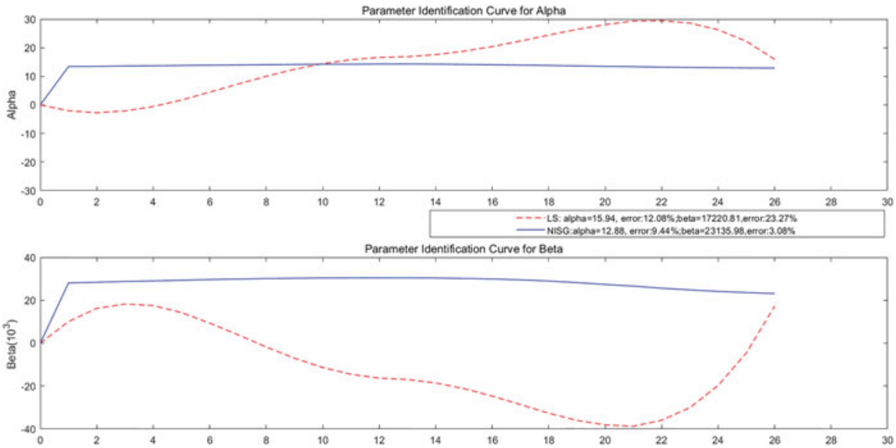

Figure 4. *Comparison of identification results (LS and NISG) for Yu Kun.*

Table 3. *Particulars of Yu Kun.*

Length between perpendiculars L(m)	116.0
Breadth (moulded) B(m)	18.0
Designed draught D(m)	5.4
Volume of displacement $\nabla(m^3)$	5,735.5
Block coefficient C_b	0.56
Trial speed V(kn)	16.7
Rudder area $A_R(m^2)$	11.46
Longitudinal centre of gravity x_c(m)	–0.51

Table 4. *Mathematical model parameters for Yu Kun.*

Turning ability index K(1/s)	0.31
Following index T(s)	64.53
α	14.22
β	22,444.52

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For the ship *Yu Kun*, the identification accuracy of the NISG method was still 11.4% higher than the LS method under the circumstances of only a small amount of test data, thus proving the validity and generalisability of the algorithm.

5. Conclusions

In this paper, a new ship model parameter identification algorithm, based on arc tangent nonlinear innovation, has been proposed. The algorithm combines the essence of multi-innovation system identification and nonlinear feedback control. On the basis of the simulation and comparison that was undertaken, the following conclusions can be drawn:

(1) The algorithm needs less test data for parameter identification. In the simulation, its identification accuracy reached about 94% in the case of only 26 sets of test data. The algorithm provides a reference for other identification problems when there is only a scant amount of data.
(2) The identification accuracy of the algorithm was higher than the other algorithms tested. Across the simulations of two ships, *Yu Peng* and *Yu Kun*, the identification accuracy of the algorithm was about 12% better than the LS method, confirming its practical value.
(3) The identification speed of the algorithm was also faster than its potential competitors and the identification curve was smooth, with little fluctuation.

In this particular study, the parameters of the ship model had already been established, so it was possible to verify the validity and accuracy of the identification algorithm. In future research, the ship model can be identified directly on the basis of the results of this study after the collection of only a small amount of real ship test data. This can help to offset the typical need for complex calculations and low accuracy of other associated theoretical approaches. Multi-innovation and nonlinear innovation may also be combined in the future to further extend the scope of multi-model and multi-parameter approaches in ship model identification research.

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