8-23-2020

Nonlinear innovation identification for ship maneuvering modeling via the full-scale trial data

Chunyu Song

WORLD MARITIME UNIVERSITY

Dalian, China

NONLINEAR INNOVATION IDENTIFICATION FOR SHIP MANOEUVRING MODELING VIA THE FULL-SCALE TRIAL DATA

By

W1904176

The People's Republic of China

A research paper submitted to the World Maritime University in partial Fulfillment of the requirements for the award of the degree of

MASTER OF SCIENCE

In

MSEM

2020

DECLARATION

I certify that all the material in this research paper that is not my work has been identified, and that no content is included for which a degree has previously been conferred on me.

The Contents of this dissertation reflect my personal views and are not necessarily endorsed by the University.

(Signature): W1904176

(Data): June 28, 2020

Supervised by:

XXX

Professor of Dalian Maritime University

ACKNOWLEDGEMENT

I have made gratifying achievements in MSEM over the past two years; therefor I would like to be obliged to those who gave me a hand in the process of writing the article this paper. Additionally, I especially acknowledged the help of my tutor, Professor XXX of Dalian Maritime University, who has given me constructive suggestions in the academic researches. In the process of revising this paper, he has spent a lot of time and vigor reviewing each manuscript and offered me inspiring advice. It was his patient guidance and insightful criticism that contributed to the successful completion of this paper. Second, I would also express my gratitude to all the professors who work for this master program. What they did for the program makes me have a good command of my subject. Finally, I should appreciate my beloved parents and classmates for their selfless help and support without any complaint.

ABSTRACT

Title of Dissertation: **Nonlinear Innovation Identification for Ship Maneuvering Modeling via the Full-Scale Trial Data**

This research involves a 4-DOF ship maneuvering identification modeling with full-scale trial data. In order to avert the inversion of the multi-innovation matrix in the traditional multi-innovation least squares (MILS) algorithm, based on the recognition concept new multi-innovation least squares (TMILS) algorithm to identify the innovation of the stochastic gradient hyperbolic tangent nonlinearity. And a lot of work and efforts have been made to ensure the consistency and final convergence. Therefore, combine relevant data and statistical indicators derivation a more effective hyperbolic tangent nonlinear innovation identification scheme to identify ship maneuvering motion. Compared with the previous results, this design scheme has significant computational advantages, requiring fewer parameters, higher accuracy, faster identification speed and higher computational efficiency. At the same time, an example is given to illustrate the effectiveness of the algorithm, especially for identification applications with full-scale trial data.

KEY WORDS: Ship maneuvering model, nonlinear innovation, identification modeling, full-scale trial.

LIST OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

DOF4	Degrees Of Freedom
MILS	Multi-innovation Least Squares
TMILS	Transformed Multi-innovation Least Squares
IMO	International Maritime University
PID	Proportion Integration differentiation
LQ	Linear-Quadratic
LQG	Linear-Quadratic-Gaussian
CFD	Computational Fluid Dynamics
ANN	Artificial Neural Network
EKF	Extended Kalman Filter
SVM	Support Vector Machines
EBM	Estimation-Before-Modeling

CHAPTER 1: INTRODUCTION

1.1 Background Information

Since the 21st century, economic globalization, capital internationalization and the rapid development of technologies have not only cast a profound influence on world economy and trade, but also brought many opportunities and challenges. Marine transportation is widely used all over the world owing to its superiority on capacity and economy [1-3].

As we all know, maritime transportation has always been one of the most effective, safe and environmentally friendly long-distance transportation methods for bulk cargoes. It is capable of undertaking more than 80% of the world's trade volume. And no trade between continents can be realized without the international maritime transportation. The shipping industry will become the key to the globalized economy for its crucial role in today's international trade. Therefore, safety, green and efficiency are particularly important for the marine shipping industry.

In the field of ship maneuvering modeling, there are two purposes for the built of ship motion mathematical model. One is to establish a ship maneuvering simulator. That could provide a basic simulated platform for studying the performance of ship maneuvering motion and the training of seafarers. The other is to directly design the controller to implement the automation task for marine ships, e.g. the course-keeping task, the path-following one etc. Actually, the ship maneuvering mathematical model is mainly separated into two parts for the nonlinear mathematical model and the linear one. The former is employed to design of ship maneuvering simulator and to train and optimize the nonlinear controller such as neural network controller and fuzzy controller. While, the latter one is to simplify the closed-loop performance simulation and can be systematically regarded as the basis of the linear controller, e.g. PID, LQ, LQG, H robust controllers[4]. Thus, the ship maneuvering modeling As a critical and essential topic in the relevant research fields, the ship maneuvering modeling involes the marine cybernetics, ship design evaluation and marine traffic simulation. Especially, the 4 degrees of freedom (DOF) motions have a close relationship with the analysis of ship maneuverability and navigation safety. Motivated by the abovementioned analysis, we should make more efforts to enhance the accuracy of ship maneuvering modeling. That could promote the smooth implementation of the work of IMO's (international maritime organization) philosophy, i.e. “Safe, Secure and Efficient Shipping on Clean Oceans” [5].

1.2 Review of Previous Research

In previous studies, the ship modeling theory based on physical considerations has been developed with the development of navigation and maneuvering operations. It has two unique methods: Taylor series expansion[6] and modular (i.e., modular) expansion. (e.g. Hull-propeller-rudder) handling[6-8]. According to the authors, the modular approach has great potential for development due to its wide effectiveness and high accuracy on some types of ships.For example, the study of “Esso Osaka” maneuvering motion equations and the research of super-large aircraft carrier “Williamson” steering [9-10]. It is aimed to promote and validate models with the free running model data or the full-scale trial data. However, it is easy to find many influential results in the literature. For example[11-12], for the first time, the Estimation-Before-Modeling (EBM) method was employed by Yoon and Rhee to deal with the problem about ship maneuvering modeling, which can be regarded as a valid application in the field of the aerodynamic model. However, it is responsible for the limitations of evidence-based medicine. The extended Kalman filter (EKF) applied in Step 1 largely depends on the initial value of parameters and has no influence on the uncertainty of the model [13].In artificial intelligence technology, artificial neural network (ANN) and support vector machine (SVM) can effectively overcome the above limitations. Rajesh and Bhattacharyya[14] attempted to use ANN to match the sum of all nonlinear terms (that is, the left-hand part of the equation of motion), rather than to determine the hydrodynamic derivative. SVM is superior to neural network in the generalization of finite samples and global optimal extremum. The results [12-14] show the great advantages of the new regression method. In addition, two classical methods of identification of ship maneuvering coefficient are introduced. The system identification technology adopted in [15] includes EKF and constrained least square method. Through the processing of several free running tests, it is concluded that the system identification using connected data can obtain the prediction results with high accuracy and good universality. Herrero and Gonzalez[16] proposed a new nonlinear maneuvering motion recognition scheme, in which the model structure was first selected by step method. Then, the nonlinear prediction error method of trackless Kalman filter is used to improve the parameter estimation. However, there are still many problems to be solved in the above research work :(1) the performance of the Abkowitz model structure with its inherent wide effectiveness and prediction accuracy has great limitations. (2) Based on the previous work, the model structure identified by the fin system is determined. This may not be suitable for different types of ships.Although [17] is an exception, the selection of model structure is still in the rough stage and deserves further study. (3) Most algorithms are verified by simulation data or free-running model tests. However, full-size test verification is more rigorous and cannot be replaced by simulation verification. (4) For the system with missing measured data, the correct algorithm cannot be used for processing.

1.2.1 The Development of Ship Maneuvering Mathematical Model

The core basic problem of ship maneuvering identification lies in its mathematical model of ship motion. The research can date back to the work of Davidson and Schiff in 1946. This research considers the relation between the transverse translational motion and the heading change motion of the ship, for the first time proposes a linear equation describing the motion of the ship's operation and has been used and developed up to now. Around the 1970s, with the emergence of super large oil tankers and the development of advanced ship motion controllers, Modern control theory, advanced measurement technology and system identification theory have further promoted the mathematical model of ship motion development. Research work, achieved a lot of excellent results. From a methodology point of view, the research of ship motion mathematical model can be divided into two branches [14]: mechanism modeling and identification modeling. However, regardless the historical development or the theoretical development maturity, the research on identification modeling is based on the results of mechanism modeling to some extent. The combination of advanced identification technology and mechanism modeling structure is also a mainstream trend in the development of current ship motion mathematical models.

1.2.2 The Identification Modeling for Ship Maneuvering Motions

There are two main methods used in ship maneuverability prediction in the previous mathematical models: one is Abkowitz's [16] model, also called Global Model, in this model, the hydrodynamic force acting on the ship-propeller-rudder system is considered as a whole and the hydrodynamic expression is expanded in Taylor series near the equilibrium point of the motion state of the ship-propeller-rudder system. The fluid dynamics acting on the hull are restricted by the Taylor series at the equilibrium position. The other is the MMG model [19], also called the separation model, which on the basis of the former model, decomposes the hydrodynamic force into three parts acting on the hull, propeller and rudder, the interaction among hull, propeller and rudder is fully considered. Compared with the holistic mathematical model, the separated mathematical model is established based on deep theoretical analysis and extensive experimental research, and pays more attention to the wide effectiveness in different ship motion states. The Abkowitz model and the MMG [19] model are also called as hydrodynamic models. In addition to the hydrodynamic model, in the study of ship maneuvering and control also use a response model. This mathematical model reflects the response of the ship to the turning motion of the steering wheel and is mainly applied to the design of the autopilot, but it can also be applied to simple control motion prediction.

In recent years, the research achievements of domestic and foreign scholars in the modeling of ship motion mechanism are common occurrence. Whether it is "holistic type" or "separation type", they are only different from the idea of analyzing the operation mechanism of the system. At present, there are three kinds of parameter acquisition methods in ship motion model: constraint model test, empirical formula, hydrodynamic calculation [20]. Identification modeling is the theory and method to study the system mathematical model based on the measurement data of ship model or the full-scale ship test. In 1980, Abkowitz constructed a nonlinear ship motion mathematical model by means of extended Kalman filter technology. And the basic data is from the full-scale ship test [18]. In this research, the linear hydrodynamic derivatives were identified by employing the 10/10 °Z test data. While, the nonlinear hydrodynamic ones were based on the 35° tuning maneuvering test. Then the identification results are used to predict and compared with the test results of the constrained ship model pool to correct the related model parameters. Besides, the research test object was ESSO large tanker, a perfect sea trial in the Gulf of Mexico in 1977，Eight days, $100,000, It is the largest maritime test in the field of ship modeling and design. It is a significant impact to the related research work.

In recent years, with the maturity of modeling research of ship motion mechanism and the research of the defects of the above three methods of obtaining ship hydrodynamic, researchers have gradually shifted their focus to the research of identification modeling and have obtained some meaningful results. Under the framework of the MMG model, the extended Kalman filter is used to test the Z-shape of the ship, the data of rotary test and large angle Z-shaped test (using theoretical simulation test) are compared and identified. The significant conclusion can be referred by the authors that it is more accurate to utilize the large angle zig-zag test data in the identification experiment for marine ships. Furthermore, Hyeon explores model identification technology in aviation. Ebm (Estimation-Before-Modeling) in the ship motion identification method [22]. Zou Zaojian has applied the SVM method to ship model identification for the first time and has achieved many useful results [23-24]. However, in these studies, most of the identification results are based on the simulation data of the ship motion model without interference, the data of the real ship test is not accurate in the sensor measurement. The disturbance of the marine environment is inevitable and the scale effect of the ship model and the real ship dynamic performance is not considered in the current work. Perez T [25] carries out model identification research on the premise of considering the actual survey conditions of ship engineering. A two-step identification algorithm is proposed by virtue of the sensitivity weight factor and the unscented Kalman filter. And a modern high-speed three-body ship is employed to make ship trials and simulation experiments. It has been proved that the method is accurate and available in practical engineering. Ross A [26] uses three common methods for ship maneuverability prediction (auto-ship model test, system prediction based on computational fluid dynamics theory and system simulation based on constrained ship model test), combined with system identification techniques (the article attempts extended kalman filtering technique and constrained least squares method) to carry out the study of hydrodynamic derivative estimation in the process of ship design. These characteristics require the instruments and equipment used in the attitude measurement of ships and the resources of ships that can be competent for the test measurement of real ships are limited. With the development of the identification theory, the system parameter estimation method and various identification application soft-wares have been greatly developed. The convergence rate and estimation accuracy of the identification method have also achieved rich results. The multi-innovation identification, the principle of hierarchical identification and the concept of coupled identification are new ideas in the field of model identification, which would provide the great significance support to the development of system identification disciplines. Therefore, the author desires to apply the new method into the research of ship motion identification modeling. And the "Yukun" Ship of Dalian Maritime University will carry out relevant tests to provide data for the identification and modeling work [27-28].

1.3 The Outline of the Identification Method

System identification is the identification of model structure and system parameters of actual equipment. In practical engineering, the factory can be described by a mathematical model representing the relationship between the input and output of the system. Mathematical models generally have their specific structure and parameters. Therefore, system identification includes system structure identification and parameter estimation.In the existing research works, there are two common identification methods, the mechanism identification method and the statistical identification one. Previous has organic mechanism identification method and statistical identification method. The mechanism deduces the analytic expression of the system model obtains the structure form of the model and obtains the system parameters by the method of measurement. The latter studies the identification method to identify the structure and parameters of the system by measuring the input and output data of the system and making use of a large number of observed data.

Gradually scholar develops a new way to determine system transfer function by the step response identification method (Impulse response identification method).

At the end of the 18th century, German mathematician Gauss proposed that least squares could be used for dynamical system identification, for parameter fitting of static systems, for linear systems, and for nonlinear systems. The Least squares have off line identification methods and on line identification methods, recursive identification and iterative identification methods. Based on this, a gradient class identification method is developed, which requires less computation than least squares. Multi-innovation identification theory is a new identification theory developed in recent years. The method of multi-innovation identification is inspired by the idea of discontinuous iteration of reference [29] algorithm. At first, the mathematical expression of the variable recurrence interval multi-innovation generalized projection identification algorithm is given by analogy method [30]. After in-depth study, the multi-innovation projection identification algorithm, multi-innovation stochastic gradient algorithm, multi-innovation least square identification algorithm and multi-innovation least square algorithm [30-33] are derived in detail. But from the beginning of the least squares algorithm, which cannot be identified online. Because it cannot identification online and it has a large amount of computation, but the recursive least squares only use the current system information when the parameters are updated. It leads to low identification accuracy and slow convergence speed. With the development of research, the identification error is reduced, and the identification speed is improved. But the identification accuracy is still very poor. The research focuses on improving the convergence speed and identification efficiency, but the identification effect is not well in the few data. So this paper shows the identification of nonlinear innovation hyperbolic tangent function with full-scale trial data based on multi-innovation least squares and stochastic gradient Algorithms [34-35]. This algorithm needs only a small amount of data, the calculation is simple and the accuracy gets greatly improved. This algorithm can be used in a variety of situations.

1.4 Objective of Study

Based on the research results in the system identification field and in order to improve ship maneuvering modeling, a hyperbolic tangent function nonlinear innovation identification algorithm is proposed by 4-DOF ship maneuvering modeling with full-scale trial data. Through performance analysis and simulation, it shows that this scheme can reduce parameters, improve computational efficiency and increase accuracy. It does not need the known structure of ship maneuvering model. The engineering feasibility and effectiveness of the scheme are proved by the application experiment.Through compared experiments, comparison of results between different degrees of the same degree and different degrees of the same type. Build the implementation flow chart of the algorithm. The scheme combines the index and correlation coefficient to estimate the structure and parameters of the ship maneuvering regression model. The validity of the algorithm is verified by a series of full-size test data on the research ship "Yukun" of Dalian Maritime University.

That is convicing and meaningful for applying the proposed algorithm in the practical engineering. It can be used to improve maritime safety and improve the efficiency of maritime transport. It can also be used in ship motion simulation and controller design. At the same time, it can protect the marine environment. In addition, the scheme can be extended to other online identification or prediction systems in the field of ocean engineering. It has important practical significance.

1.5 Chapter Organization of this Paper

This paper is mainly divided into five parts. Chapter Ⅰ introduces what are ship motion control and related modeling theories on ship control and maneuvering. Introduce the development of ship maneuvering mathematical model and identification algorithm in China as well as foreign countries and from the ancient time to the present. Introduce the ship maneuvering identification model methods and the significance of improving the effectiveness of the algorithm, as well.

For Chapter II, introduce the classification of the ship maneuvering mathematical model and describe the basic theory. In addition, author derivation and verification the relevant formulas about kinematical equation and kinetics equation of marine ships. Besides, introduce autopilot models with the 1 DOF simplified forms (Nomoto model and Nonlinear Nomoto model).

For Chapter III, introduce the nonlinear innovation identification modeling process. And design the nonlinear innovation stochastic gradient algorithm and make related identification algorithm experiments.

Chapter IV introduces what is 4 degrees of freedom (DOF) and carries out the identification experiments under the full-scale trial data. At the same time, propose the 4 degrees of freedom (DOF) nonlinear innovation hyperbolic tangent identification algorithm with full-scale trial data and verified is convergence.

Chapter V summarizes the full text. For the improved ship maneuvering modeling, a novel nonlinear innovation-based algorithm is proposed by use of the hyperbolic tangent function. The scheme can reduce the parameters and improve the calculation efficiency and accuracy. It does not need the known structure of ship maneuvering model. The feasibility and effectiveness of the scheme are proved by application test. In addition, the scheme can also be extended to other on-line identification or prediction systems in the field of ocean engineering. Further work will focus on the modeling of ship maneuvering recognition in the dual rate measurement engineering environment.

CHAPTER 2: INTRODUCTION

2.1 Classification of Ship Maneuvering Mathematical Models

In fact, the ship motion mathematical model is to abstract the ship motion dynamic characteristics into a group of special differential equations.

The main purposes of building ship motion mathematical model include model prediction, real-time simulation and controller/observer design. According to the application purpose different, the complexity of the model structure and parameters varies are different. And through the mathematical models in different application backgrounds to act on the ship control system, the mathematical models of ship motion can be divided into three categories [36]: simulation model, design model (oriented to controller design) and design model (oriented to observer design).

Simulation model: This kind of mathematical model can accurately describe the actual ship motion time domain response condition. It is mainly used to test the control algorithm in the theoretical research stage. The 6-dof nonlinear ship mechanism model is a typical simulation model, which can describe ship dynamics, execution servo system, measurement system, wind and wave and other Marine environmental disturbances. The large-scale ship control simulator adopts this kind of simulation model to provide a basic simulation test platform for studying the performance of ship closed-loop system.

Design model (oriented to controller design): In general, this model is mainly used for control law design. Taking the PID controller as an example, the parameters of gain coefficient, integral coefficient and differential coefficient in the controller can be utilize by using the Nomoto model and the closed-loop gain shaping algorithm. In this system, the Nomoto model is the design model.

Design model (oriented to observer design): This kind of model is also a simplified expression of the simulation model. But it is different from the design model for controller design. It is mainly used to capture the influence of sensor noise and environmental disturbance on the dynamic response process of the controlled object.

According to the different system characteristic equations, the ship motion mathematical model can be divided into linear model and nonlinear model.

There are two purposes about the study of ship mathematical models: One is to establish ship motion simulators (also called ship motion simulators) with different degrees of precision, which is used to study the ship maneuvering characteristics, study the closed-loop control system of ship motion and evaluate the performance of ship motion controllers. This model must be nonlinear to contain as many mechanism details as possible. Currently, there are some advanced control strategies. Such as adaptive control, robust control, etc. Also require the system modeling to be able to describe nonlinear characteristics in essence. Furthermore, if the purpose of system modeling is to construct a simulation platform, such as a large ship maneuvering simulator, so we must adopt the nonlinear ship motion mathematical model to improve the reality sense of the ship maneuvering process. The other model is intended for ship motion controller design. This model is primarily linear. Up to now, linear feedback control theory is still the only branch to provide a controller design systematic approach. When using neural network control or fuzzy control, the nonlinear ship motion mathematical model can provide training and learning data. From the view of controller design, the linear model can be applied in most cases. Because the closed-loop feedback control can make the relevant output variables in the system have a small deviation. Linear system theory is the most mature, largest and most complete achievement in the whole system analysis field. The baud diagram method, root trajectory method or in modern control theory the optimal control and filtering are built on the basis of linear model [37]. As the controlled object, it is the starting point to design a linear controller to build a linearized model of the ship's motion process.

From the view of system description, the mathematical model of ship motion can be divided into transfer function type and state space type (differential equations form).

The transfer function mathematical model is used to analyze the dynamic behavior of ship motion in the field. The transfer function is basis on the Laplace transform. Through describe the parameters of the system itself to change the input and output relation. The transfer function mathematical model usually cannot indicate the physical characteristics and structure of the system. And many other motion control systems can also be described by the transfer function of the same form. Nomoto model is a typical transfer function ship motion mathematical model. It is used to analyze the dynamic behavior of ship motion in the field of classical control theory and intelligent control.

Ship motion controller is the foundation of ship motion controller. It can have multiple levels of modeling solutions. At the same time, different size models are used for different design purposes and accuracy requirements. The mathematical model of classical control theory based on transfer function was limited by manual calculation at that time. With the development of computer technology, the mathematical model of modern control theory based on state space theory adopts the state space model composed of multiple differential equations.This kind of model focuses on time domain analysis and focuses on the internal states and internal relations of the system. Abkowitz model, Norrbin model and MMG model are all typical state space models [39].

2.2 Basics Theory and Preliminaries

The establishment of the ship motion mathematical model requires the construction of the reference coordinate system for describing the relevant motion variables. As shown in Fig. 1, there are the inertial coordinate system and the attached coordinate system respectively. In Fig. 1, $O-X_0Y_0Z_0$ is the inertial coordinate system, which is usually selected $t=0$ as the ship's center position of gravity at the moment, OX_0 pointing due north in the static plane, OY_0 pointing due east in the static plane, and OZ_0 pointing to the center of the earth perpendicular to the static plane. $O-XYZ$ Is the attached coordinate system, which is usually selected as the ship's center position of gravity else. And ox points to the bow, oy starboard and oz keel along the ship longitudinal section. The ship motion with 6 degrees of freedom is the motion with the ox, oy, oz movement and rotation of the three coordinate axes in the attached coordinate system. The motion includes longitudinal motion (forward motion), lateral motion (lateral drift) and vertical motion. The rotation is described by forward velocity u, transverse velocity v and vertical velocity w. Motion includes yaw, roll, and pitch. The yaw angular velocity r, roll angular velocity p and pitch angular velocity q. In inertial coordinates, ship motion can be described by space position

$[x, y, z]^{\mathrm{T}}$ and attitude Angle $[\varphi, \theta, \psi]^{\mathrm{T}}$. φ Is the roll Angle, θ is the pitch Angle and ψ is the forward Angle.

It is convenient that make the reference frame to solve problems. Under normal conditions, the analysis ship motion, ship seaworthiness and the dynamics part of controller design are mainly carried out in the attached coordinate system. In this paper, the kinematics of ship trajectory problems, such as track keeping control and dynamic positioning control need to be discussed by inertial coordinate system .Therefore, the establishment of ship motion mathematical model usually requires specific consideration according to specific problems. In the following chapter, the author will directly introduce the relevant research work of ship modeling under the reference coordinate system shown in Fig. 1.

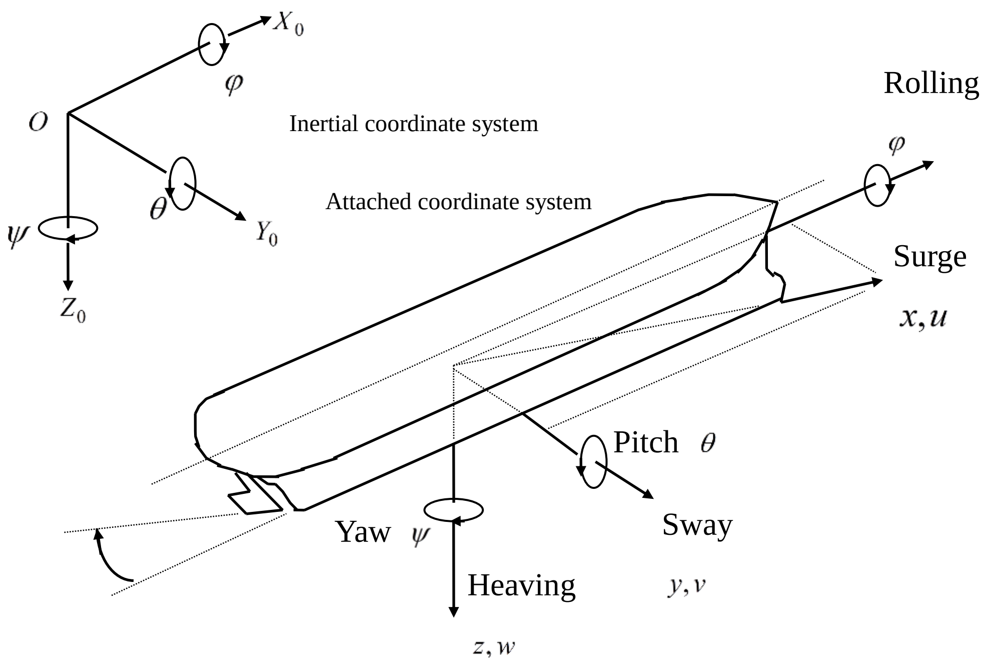

Fig.2.1 Describes ship motion in inertial and appendage coordinates

2.2.1 Kinematical Equation of Marine Ships

Ship kinematics equation adopts the usual mechanical treatment method, chooses the coordinate system, determines the parameters characterized the motion and establishes motion equation. The ships arbitrary motion in real marine environment can be regarded as the superposition of moving and rotating motion. The ship motion with six degrees of freedom (linear motion along three coordinate axes and rotation motion around three coordinate axes) can be described in the attached coordinate system by using the motion velocity variable $[u,v,w]^{\mathrm{T}}$ and the rotation angular velocity variable $[p,q,r]^{\mathrm{T}}$. And also in the inertial coordinate system by using the derivative of the position coordinate variable $[\dot{x},\dot{y},\dot{z}]^{\mathrm{T}}$ and the derivative of the attitude Angle variable $[\dot{\varphi},\dot{\theta},\dot{\psi}]^{\mathrm{T}}$. For convenient description, the ship attitude vector and velocity vector shown in Eq. (2-1). There is a kinematic relation between the two units in Eq. (2-2).

$$\begin{aligned}\eta &\triangleq [x \quad y \quad z \quad \varphi \quad \theta \quad \psi]^{\mathrm{T}} \in R^6 \\ v &\triangleq [u \quad v \quad w \quad p \quad q \quad r]^{\mathrm{T}} \in R^6\end{aligned} \tag{2-1}$$

$$\dot{\eta} = J(\eta)v \tag{2-2}$$

Where, $J(\eta)$ is the transformation matrix, specifically expressed as Eq. (2-3) and Eq. (2-4).

$$J(\eta) = \begin{bmatrix} J_1(\varphi,\theta,\psi) & 0_{3\times3} \\ 0_{3\times3} & J_2(\varphi,\theta,\psi) \end{bmatrix} \tag{2-3}$$

$$J_1(\cdot)=\begin{bmatrix}\cos\psi\cos\theta & -\sin\psi\cos\varphi+\cos\psi\sin\theta\sin\varphi & \sin\psi\sin\varphi+\cos\psi\cos\varphi\sin\theta\\ \sin\psi\cos\theta & \sin\psi\cos\varphi+\sin\psi\sin\theta\sin\varphi & -\cos\psi\sin\varphi+\sin\psi\cos\varphi\sin\theta\\ -\sin\theta & \cos\theta\sin\varphi & \cos\theta\cos\varphi\end{bmatrix}$$
$$J_2(\cdot)=\begin{bmatrix}1 & \sin\varphi\tan\theta & \cos\varphi\tan\theta\\ 0 & \cos\varphi & -\sin\varphi\\ 0 & \sin\varphi\sec\theta & \cos\varphi\sec\theta\end{bmatrix},\cos\theta\neq 0 \tag{2-4}$$

In fact, ship motion modeling tasks (such as ship dynamic positioning controller, path tracking controller design, etc.) in ocean engineering practice are mainly concerned with the changes of ship's bow Angle ψ and navigation trajectory x, y. That the ship's motion in the horizontal plane. For most large ships, heave, pitch and roll have little effect on ship plane motion. Therefore, its influence can be ignored. At the same time, the attitude vector $\eta=[x,y,\psi]^{\mathrm{T}}\in R^3$ and velocity vector $v=[u,v,r]^{\mathrm{T}}\in R^3$ can be redefined. And get the ship plane motion relations (2-5) and (2-6). Thus, it satisfied $R^{-1}(\psi)R(\psi)=I_{3\times3}$.

$$\dot{\eta}=R(\psi)v, R^{-1}(\psi)=R^{\mathrm{T}}(\psi)=R^{\mathrm{T}}(\psi) \tag{2-5}$$

$$R(\psi)=\begin{bmatrix}\cos\psi & -\sin\psi & 0\\ \sin\psi & \cos\psi & 0\\ 0 & 0 & 1\end{bmatrix} \tag{2-6}$$

2.2.2 Kinetics Equation of Marine Ships

For the modeling of the kinetics equations, some assumptions are useful. (1) The ship is considered as a rigid body. (2) The coordinate system is a typical inertial system. Based on the Neuton geostatic and the momentum moment theorems, one can conduct the force analysis for the ship hull. The translational dynamics equations and the rotational dynamics equations can be derived as Eq. (2-7).

$$\begin{cases} m\left[\dot{u}+qw-rv-x_G\left(q^2+r^2\right)+y_G\left(pq-\dot{r}\right)+z_G\left(pr+\dot{q}\right)\right]=X \\ m\left[\dot{v}+ru-pw+x_G\left(qp+\dot{r}\right)-y_G\left(r^2+p^2\right)+z_G\left(qr-\dot{p}\right)\right]=Y \\ m\left[\dot{w}+pv-qu+x_G\left(rp-\dot{q}\right)+y_G\left(rq+\dot{p}\right)-z_G\left(p^2+q^2\right)\right]=Z \\ I_{XX}\dot{p}-\left(I_{yy}-I_{zz}\right)qr-I_{xy}\left(\dot{q}-rp\right)-I_{xz}\left(\dot{r}+pq\right)-I_{yz}\left(q^2-r^2\right)+my_G\left(\dot{w}+pv-qu\right)-mz_G\left(\dot{v}+ru-pw\right)=K \\ I_{yy}\dot{q}-\left(I_{zz}-I_{xx}\right)rp-I_{yz}\left(\dot{r}-pq\right)-I_{xy}\left(\dot{p}+qr\right)-I_{xz}\left(r^2-p^2\right)-mx_G\left(\dot{w}+pv-qu\right)+mz_G\left(\dot{u}+qw-rv\right)=M \\ I_{zz}\dot{r}-\left(I_{xx}-I_{yy}\right)pq-I_{xy}\left(\dot{p}-qr\right)-I_{yz}\left(\dot{q}+rp\right)-I_{xy}\left(p^2-q^2\right)+mx_G\left(\dot{v}+ru-pw\right)-my_G\left(\dot{u}+qw-rv\right)=N \end{cases} \quad (2\text{-}7)$$

Where, X,Y,Z,K,M,N respectively represent longitudinal force, transverse force and vertical force, roll moment, pitching moment and forward moment and m represent the mass of the ship. x_G, y_G, z_G Is the coordinates of the ship's center of gravity in the attached coordinate system, I_{xx}, I_{yy}, I_{zz} respectively represent ship's mass around x, y, z the moment of inertia of the axis. And I_{xx}, I_{yy}, I_{zz} respectively represent the ship's mass xoy, yoz, xoz the moment of inertia of against the plane.

In general, the hull is symmetric in the plane of the appendage xz coordinate system. It exists under this condition $I_{xy} = I_{yz} = 0, y_G = 0$. Furthermore, based on the above considerations, on the basis of Eq. (2-7), slight pitching and heave motion as well as their coupling motion to other degrees of freedom can be ignored. And there are $w = q = \theta = \dot{w} = \dot{q} = \dot{\theta} = 0$. By making the above assumption, the ship's 4-degree of freedom dynamic relationship can be obtained [40] as shown in Eq. (2-8)

$$\begin{cases} m\left(\dot{u}-vr-x_G r^2+z_G pr\right)=X \\ m\left(\dot{v}+ur+x_G\dot{r}-z_G\dot{p}\right)=Y \\ I_{xx}\dot{p}-mz_G\left(\dot{v}+ur\right)=K \\ I_{zz}\dot{r}+mx_G\left(\dot{v}+ur\right)=N \end{cases} \quad (2\text{-}8)$$

The dynamic relation of ship plane motion is Eq. (2-9).

$$
\begin{cases}
m\left(\dot{u} - vr - x_G r^2\right) = X \\
m\left(\dot{v} + ur + x_G \dot{r}\right) = Y \\
I_{zz}\dot{r} + m x_G \left(\dot{v} + ur\right) = N
\end{cases}
\tag{2-9}
$$

In the above ship dynamics model, the right side of the equation X, Y, Z, K, M, N is the force acting on the ship. It is a multivariate nonlinear function of ship motion variables and control variables. From the perspective of analysis and application, the forces acting on the moving ship can be divided into three categories, namely, control force, environmental disturbance force and fluid power. Control force via the control force generated by special control devices arranged on or outside the ship to make the ship carry out the expected control maneuvering, which usually includes the transshipment force of the rudder blade, the thrust force of the main propelling propeller and the side thrust force of the side thruster. The environmental disturbance force mainly includes wind force, wave force and flow force. The wind force mainly acts on the superstructure of the ship and its value is related to the apparent wind strength and the wind side Angle. Meanwhile its function point is related to the center of the side projection area of the superstructure. The wave force applied to the underwater hull surface decreases in strength from the surface downward, depending on the strength of the wind and the frequency of wave encounters. The wave force can be divided into primary force and secondary force. The primary force is an alternating force with high frequency and large value and its value can be an order of magnitude larger than the propulsive force. However, due to the filtering effect of the ship as a dynamic system, the ship motion amplitude caused by the wave is usually limited. The secondary force is a small value, slow time - varying partial value action and causes the ship drift movement. Fluid dynamics is the reaction force of the fluid on the surface of the ship in contact with it and is the sum of the positive pressure. At the same time, shear stress effects on the surface according to a certain distribution law. The study of fluid dynamics is the most complex part of the forces on the hull.

2.3 Autopilot Models with the 1 DOF Simplified Forms

The response mathematical model also called the transfer function mathematical model. It can be used to analyze the dynamic behavior of ship motion in the classical control theory as well as in the field of intelligent control. This chapter introduce the Nomoto model and the nonlinear Nomoto model. First to introduce the former, considering the hull design left and right symmetry, the relevant hydrodynamic derivatives $X_{\dot{v}}, X_{\dot{r}}, X_v, X_r, X_\delta, Y_{\dot{u}}, Y_u, Y_{\dot{u}}, N_{\dot{u}}, N_u$ are 0. Meanwhile, the left end of the ship kinematics equation is linearized to obtain the linear mathematical model of plane motion, as shown in Eq. (2-10).

$$\begin{aligned}
&m\Delta\dot{u} = X_u\Delta u + X_{\dot{u}}\Delta\dot{u} \\
&m\dot{v} + mu_0 r + mx_G\dot{r} = Y_v v + Y_r r + Y_{\dot{v}}\dot{v} + Y_{\dot{r}}\dot{r} + Y_\delta\delta \\
&I_{zz}\dot{r} + mx_G\dot{v} + mx_G u_0 r = N_v v + N_r r + N_{\dot{v}} v + N_{\dot{r}} r + N_\delta\delta
\end{aligned} \tag{2-10}$$

Where, the matrix form can be expressed as Eq. (2-11).

$$\begin{bmatrix} m - X_{\dot{u}} & 0 & 0 \\ 0 & m - Y_{\dot{v}} & mx_G - Y_{\dot{r}} \\ 0 & mx_G - N_{\dot{v}} & I_{ZZ} - N_{\dot{r}} \end{bmatrix}\begin{bmatrix} \Delta\dot{u} \\ \dot{v} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} X_u & 0 & 0 \\ 0 & Y_v & Y_r - mu_0 \\ 0 & N_v & N_r - mx_G u_0 \end{bmatrix}\begin{bmatrix} \Delta u \\ v \\ r \end{bmatrix} + \begin{bmatrix} 0 \\ Y_\delta \\ N_\delta \end{bmatrix}\delta \tag{2-11}$$

$$\dot{X} = AX + B\delta \tag{2-12}$$

Where, as Eq. (2-13)

$$A = \left(I'\right)^{-1} P' = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, B = \left(I'\right)^{-1} Q' = \begin{bmatrix} b_{11} \\ b_{21} \end{bmatrix} \tag{2-13}$$

And as Eq. (2-14)

$$
\begin{aligned}
a_{11} &= \left[\left(I_{zz}^{'} - N_{\dot{r}}^{'}\right)Y_{v}^{'} - \left(m^{'}x_{G}^{'} - Y_{\dot{r}}^{'}\right)N_{v}^{'}\right]V / S_1 \\
a_{12} &= \left[\left(I_{zz}^{'} - N_{\dot{r}}^{'}\right)\left(Y_{r}^{'} - m^{'}\right) - \left(m^{'}x_{G}^{'} - Y_{\dot{r}}^{'}\right)\left(N_{r}^{'} - m^{'}x_{G}^{'}\right)\right]LV / S_1 \\
a_{21} &= \left[-\left(m^{'}x_{G}^{'} - N_{\dot{v}}^{'}\right)Y_{v}^{'} + \left(m^{'} - Y_{\dot{v}}^{'}\right)N_{v}^{'}\right]V / \left(LS_1\right) \\
a_{22} &= \left[-\left(m^{'}x_{G}^{'} - N_{\dot{v}}^{'}\right)\left(Y_{r}^{'} - m^{'}\right) + \left(m^{'} - Y_{\dot{v}}^{'}\right)\left(N_{r}^{'} - m^{'}x_{G}^{'}\right)\right]V / S_1 \\
b_{11} &= \left[\left(I_{zz}^{'} - N_{\dot{r}}^{'}\right)Y_{\delta}^{'} - \left(m^{'}x_{G}^{'} - Y_{\dot{r}}^{'}\right)N_{\delta}^{'}\right]V^2 / S_1 \\
b_{21} &= \left[-\left(m^{'}x_{G}^{'} - N_{\dot{v}}^{'}\right)Y_{\delta}^{'} + \left(m^{'} - Y_{\dot{v}}^{'}\right)N_{\delta}^{'}\right]V^2 / \left(LS_1\right) \\
S_1 &= \left[\left(I_{zz}^{'} - N_{\dot{r}}^{'}\right)\left(m^{'} - Y_{\dot{v}}^{'}\right) - \left(m^{'}x_{G}^{'} - Y_{\dot{r}}^{'}\right)\left(m^{'}x_{G}^{'} - N_{\dot{v}}^{'}\right)\right]L
\end{aligned}
\tag{2-14}
$$

Eq. (2-12) shows that under the premise of linearization, the forward motion of the ship is decoupled from the motion on the other two degrees of freedom. From the perspective of speed control, the freedom motion can be considered separately. There is a strong coupling between yaw and bow motion and the motion in these two degrees of freedom is closely related to the design of ship's course and track controller [41]. As is known to all, the famous Nomote model Eq. (2-15)

$$
G_{\psi\delta}\left(s\right) = \frac{\psi\left(s\right)}{\delta\left(s\right)} = \frac{K}{s\left(Ts+1\right)} \tag{2-15}
$$

In fact, it is a typical characteristic parameter K,T to describe the ship handling characteristics, which has a definite physical meaning. The parameter K reflects the advantages and disadvantages of the ship's cycle performance and is called "cyclist index". The larger the K, the larger the turning moment rudder can generate and the smaller the damping moment; On the contrary, the smaller the K, the smaller the turning moment and the greater the damping . It is called the “following index”, which reflects the ship’s rapid response to rudder equipment, course stability and the following performance. The smaller the T, the smaller the ship’s interior and the large the damping moment, vice versa. In engineering practice, the operator always hopes that the ship has a large positive value K , a small positive value T and a good ship handling performance. In order to solve the linear response model, 8 ship parameters are required to be known, that is, speed V, length L, ship width B, full-load draft T, square coefficient C_b, ship displacement ∇, longitudinal coordinates of ship's center of gravity x_G and rudder blade area A_δ. Furthermore, Nomoto model parameters K,T can also be identified by using real ship maneuverability test data (including z-shape test and cycle test).

The linear response model is used in the sense of "linear average" to describe moderate amplitude maneuvering motion. The slope of the relative hydrodynamic curve of the state of motion is used to calculate the relative hydrodynamic derivative. In the nonlinear case, the relevant hydrodynamic derivatives will be mainly dependent on r to change. Reference [42] shows a typical nonlinear response type of mathematical model research results, seize the ship dynamic $\delta \to \dot{\psi} \to \psi$ from the main vein, the differential equation is obtained preserves the nonlinear influence factors, even the ocean environment interfere or become a distraction rudder Angle together constitute a kind of input signal and the actual Angle δ into the model of the ship..

Based on the second-order Nomoto model Eq. (2-15), it can be further converted into the description form of differential Eq. (2-16).

$$\ddot{\psi} + \frac{1}{T}\dot{\psi} = \frac{K}{T}\delta \tag{2-16}$$

In order to describe the nonlinear hydrodynamic influence in the process of ship motion, introduce the nonlinear term $(K/T)H(\dot{\psi})$ instead of Eq. (2-16). Thus shown as Eq. (2-17)

$$H(\dot{\psi}) = \alpha\dot{\psi} + \beta\dot{\psi}^3 \tag{2-17}$$

Further arrangement can get nonlinear response mathematical model Eq. (2-18) and Eq. (2-19).

$$\ddot{\psi}+\frac{K}{T}H(\dot{\psi})=\frac{K}{T}\delta \tag{2-18}$$

$$\dot{\psi}\to\delta_f:\delta_f=H(\dot{\psi})-\frac{1}{K}\dot{\psi}=\left(\alpha-\frac{1}{K}\right)\dot{\psi}+\beta\dot{\psi}^3 \tag{2-19}$$

Supplementary instruction, Fig. 2.2 δ_f can be calculated according to Eq. (2-8) and the block diagram can use by Simulink simulation. Fig. 2.2 shows the structure diagram of the nonlinear response mathematical model discussed in this section

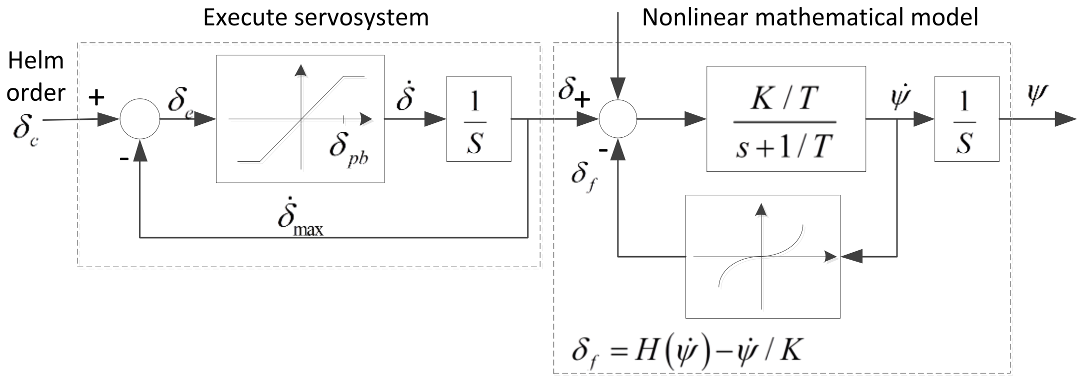

Fig.2.2 Description of ship motion variables in inertial and appendage coordinate systems

2.4 Chapter Summary

This chapter introduces the classification of mathematical models of ship operation, systematically elaborate responsive mathematical model basic theory and include Kinetics Equation of Marine Ships and Kinematical Equation of Marine Ships. Specific introduce the linear mathematical model of ship plane motion. Based on that, it is concluded that the linear/nonlinear response mathematical model (i.e., Nomoto model and nonlinear Nomoto model) deductive process.

CHAPTER 3: Nonlinear Innovation Identification for Autopilot Models

In this chapter, first, introduce the nonlinear Nomoto model as the ship mathematical model. And then derive the stochastic gradient algorithm. The algorithm is deduced and verified by experiments. By the linear regression model, meanwhile, analogy introduce forgetting factor the stochastic gradient algorithm. Process the innovation with hyperbolic tangent function. At the same time, the nonlinear innovation identification via the hyperbolic tangent function is obtained. Finally, scholars through matlab programming get a comparison of the identification effect and through the calculation obtain the accuracy of the situation. After the model is constructed, the ship dynamics can be estimated by observing the comparison of the response.

3.1 Problem Description

The following factors must be considered :1. Reference research on nonlinear identification methods. Stability and parameter convergence are also discussed. 2.Specifies a sequence of ship operations that can be used to identify. 3.Simulation and experimental data are used to estimate the parameters of the model. The results are discussed and the results of parameter estimation and convergence are given. It also shows which operations have the best convergence. The closed loop simulation system of autopilot based on model is used. The Eq. (3-1) is shown as:

$$\ddot{\psi} + \frac{K}{T}\left(\alpha\dot{\psi} + \beta\dot{\psi}^3\right) = \frac{K}{T}\delta \tag{3-1}$$

Where ψ is heading angle, $\dot{\psi}$ is yaw rate, $\ddot{\psi}$ angular acceleration, δ is rudder angle, K and T are the ship maneuverability indices, α and β are the nonlinear coefficients of yaw rate ψ. And process the innovation with hyperbolic tangent function. Utilize the nonlinear Nomoto model and Nomoto model with random disturbance to carry out rotary simulation experiments. Comparison results by the improved and original algorithm. Simulink was imported into Matlab to implement the maneuvering model and Suggestions. An overview of the simulation environment is also described.

Objective: To develop a nonlinear innovation algorithm :(1) To select model structure and parameter estimation according to ship dynamic characteristics in parallel. (2) This identification scheme is easy to implement and effective under two simulation conditions. Therefore, the purpose of this chapter is to develop a method to identify nonlinear innovation. (3) The algorithm can effectively improve the identification accuracy.

3.2 Design of the Nonlinear Innovation Algorithm

First, the formula of stochastic gradient algorithm is derived. On this basis, the nonlinear innovation algorithm is derived. Finally, the author deduced the nonlinear innovation hyperbolic tangent function.

3.2.1 The Stochastic Gradient Algorithm

Taking the nonlinear Nomoto model as the plant, it can be rewritten as the linear regression form, i.e. Eq.(3-2). Note, in the proposed algorithm, the differential operation can be calculated by using the differentiate operation, i.e. $\dot{r} = \left(r(t) - r(t-1)\right)/h$, h denotes the sampling time span.

$$
\begin{aligned}
&y(t)=\boldsymbol{\varphi}^{\mathrm{T}}\boldsymbol{\theta}+v(t),\\
&y(t)=\left(r(t)-r(t-1)\right)/h\\
&\boldsymbol{\theta}=\left[-\frac{k\alpha}{T},-\frac{k\beta}{T},-\frac{k}{T}\right]^{\mathrm{T}}\\
&\boldsymbol{\varphi}=\left[r,r^{3},\delta\right]^{\mathrm{T}}
\end{aligned}
\tag{3-2}
$$

where $y(t)$ is system output, $\varphi(t)$ is regression information vector， θ is the model parameters to be identified, $v(t)$ is zero mean value random noises. For the linear regression model (3-2), the stochastic gradient (SG) can be derived as follows[43].

$$\hat{\boldsymbol{\theta}}(t)=\hat{\boldsymbol{\theta}}(t-1)+\frac{\boldsymbol{\varphi}(t)}{r(t)}e(t) \tag{3-3}$$

$$e(t)=y(t)-\boldsymbol{\varphi}^{\mathrm{T}}(t)\hat{\boldsymbol{\theta}}(t-1) \tag{3-4}$$

$$r(t)=r(t-1)+\left\|\boldsymbol{\varphi}(t)\right\|^{2} \tag{3-5}$$

Where $\hat{\theta}(t)$ and $\hat{\theta}(t-1)$ are estimates of θ 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 co-variance matrix and has less computational complexity. But its convergence speed is slower and identification accuracy is lower.

3.2.2 The Nonlinear Innovation Identification Algorithm

Inspired by the nonlinear feedback algorithm in the literatures [44]-[45] and the stochastic gradient identification algorithm, the innovation can be processed by the nonlinear hyperbolic tangent function. That could improve the identification performance of the related model parameters. Thus, the improved stochastic gradient algorithm based on nonlinear innovation (NISG) is presented as Eq.(3-6), (3-7), (3-8).

$$\hat{\boldsymbol{\theta}}(t) = \hat{\boldsymbol{\theta}}(t-1) + \frac{\boldsymbol{\varphi}(t)}{l(t)} e^{'}(t) \tag{3-6}$$

$$e^{'}(t) = \tanh(\omega e) \tag{3-7}$$

$$l(t) = l(t-1) + \|\boldsymbol{\varphi}(t)\|^2 \tag{3-8}$$

The definition of the related variables is same to Eq.(3-3). Note, in Eq. (3-7), ω are the angular frequency and it can be selected randomly between 0.1- 1.0.

Next, the convergence performance of the algorithm is analyzed according to martingale convergence theorem and stochastic process theory [45].

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

$$\begin{aligned} &E\left[v(t) \mid F_{t-1}\right] = 0, a.s.; \\ &E\left[v^2(t) \mid F_{t-1}\right] = e_v^2(t) \le e_v^2 < \infty, a.s.; \\ &\lim_{t\to\infty}\sup \frac{1}{t}\sum_{t=1}^{t} v^2(i) \le e_v^2 < \infty, a.s.. \end{aligned} \tag{3-9}$$

Where: “$a.s.$”means “almost surely”.

Lemma 1: For stochastic gradient algorithms Eq. (3-6), Eq. (3-8), the following conclusions are valid:

$$
\begin{aligned}
&a)\lim_{a\to\infty}\sum_{i=0}^{t}\frac{\|\boldsymbol{\varphi}(i)\|^2}{r(i-1)r(i)}<\infty, a.s.. \\
&b)e(t)=\frac{r(t-1)}{r(t)}Z(t) \\
&e(t)=y(t)-\boldsymbol{\varphi}^{\mathrm{T}}(t)\boldsymbol{\theta}(t) \\
&Z(t)=y(t)-\boldsymbol{\varphi}^{\mathrm{T}}(t)\hat{\boldsymbol{\theta}}(t-1)
\end{aligned}
\tag{3-10}
$$

Lemma 2: For algorithms Eq. (3-6), Eq. (3-8), if there are constants T_0, U and integer, which can make the following strong persistent excitation conditions established.

$$
\begin{aligned}
&\mathrm{TI}\le\frac{1}{N}\sum_{I=0}^{N-1}\boldsymbol{\varphi}(t-i)\boldsymbol{\varphi}^{\mathrm{T}}(\mathrm{T}-\mathrm{I})\le\mathrm{UI},\mathrm{a.s.} \\
&0<\mathrm{T}<\mathrm{U}<\infty, \mathrm{N}\ge n \\
&r(t-N)+nNT\le r(t)\le r(t-N)+nNU \\
&nT(t-N)\le r(t)\le nU(t-N)+1 \\
&0<nT<\lim_{t\to\infty}\frac{r(t)}{t}\le nU<\infty
\end{aligned}
\tag{3-11}
$$

If the noise hypothesis Eq. (10) and the strong persistent excitation condition Eq. (3-11) holds. Then, the estimated parameters given by the stochastic gradient algorithms Eq. (3-3) and Eq. (3-5) almost surely converge to the true parameters, i.e.

$\lim \hat{\theta}(t) = \theta$.

For the improved stochastic gradient algorithm based on nonlinear innovation, in the Eq. (3-7), $\omega e(t)$ is generally small in marine practice, $e^{'}(t) = \tanh(\omega e)$ is expressed by Taylor series expansion:

$$\tanh(\omega e) \approx \frac{e^{\omega e} - e^{-\omega e}}{e^{\omega e} + e^{-\omega e}} \approx \omega e \le e \tag{3-12}$$

For Eq. (3-12), $r(t)$ becomes $r'(t) = 0.5\omega r(t)$, Eq. (3-9)-(3-11) still hold. Then the estimated parameters given by the improved stochastic gradient algorithms Eq. (3-6) and Eq. (3-7) almost surely converge to the true parameters.

3.3 Identification Experiments

Using the stochastic gradient algorithms and the nonlinear innovation algorithm identify the linear parameters T, K and nonlinear parameters α, β . Combining the identification of multi-information system with the main theory of nonlinear feedback control, propose a new identification algorithm of ship model parameters for nonlinear innovation processing via hyperbolic tangent function. In different rudder angles, comparison the condition of heading angle output. And by ship trajectory comparison confirm the effectiveness and universality of the method. Finally, comparison simulation experiments observe the convergence change and the improvement of identification accuracy

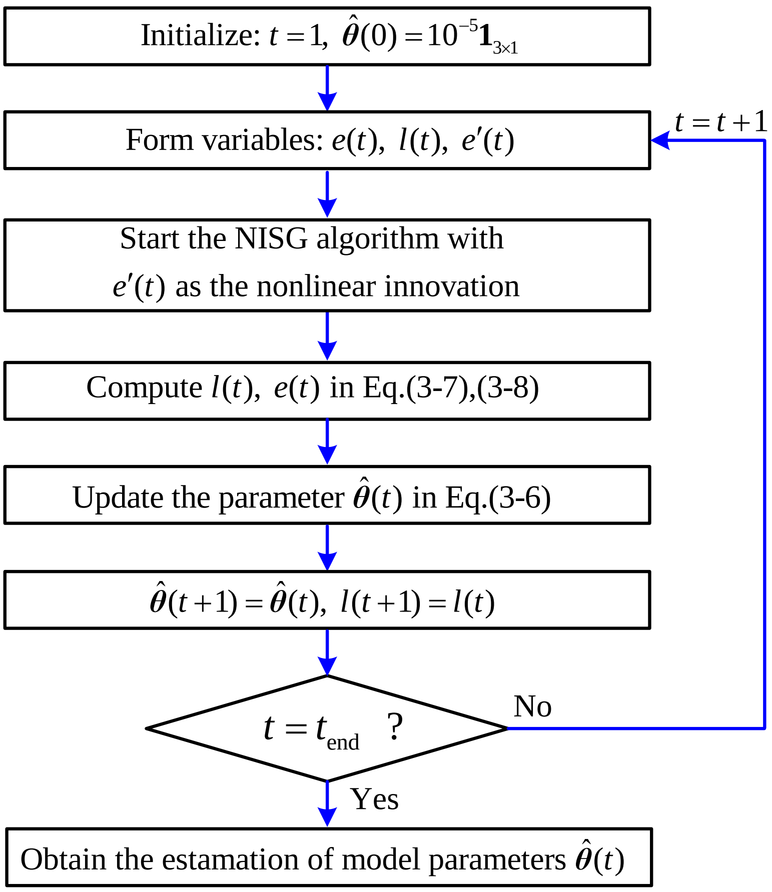

Fig3. 1 The implementation flowchart of the NISG algorithm

3.3.1 Nonlinear Innovation Identification for NOMOTO Model

This example takes an automobile transport ship "Hual Trooper" as the simulation object. As shown in Table 3-1 and Table 3-2 through the Stochastic Gradient Algorithm observe $\hat{T}$ and $\hat{K}$ convergence condition. But in the experiment we have to switch $\frac{1}{T}$ and $\frac{K}{T}$. In ship mathematical model "Hual Trooper" $K=0.15, T=47.61, \alpha=13.27, \beta=11087.20$. As shown in Fig. 3.2

TABLE 3-1 PARTICULARS OF “Hual Trooper”

Ship loading status		Numerical
Length between perpendiculars	$L(\mathrm{m})$	190.0
Breadth(molded)	$B(\mathrm{m})$	32.26
Designed draught	$D(\mathrm{m})$	6.9
Block coefficient	C_b	0.535
Trial speed	$V(\mathrm{kn})$	20.8
Rudder area	$A_R(\mathrm{m2})$	34.1

TABLE 3-2 SHIP MATHEMATICAL MODED PARAMETER OF “Hual Trooper”

Parameters	Truth
K	0.15
T	47.61
α	13.27
β	11087.20

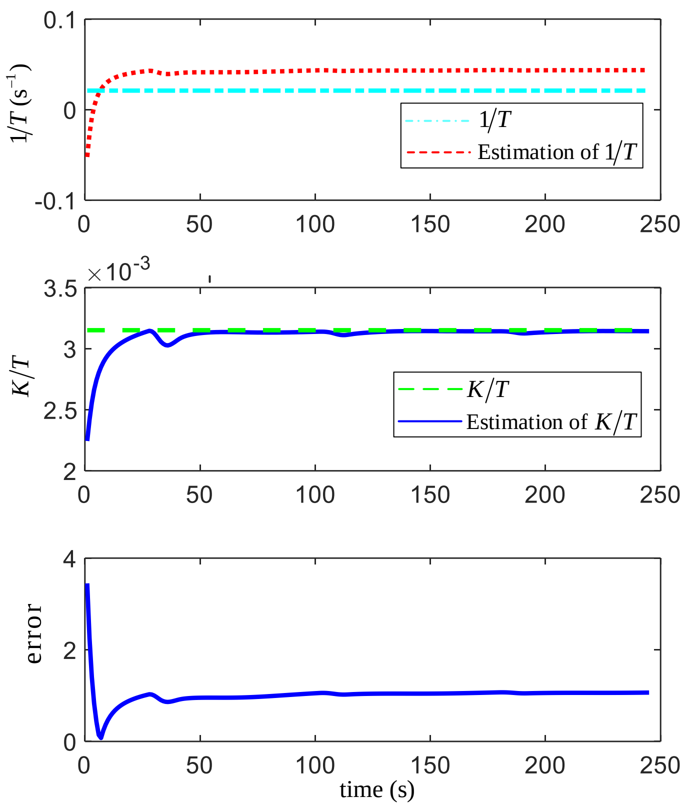

Fig.3. 2 using the stochastic gradient algorithm obtained Estimation of $1/T, K/T$

Thus, using the stochastic gradient algorithm obtained $\hat{K} = 0.072, \hat{T} = 22.9088$, . As shown in Fig.3.3. Using the nonlinear innovation algorithm observe $\hat{K}$ and $\hat{T}$ convergence condition.

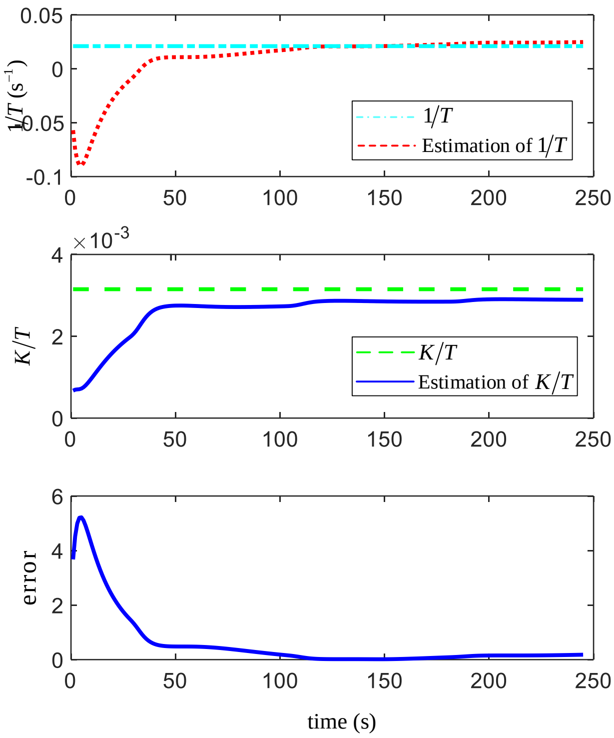

Fig.3. 3.Using the nonlinear innovation algorithm obtained Estimation of $1/T$, K/T

Using the nonlinear innovation algorithm obtained $\hat{K} = 0.1165, \hat{T} = 40.2886$.

As shown in Table 3-3. For the stochastic gradient algorithm: the error of $\hat{K}$ is 52%, the error of $\hat{T}$ is 52% and the mean error is 52%; For the nonlinear innovation algorithm, The error of $\hat{K}$ is 22.3%，the error of $\hat{T}$ is 15.3% and the mean error is 18.80%, the accuracy of the model is up to 81.2%.

TABLE 3-3 Comparison of" Hual Trooper “PARAMETERS identification

	the stochastic gradient algorithm	the nonlinear innovation algorithm
$\hat{K}$	52%	22.3%
$\hat{T}$	52%	15.3%
Mean error	52%	18.80%
Model accuracy up to 81.2%		
33.2% increase in identification		

3.3.2 Nonlinear Innovation Identification for Nonlinear NOMOTO Model

In order to further test the identification effect of the algorithm, add two parameters. Similarly, ship mathematics adopts nonlinear Nomoto model $\alpha = 13.27, \beta = 11087.20$. Using the stochastic gradient algorithm and the nonlinear innovation algorithm identify nonlinear parameters α、β respectively. As shown in Fig.3.4.

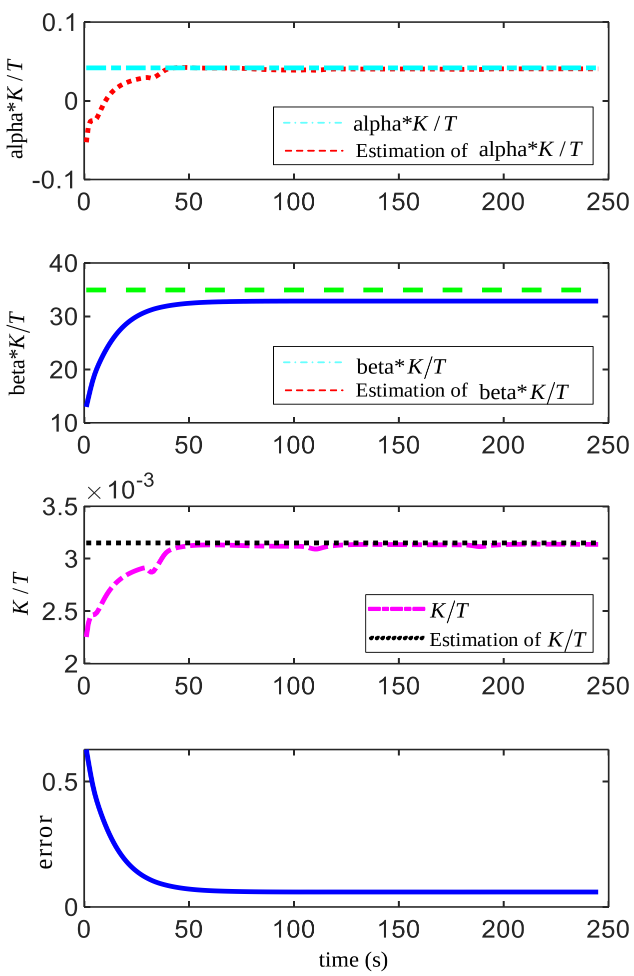

Fig.3.4 using the stochastic gradient algorithm obtained Estimation of $\alpha K/T$, $\beta K/T$, K/T

Thus, under the stochastic gradient algorithm, the nonlinear parameters $\hat{\alpha} = 12.9176, \hat{\beta} = 10472$. The error of α is 2.6%, the error of β is 5.5% and the mean error is 4.05%. Similarly, using the nonlinear innovation algorithm identify parameters. As shown in Fig.3.5.

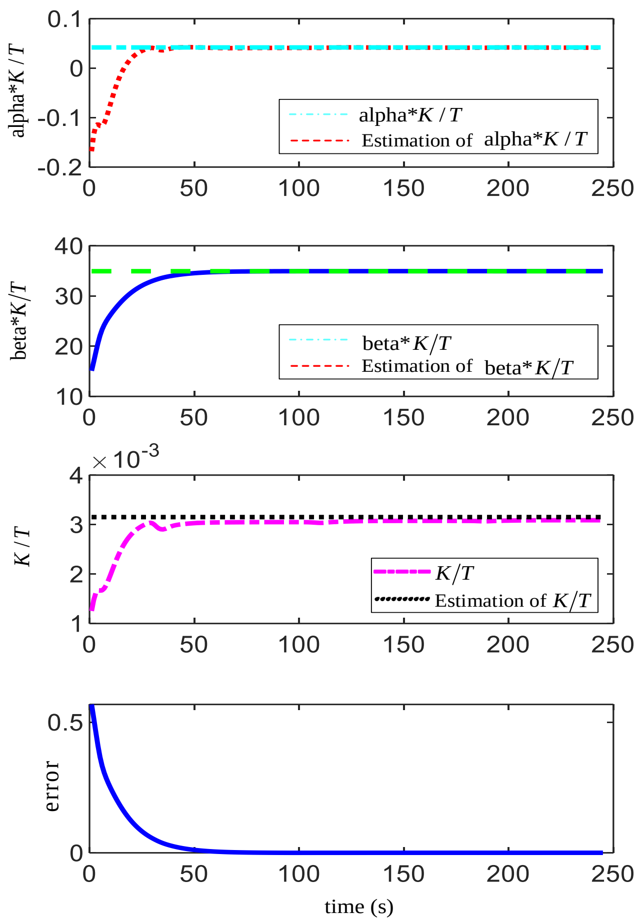

Fig.3.5 using the nonlinear innovation algorithm obtained Estimation of $\alpha K/T, \beta K/T, K/T$

TABLE 3-4 Comparison of" Hual Trooper “PARAMETERS identification

	the stochastic gradient algorithm	the nonlinear innovation algorithm
$\hat{\alpha}$	2.6%	0.04%
$\hat{\beta}$	5.5%	2%
Mean error	4.05%	1.02%
Model accuracy up to 98.98%		
3.03% increase in identification		

Furthermore， under the nonlinear innovation algorithm the parameters are $\hat{\alpha} = 13.3975, \hat{\beta} = 11317$. The error of α is 0.04%，the error of β is 2% and the mean error is 1.02%. Therefore, the accuracy of the model is up to 98.98%. In order to further prove the accuracy and universality of the algorithm. Utilize identification parameters compared with reality model parameters. Use 5°, 10° and 20° rudder angles, respectively. Use zigzag test data. Compare the heading Angle $\dot{\psi}$ output conditions. As shown in Fig.3.6. At the same time, compare ship trajectories in different rudder angles. As shown in Fig.3.7. The accuracy of the mathematical model is confirmed using Matlab. Make the comparison more intuitive. It can be concluded that the identification accuracy is improved by 70 percent by calculation. It is proved that the nonlinear innovation algorithm is faster and more accurate. The algorithm is quick to identify. Looking at the identification process and the results, this algorithm has a faster identification speed, the data change is intuitive and comprehensive, and the accuracy of identification is improved. It can be seen that the random gradient algorithm improved by the hyperbolic tangent function is closer to the real value.

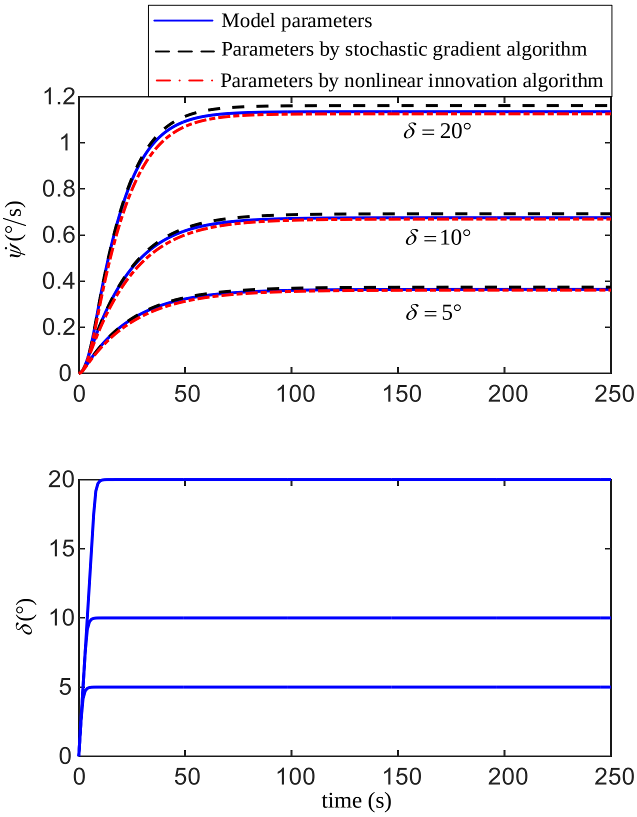

Fig.3.6 Comparison of the system output $\dot{\psi}$ under the different rudder angle.

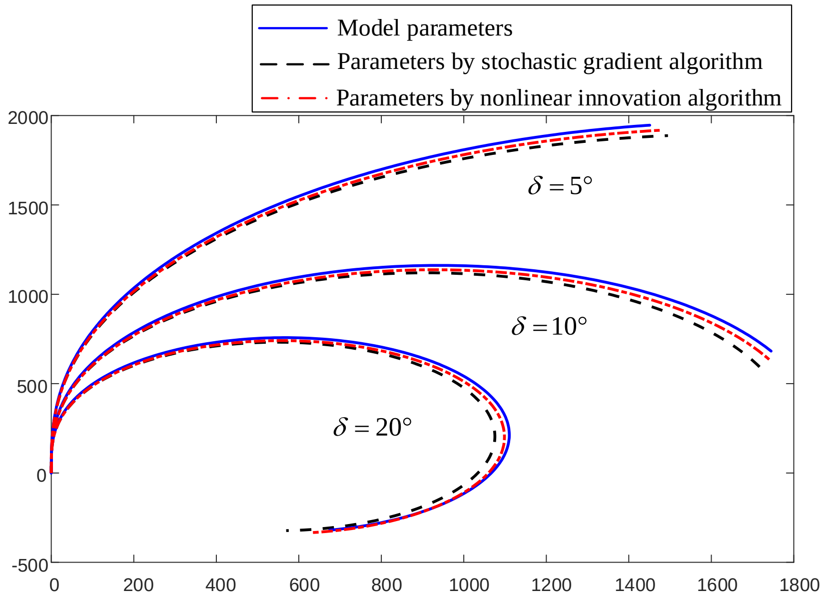

Fig.3.7 Compare ship motion trajectories in the different rudder angles.

Combining the main theories of multi-innovation system identification and nonlinear feedback control, a new algorithm for the identification of ship model parameters for nonlinear innovation processing of the hyperbolic tangent nonlinear function is further proposed. Through the comparison and simulation experiments: The algorithm is quick to identify. Looking at the identification process and the results, this algorithm has a faster identification speed, the data change is intuitive and comprehensive, and the accuracy of identification is improved.

3.4 Chapter Summary

In this chapter, a novel nonlinear innovation based identification algorithm is proposed for the ship mathematical model. The nonlinear hyperbolic tangent function is used to deal with the identification of new interest. In this chapter, only the main theories of multi-innovation system identification and nonlinear feedback control are combined. The algorithm for identifying the parameters of the ship model with nonlinear innovation processing of the hyperbolic tangent function is further proposed. The computational complexity and accuracy problems are lower than that of the other existing algorithms. The algorithm presented in this chapter requires only a small amount of data and the calculation is simple and the accuracy is greatly improved. The algorithm can be used in a variety of cases.

CHAPTER 4: Nonlinear Innovation Identification for 4 DOF Ship Maneuvering Mathematical Model

The identification problem was solved by establishing a 4-dOF ship maneuvering mathematical model. The existing research work rarely considers the choice of model structure, which is meaningful and inevitable in practical ship engineering. The engineering availability and effectiveness of the scheme are verified by application experiments. The identification scheme is effective and easy to be implemented under both simulation and real vehicle test conditions.

4.1 System Description and Preliminaries

Represents the expectation operator; E Represents the absolute value of a determinant or scalar variable of a square matrix. $|\cdot|$ Is the trace of the square matrix, is the minimum eigenvalue of the symmetric matrix X , is the estimation and estimation error. That means the constant is positive. These come from everywhere. Is the current sampling time, represents the return value of sampling step, and the superscript ' 'represents the normalization of corresponding variable and prime number system [1-9].

$$
\begin{aligned}
&(m+m_x)\dot{u}-(m+m_y)vr = X_H + X_P + X_R \\
&(m+m_y)\dot{v}+(m+m_x)ur = Y_H + Y_P + Y_R \\
&(I_x+J_x)\dot{p}-m_x l_x ur + mgGZ(\phi) = K_H + K_P + K_R \\
&(I_Z+J_Z)\dot{r} = N_H + N_P + N_R
\end{aligned}
\tag{4-1}
$$

Where u, v, r, p, ϕ denote linear and angular velocities, roll angle respectively; are the mass of the ship, the moments of inertia with respect to the x-axis, z-axis and the corresponding added mass and added moment of inertia. In the third equation, I_x is the X coordinate value for the added mass m_x .GZ denotes the metacentric arm with respect to the x-axis. $g = 9.8N/kg$ is the Newtonian universal of gravity. In addition, all of the above can be estimated with sufficient accuracy. The point of consideration is to determine the correct part of the equation. In this note, a damping force expression is attempted to describe the force or torque of the hull. According to the proposed identification scheme, detailed parts can be constructed automatically for different types of ships. It could be expressed as $X_H = X_{uu}u^2 + X_{uuu}u^3 + \cdots + X_{uv\phi\phi}uv\phi^2$, as well as Y_H, K_H, N_H . These coefficients $X_{uu}, X_{uuu}, ..., N_{|r|r}$ are the so-called hydrodynamic derivatives that would be estimated by the proposed identification scheme:

$$\begin{aligned}
&X_H : u^2, u^3, v^2, r^2, vr, uv^2, uv\phi^2, T(J_P), -F_N \sin\delta \\
&Y_H : uv, up, u^2v, r^3, vr^2, uvp^2, urp^2, |v|v, |r|v, |v|r, |r|r, -F_N \cos\delta \\
&K_H : p, uv, ur, u^2v, v^3, v^2r, vr^2, uv\phi^2, ur\phi^2, |v|v, -F_N \cos\delta \\
&N_H : uv, up, u\phi, u^2r, u^2v, v^3, r^3, vr^2, v^2r, urp^2, |r|v, |v|v, -F_N \cos\delta
\end{aligned} \tag{4-2}$$

Forces and moments for the propeller X_P, Y_P, K_P, N_P and the rudder X_R, Y_R, K_R, N_R are expressed as

$$\begin{aligned}
&X_R = -(1-t_R)F_N \sin\delta, \\
&Y_R = -(1+a_H)F_N \cos\delta, \\
&K_R = (1+a_H)Z_{HR}F_N \cos\delta, \\
&N_R = -(X_R + a_H x_H)F_N \cos\delta, \\
&T(J_P) = \rho|n|nD_P^4K_T(J_P), \\
&K_T(J_P) = J_0 + J_1J_P + J_2J_P^2
\end{aligned} \tag{4-3}$$

$$\begin{aligned}
&T(J_p) = \rho|n|nD_P^4K_T(J_p) \\
&K_T(J_p) = J_0 + J_1J_p + J_2J_p^2
\end{aligned} \tag{4-4}$$

Where t_P, n, D_P, K_T, J_P are the thrust deduction fractions, propeller revolution per second, propeller diameter, the thrust coefficient and the advance ratio of propeller, respectively, J_0, J_1, J_2 are the hydrodynamic coefficients for the open water propeller characteristics. For the rudder force/moment, δ, x_R, z_{HR} denote the rudder angle, the x and z directional center of normal force acting on the rudder. Also t_R, a_H, x_H are used to describe the interaction of the hull and rudder. In the identification scheme, the parameter formulas $(1\text{-}t_R),(1+a_H),(1+a_H)z_{HR},(x_R+a_H x_H)$ are considered as coefficients to be estimated.

The mathematical model Eq. (4-1)-(4-4) provides a generalized family model, which could describe the nonlinear dynamic for ships of different types. In order to address the identification problem, one introduces several new variables Eq. (4-5)-(4-7) to rearrange the ship maneuvering mathematical model. To facilitate the expression and save space, the ellipsis points are used in Eq. (4-6), (4-7), which denote the terms and hydrodynamic derivatives corresponding to Eq. (2):

$$\begin{aligned}
&Z_u(V,t) := (m+m_x)\dot{u} - \left(m+m_y\right)vr,\\
&Z_v(V,t) := \left(m+m_y\right)\dot{v} + (m+m_x)ur,\\
&Z_p(V,t) := (I_x+J_x)\dot{p} - m_x l_x ur + mgGZ(\phi),\\
&Z_r(V,t) := (I_z+J_z)\dot{r}, V = [u,v,p,r]^{\mathrm{T}}
\end{aligned} \tag{4-5}$$

$$\begin{aligned}
&\varphi_u(V,t) = \left[u^2,u^3,...,uv\phi^2,T\left(J_p\right),-F_N\sin\delta\right]^{\mathrm{T}} \in R^{11\times1},\\
&\varphi_v(V,t) = \left[uv,ur,up,...,|r|r,-F_N\cos\delta\right]^{\mathrm{T}} \in R^{17\times1},\\
&\varphi_p(V,t) = \left[p,p^3,ur,...,|r|r,-F_N\cos\delta\right]^{\mathrm{T}} \in R^{17\times1},\\
&\varphi_r(V,t) = \varphi_v(V,t)
\end{aligned} \tag{4-6}$$

$$
\begin{aligned}
&\vartheta_u = \left[X_{uu}, X_{uuu}, \ldots, X_{uv\phi\phi}, C_P, C_{Ru} \right]^{\mathrm{T}}, \\
&\vartheta_v = \left[Y_{uv}, Y_{ur}, Y_{up}, \ldots, Y_{|r|r}, C_{Rv} \right]^{\mathrm{T}}, \\
&\vartheta_p = \left[K_p, K_{ppp}, K_{uv}, \ldots, K_{|r|r}, C_{Rp} \right]^{\mathrm{T}}, \\
&\vartheta_r = \left[N_{uv}, N_{ur}, N_{up}, \ldots, N_{|r|r}, C_{Rr} \right]^{\mathrm{T}}, \\
&C_P = 1 - t_P, C_{Ru} = 1 - t_R, C_{Rv} = 1 + a_H, \\
&C_{Rp} = -(1 + a_H) z_{HR}, C_{Rr} = x_R + a_H x_H
\end{aligned}
\tag{4-7}
$$

Based on Eq. (4-5)-(4-7), the ship manicuring mathematical model Eq. (4-1) is rearranged as a linearized regression model Eq. (4-8). In the following representation, one would omit the subscript $i = u, v, p, r$ in case that it does not affect reader's correct understanding of the identification problem:

$$
Z_i(V,t) = \varphi_i^{\mathrm{T}}(V,t)\vartheta_i + \omega_i(t), i = u, v, p, r \tag{4-8}
$$

In Eq. (4-8), $Z_i(V,t), \varphi_i(V,t)$ are the output scalar and the information vector that consist of the measured ship manicuring motion variables V at time $t, \omega_i(t)$ is the noise term.

4.2 Design of the Improved Nonlinear Innovation Algorithm

In order to show the superiority of the nonlinear innovation algorithm proposed in this note, the nonlinear innovation algorithm would be briefly presented for the comparison. Considering the linear regression model Eq. (4-8), the estimation $\hat{\vartheta}$ of the parameter vector ϑ is generated by the following Eq. (4-9):

$$
\begin{aligned}
&\hat{\vartheta}(t) = \hat{\vartheta}(t-1) + P(t)\Phi(l,t)E(l,t)\tanh(\omega e), \\
&E(l,t) = Z(l,t) - \Phi^{\mathrm{T}}(l,t)\hat{\vartheta}(t-1), \\
&P^{-1}(t) = P^{-1}(t-1) + \Phi(l,t)\Phi^{\mathrm{T}}(l,t)
\end{aligned}
\tag{4-9}
$$

In Eq. (4-10), n is determined by size of the information vector $\varphi(t)$:

$$
\begin{aligned}
&Z(l,t)=\left[Z(t),Z(t-1),...,Z(t-l+1)\right]^{\mathrm{T}}\in R^{l\times 1},\\
&\Phi(l,t)=\left[\varphi(t),\varphi(t-1),...,\varphi(t-l+1)\right]\in R^{n\times 1}
\end{aligned}
\tag{4-10}
$$

The nonlinear innovation algorithm can be presented in the form of Eq. (4-11).

$$
\begin{aligned}
&\hat{\vartheta}(t)=\hat{\vartheta}(t-1)+L(t)\left[Z(l,t)-\Phi^{\mathrm{T}}(l,t)\hat{\vartheta}(t-1)\right]\tanh\left(\omega e\right),\\
&L(t)=P(t-1)\Phi(l,t)\left[I_l+\Phi^{\mathrm{T}}(l,t)P(t-1)\Phi(l,t)\right]^{-1},\\
&P(t)=P(t-1)-L(t)\Phi^{\mathrm{T}}(l,t)P(t-1)
\end{aligned}
\tag{4-11}
$$

Next, the nonlinear innovation algorithm will be further introduced and the convergence will be proved.

4.2.1 The Improved Nonlinear Innovation Algorithm

In this part, one presents a novel nonlinear innovation algorithm with a high computational efficiency. In order to tackle the burden-some problem, the matrix inverse $\left[I_1+\Phi^{\mathrm{T}}(l,t)P(t-1)\Phi(l,t)\right]^{-1}$ is decomposed into l sub-innovation update steps. The so-called nonlinear innovation algorithm is presented as Eq. (4-12).

$$
\begin{cases}
\hat{\vartheta}_i(t)=\hat{\vartheta}_{i-1}(t)+L_i(t)\left[Z(t,i)-\varphi^T(t,i)\hat{\vartheta}_{i-1}(t)\right]\tanh(\omega \mathrm{e})\\
L_i(t)=P_{i-1}(t)\varphi(t,i)/\left[1+\varphi^T(t,i)P_{i-1}(t)\varphi(t,i)\right]\\
P_i(t)=P_{i-1}(t)-L_i(t)\varphi^T(t,i)P_{i-1}(t)\\
i=1,2,...,l\\
\hat{\vartheta}_0(t)=\hat{\vartheta}_l(t-1),P_0(t)=P_l(t-1),L_0(t)=L_l(t-1)
\end{cases}
\tag{4-12}
$$

Especially for ship maneuvering identification requiring large value algorithm or system feature extraction, nonlinear innovative algorithm is superior to other algorithms in computational efficiency. For industrial computing equipment, the computational burden is mainly caused by multiplication and addition of the operations included in the scheme. Therefore, the performance of the calculated load can be described by The Times of multiplication and addition.

4.2.2 Convergence of the Nonlinear Innovation Algorithm

The convergence is one important portion for the system identification scheme. For this purpose, as shown as Eq. (4-13)

$$\mathrm{E}[T(t)\big|F_{t-1}] \le T(t-1) + h(t) - g(t) \tag{4-13}$$

Base on the proposed the nonlinear innovation algorithm, we conclude the main result stated as follows.

Consider the 4 DOF ship maneuvering motion systems (1) with each DOF capable to be rearranged as the form of Eq. (4-8). The parameter estimation $\hat{\vartheta}_l(t)$ uniformly ultimately converges to be the true value ϑ by fuse of the nonlinear innovation algorithm.

Define the following error variables as Eq. (4-14):

$$\begin{aligned}
&\tilde{\vartheta}_i(t) = \hat{\vartheta}_l(t) - \vartheta, i = 1, 2, ...l \\
&\tilde{Z}(t,i) = \varphi^{\mathrm{T}}(t,i)\tilde{\vartheta}_{i-1}(t) = \varphi^{\mathrm{T}}(t,i)\hat{\vartheta}_{i-1}(t) - \varphi^{\mathrm{T}}(t,i)\vartheta \\
&\tilde{\vartheta}_i(t) = \tilde{\vartheta}_{i-1}(t) + P_i(t)\varphi(t,i)\left[\varphi^{\mathrm{T}}(t,i)\vartheta + \omega(t,i) - \varphi^{\mathrm{T}}(t,i)\hat{\vartheta}_{i-1}(t)\right]\tanh(\omega \mathrm{e}) \\
&= \tilde{\vartheta}_{i-1}(t) + P_i(t)\varphi(t,i)\left[-\tilde{Z}(t,i) + \omega(t,i)\right]\tanh(\omega \mathrm{e})
\end{aligned} \tag{4-14}$$

Thus, the error energy function $v(t)$ is constructed as Eq. (4-15).

$$
\begin{aligned}
&V_i(t) = \tilde{\vartheta}_i^{\mathrm{T}} P_i^{-1} \tilde{\vartheta}_i(t) \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{(4-15)}\\
&= \tilde{\vartheta}_{i-1}^{\mathrm{T}}(t) P_i^{-1}(t) \tilde{\vartheta}_{i-1}(t) + 2\tilde{\vartheta}_{i-1}^{\mathrm{T}}(t)\varphi(t,i)\left[-\tilde{Z}(t,i)+\omega(t,i)\right]\\
&+\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)\left[-\tilde{Z}(t,i)+\omega(t,i)\right]^2\\
&= \tilde{\vartheta}_{i-1}^{\mathrm{T}}(t)\left[P_{i-1}^{-1}(t)+\varphi(t,i)\varphi^{\mathrm{T}}(t,i)\right]\tilde{\vartheta}_{i-1}(t)\\
&+2\tilde{\vartheta}_{i-1}^{\mathrm{T}}(t)\varphi(t,i)\left[-\tilde{Z}(t,i)+\omega(t,i)\right]\\
&+\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)\left[\tilde{Z}^2(t,i)+\omega^2(t,i)-2\tilde{Z}(t,i)\omega(t,i)\right]\\
&= V_{i-1}(t)-\left[1-\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)\right]\tilde{Z}^2(t,i)+\varphi^{\mathrm{T}}(t,i)P_i(t)\\
&\times\varphi(t,i)\omega^2(t,i)+2\left[1-\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)\right]\tilde{Z}(t,i)\omega(t,i)\\
&\le V_{i-1}(t)+\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)\omega^2(t,i)+2\left[1-\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)\right]\tilde{Z}(t,i)\omega(t,i)
\end{aligned}
$$

Note, $1-\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)\ge 0$ is used in Eq. (4-15). Furthermore, sum together $V_i(t)$ for $i=1,2,\ldots,l$ and one obtains as Eq. (4-16) and Eq. (4-17).

$$
\begin{aligned}
&V_l(t)\le V_l(t-1)+\sum_{i=1}^{l}\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)\omega^2(t,i) \qquad \text{(4-16)}\\
&+2\sum_{i=1}^{l}\left[1-\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)\right]\tilde{Z}(t,i)\omega(t,i)
\end{aligned}
$$

$$
\begin{aligned}
&E[T(t)|F_{t-1}]\le\frac{V_l(t-1)}{\ln\left|P_l^{-1}(t)\right|\left[\ln\ln\left|P_l^{-1}(t)\right|\right]^c}\\
&+\sum_{i=1}^{l}\frac{\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)}{\ln\left|P_l^{-1}(t)\right|\left[\ln\ln\left|P_l^{-1}(t)\right|\right]^c}\sigma^2 \qquad \text{(4-17)}\\
&\le T(t-1)+\sum_{i=1}^{l}\frac{\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)}{\ln\left|P_i^{-1}(t)\right|\left[\ln\ln\left|P_i^{-1}(t)\right|\right]^c}\sigma^2
\end{aligned}
$$

In order to use the martingales convergence theorem, one should pay attention to the characteristic of the last term in Eq. (4-17). As shown as Eq. (4-18) and Eq. (4-19).

$$
\begin{aligned}
&\left|P_{i-1}^{-1}(t)\right|=\left|P_i^{-1}(t)\right|[1-\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)]\\
&\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)=\frac{\left|P_i^{-1}(t)\right|-\left|P_{i-1}^{-1}(t)\right|}{\left|P_i^{-1}(t)\right|} \qquad \text{(4-18)}
\end{aligned}
$$

$$\sum_{t=1}^{\infty}\sum_{i=1}^{l}\frac{\varphi^{\mathrm{T}}(t,i)P_i(t)\varphi(t,i)}{\ln\left|P_i^{-1}(t)\right|\left[\ln\ln\left|P_i^{-1}(t)\right|\right]^c} \tag{4-19}$$

$$=\sum_{t=1}^{\infty}\sum_{i=1}^{l}\frac{\left|P_i^{-1}(t)\right|-\left|P_{i-1}^{-1}(t)\right|}{\left|P_i^{-1}(t)\right|\ln\left|P_i^{-1}(t)\right|\left[\ln\ln\left|P_i^{-1}(t)\right|\right]^c}$$

$$=\sum_{t=1}^{\infty}\int_{\left|P_l^{-1}(t-1)\right|}^{\left|P_l^{-1}(t)\right|}\frac{dx}{x\ln x[\ln\ln x]^c}=\frac{-1}{c-1}\frac{1}{[\ln\ln x]^{c-1}}\Bigg|_{\left|P_l^{-1}(0)\right|}^{\left|P_l^{-1}(\infty)\right|}$$

$$=\frac{1}{c-1}\left[\frac{1}{\left(\ln\ln\left|P_l^{-1}(0)\right|\right)^{c-1}}-\frac{1}{\left(\ln\ln\left|P_l^{-1}(\infty)\right|\right)^{c-1}}\right]<\infty$$

There exists a finite random variable C_{T0} such that Eq. (4-20).

$$\begin{aligned}V_l(t)&\le C_{T0}\left[\ln\left|P_l^{-1}(t)\right|\left(\ln\ln\left|P_l^{-1}(t)\right|\right)^c\right]\\&\le C_{T0}\left\{\ln\left[tr\left(P_l^{-1}(t)\right)\right]^n\left[\ln\ln\left[tr\left(P_l^{-1}(t)\right)\right]^n\right]^c\right\}\end{aligned} \tag{4-20}$$

Since there exists $tr\left[p_l^{-1}(t)\right]\le nc_2t^{c_0+1}+n/p_0,\lambda_{\min}\left[p_l^{-1}(t)\right]\ge c_1t$ derived from the generalized persistent excitation condition (4-19), (4-21) is obtained.

$$\left\|\hat{\vartheta}(t)-\vartheta\right\|^2=O\left\{\frac{n\ln n\left(nc_2t^{c_0+1}+\dfrac{n}{p_0}\right)\left[\ln\left(n\ln\left(nc_2t^{c_0+1}+\dfrac{n}{p_0}\right)\right)\right]^c}{c_1t}\right\} \tag{4-21}$$

4.3 The Nonlinear Innovation Identification for 4 DOF Ship Maneuvering Mathematical Model

The hydrodynamic model of derivative substitution Eq. (4-1) can predict. Combined with equation of motion of the ship, Identification of ship motion is obtained finally.

The 4 DOF modeling is used as a simulation model. It is mainly used to test the effectiveness of the control strategies of fin stabilizer, rudder stabilizer or water tank stabilizer. The ship handling in waves is usually accompanied by nonlinear rolling motion with large amplitude.Therefore, considering the influence of rolling motion, the 4-DOF mathematical model of ship maneuvering is derived. By comparing the predicted results (including surge velocity, roll velocity, yaw rate, roll rate, roll Angle and rudder Angle) with the full-size test data, the validity of the recognition algorithm is verified.

4.4 Identification Experiments with the Full-Scale trial Data

The structure and parameters of the ship maneuvering equation should be carried out in strict accordance with the detailed requirements of the equation during the experiment, including the disturbance model which produces wind and the wave generated by irregular wind. First, the sea conditions are set as level 2 zigzag maneuver test $\left(\delta = 10^{\circ}\text{-}20^{\circ}\right)$ to provide data for identification.And the other is for the zigzag maneuvering test $\left(\delta = 20^{\circ}\text{-}20^{\circ}\right)$.

The main data and dimensions of “Yukun” ship are given in Table 4-1.

TABLE 4-1 The main data and dimensions of “Yukun” ship

Elements		Values
Length between perpendiculars	$L(\mathrm{m})$	105
Breadth(molded)	$B(\mathrm{m})$	18
Mean draught	$D(\mathrm{m})$	5.4
Block coefficient	C_b	0.5595
Rudder area	$A_R(\mathrm{m2})$	11.8

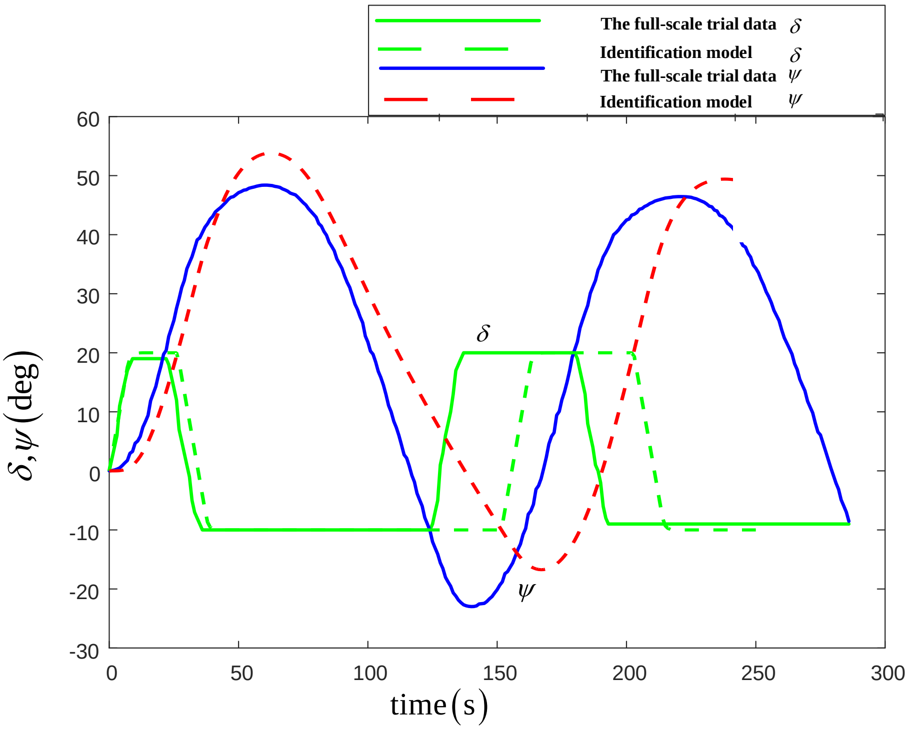

Fig.4.1 Comparison results with the identification model zigzag trial $\delta = 10^{\circ}$-20°

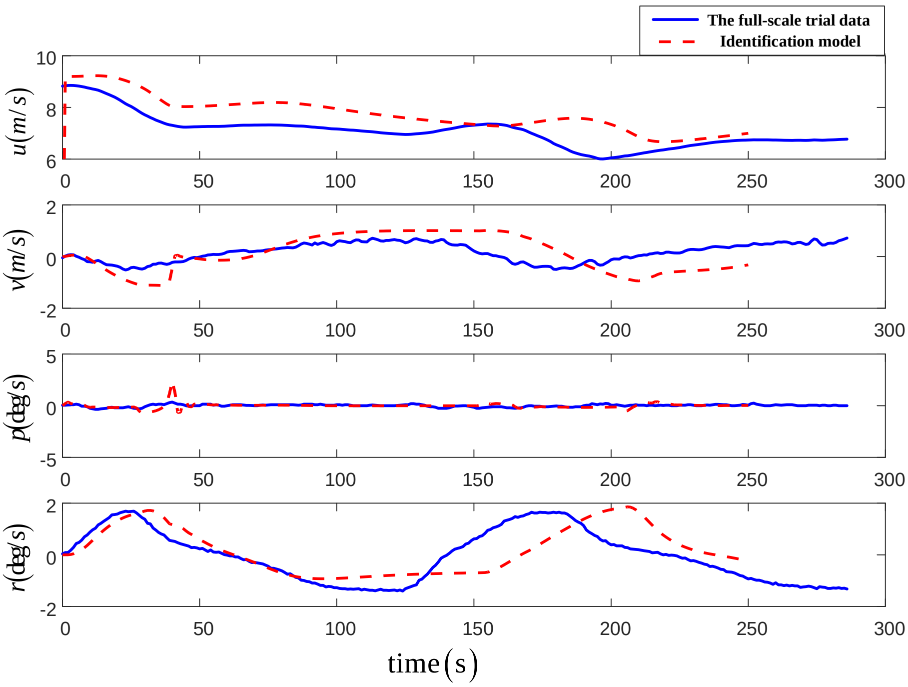

Fig.4.2 Comparison with the full-scale zigzag trial $\delta = 10^{\circ}$-20°

Using the identification result; the predicted motions are compared with the nonlinear innovation algorithm in Fig. 4-1 and Fig. 4-2. The simulation trials include zigzag tests with $(\delta = 10^{\circ}\text{-}20^{\circ})$ and $(\delta = 20^{\circ}\text{-}20^{\circ})$.

In this section, we consider a comprehensive experiment to verify the proposed recognition algorithm.

All tests were carried out under moderate sea conditions (about grade 3) and at sufficient depth. In this article, we will consider three tests for manageable space. By identifying the test data, the structure and parameters of the zigzag test $(\delta = 10^{\circ}\text{-}20^{\circ})$ ship maneuvering mathematical model are determined. Figure 4.3 and Figure 4.4 compare the recognition result with the full-size zigzag $(\delta = 20^{\circ}\text{-}20^{\circ})$, illustrating the performance of the algorithm in practical application.

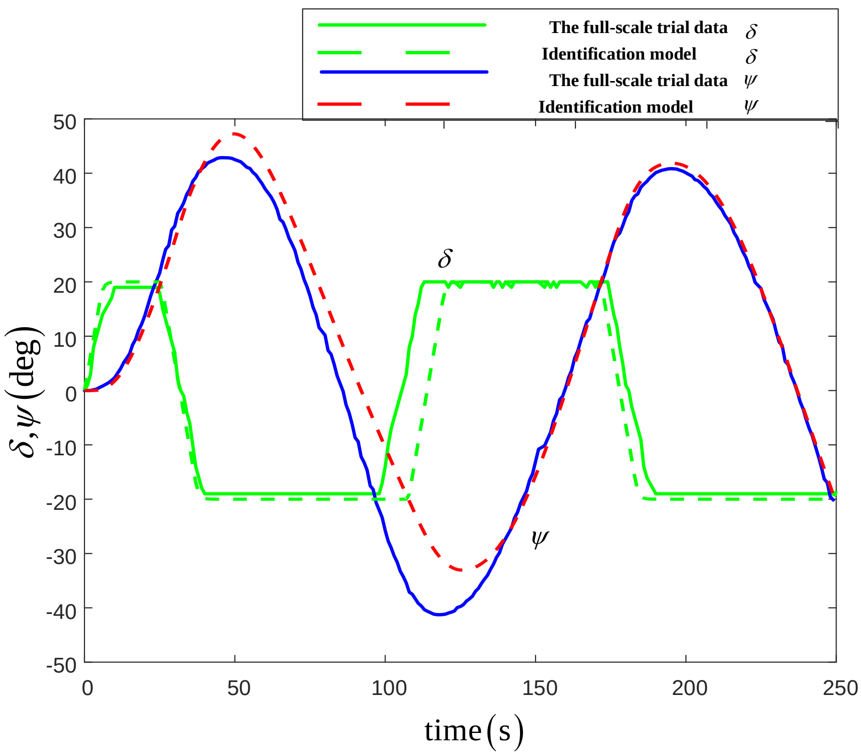

Fig.4.3 Comparison results with the identification model zigzag trial $\delta = 20^{\circ}\text{-}20^{\circ}$

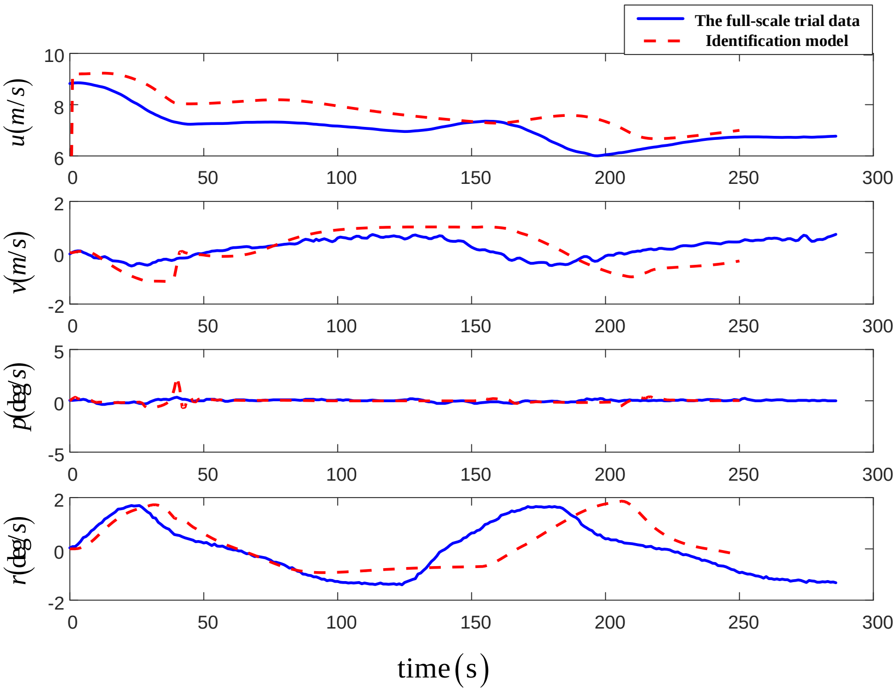

Fig.4.4 Comparison with the full-scale zigzag trial $\delta = 20^{\circ}\text{-}20^{\circ}$

The relevant variables listed in Eq. (4-22) need to be estimated by fusing of the physical measurement.

$$\begin{gathered} m^{'} = 0.009865, m_x^{'} = 0.000384, m_y^{'} = 0.007988 \\ I_z^{'} = 0.000617, J_z^{'} = 0.000469, I_x^{'} + J_x^{'} = 0.000004264 \end{gathered} \tag{4-22}$$

Utilize the “Yukun” ship to obtain zigzag experiment data. Through comparison parameters modeling get identification results. The main data are given in Table 4-2.

TABLE 4-2 The identification result for “Yukun” ship

parameters identification for the hydrodynamic force		
$X'_{uu}=0.0004$	$Y'_{urpp}=0.1464$	$C'_{Rp}=-0.0882$
$X'_{uuu}=-0.0003$	$Y'_{\lvert v\rvert v}=-0.1068$	$N'_{uv}=0.0070$
$X'_{vv}=0.3262$	$Y'_{\lvert r\rvert v}=-0.0363$	$N'_{up}=-0.0007$
$X'_{rr}=-0.0024$	$Y'_{\lvert v\rvert r}=0.0334$	$N'_{u\phi}=-0.0016$
$X'_{vr}=-0.0111$	$Y'_{\lvert r\rvert r}=0.0274$	$N'_{uur}=-0.0004$
$X'_{uvv}=-0.3364$	$C'_{Rv}=0.9274$	$N'_{uuv}=-0.0099$
$X'_{uv\phi\phi}=0.2964$	$K'_{P}=-1.66E-5$	$N'_{vvv}=-0.0419$
$C'_{p}=1.3940$	$K'_{uv}=-0.0025$	$N'_{rrr}=0.0001$
$C'_{Ru}=0.5816$	$K'_{ur}=-0.0001$	$N'_{vrr}=-0.0132$
$Y'_{uv}=0.3609$	$K'_{uuv}=0.0024$	$N'_{vvr}=0.0209$
$Y'_{up}=0.0098$	$K'_{vvv}=0.0266$	$N'_{urpp}=0.0101$
$Y'_{uuv}=-0.3548$	$K'_{vrr}=0.0072$	$N'_{\lvert v\rvert v}=0.00210$
$Y'_{rrr}=-0.0202$	$K'_{vvr}=0.0225$	$N'_{\lvert r\rvert v}=0.0126$
$Y'_{vrr}=0.1264$	$K'_{uv\phi\phi}=0.0837$	$C'_{Rr}=-0.5867$
$Y'_{vvr}=0.1460$	$K'_{ur\phi\phi}=0.0109$	
$Y'_{uvpp}=-0.2518$	$K'_{\lvert v\rvert v}=0.0006$	

Comparing with the simulation examples, the nonlinear innovation identification for ship maneuvering modeling via the full-scale trial data is more accurate. It's worth noting that there are three ways things can go wrong. (1) Some variables needed in the identification scheme cannot be directly measured. For example, acceleration and angular acceleration are derived from the differential relationship, and angular velocity is the same. Gradient is a useful Matlab function. (2) In the actual identification, the mechanism-based modeling component will introduce the uncertainty in the ship maneuvering model.While the identification process can compensate for these uncertainties, it cannot fully resolve them. (3) Ocean interference is uncontrollable and has complex dynamic characteristics. In particular, the impact of possible currents on identification modeling is very serious.

4.5 Chapter Summary

This chapter introduces the research progress of nonlinear innovation identification of ship maneuvering based on the real ship test data. The main advantage of the scheme is that it has high computational efficiency and does not need to know the structure of the ship maneuvering model. As far as I know, few existing studies consider the choice of model structure, which is meaningful and inevitable in practical ship engineering. The practicability and effectiveness of the scheme are proved by the application experiment. In addition, the scheme can be extended to other online identification or prediction systems in the field of ocean engineering.

CHAPTER 5: SUMMARY and CONCLUSIONS

By references study on system identification was carried out and suitable identification methods were chosen to verify the suggested maneuver's convergence properties. Based on the related theory the nonlinear innovation identification for ship maneuvering modeling via the full-scale trial data has been developed. The identification results indicates it has better convergence properties than the others

Based on the nonlinear innovation identification for ship maneuvering modeling via the full-scale trial data algorithm, the main contributions of this paper can be summarized as follows：

(1) In this paper, a novel nonlinear innovation identification algorithm is proposed for the ship mathematical model. The nonlinear hyperbolic tangent function is used to deal with the identification of new interest. In this paper, the main theories of the stochastic gradient algorithm and nonlinear feedback hyperbolic tangent function and full-scale trial data are combined. The algorithm for identifying the parameters of the nonlinear innovation identification for ship maneuvering modeling via the full-scale trial data is further proposed. The computational complexity problems are lower than that of the other existing algorithms. The algorithm presented in this paper requires the calculation is simple and the accuracy is greatly improved. The algorithm can be used in a variety of cases.

(2) The effectiveness of the proposed algorithm is verified by a series of comprehensive experimental data. That is convictive and meaningful for applying

the proposed algorithm in the practical engineering.

Although the maneuver method presented in this paper has achieved good results in the simulation process, there is still an opportunity for further improvement in efficiency and parameter convergence. In the future, hyperbolic tangent function can be combined with other algorithms, such as multi-innovation identification, least square method, etc. Further optimize the data. Parameters can also be added to make the conclusion more accurate. More experiments were carried out with real ship data.

REFERENCES

[1] Fossen TI. Guidance and control of ocean vehicles. New York: Wiley; 1998.

[2] Fossen TI. Handbook of marine craft hydrodynamics and motion control. New York: Wiley; 2011.

[3] Zhang G, Zhang X. Concise robust adaptive path-following control of underactuated ships using DSC and MLP. IEEE J Ocean Eng 2013; 39(4):685–94.

[4] Jia X, Zhang X. Intelligent control of ship motion and H∞ robust control [M]. Dalian: Dalian Maritime University Press. 2002: 15-33.

[5] Wang X, Zou Z & Xu, F. (2013). Modeling of Ship Maneuvering Motion in 4 Degrees of Freedom Based on Support Vector Machines. ASME 2013 32nd International Conference on Ocean, Offshore and Arctic Engineering.

[6] Norrbin NH. Theory and observation on the use of a mathematical model for ship manoeuvring in deep and confined waters. Report No.68. Sweden: SSPA; 1971.

[7] Guoqing Z, Xianku Z, Wei G . Concise robust adaptive path-following control for underactuated ships [J]. journal of harbin engineering university, 2014.

[8] The Maritime Safety Administration PRC, The Manila Amendments to the International Convention on Standards of Training, Certification and Watchkeeping for Seafarers. Dalian, China: Dalian Maritime University Press; 2010.

[9] Zhang X, Zhang G. Researches on the Williamson turn for very large carriers. Naval Eng J 2013; 125(4):113–20.

[10] Fossen TI. Handbook of marine craft hydrodynamics and motion control. New York: Wiley; 2011.

[11] Ogawa A, Kasai H. On the mathematical model of maneuvering motion of ships. Int Shipbuild Prog 1978; 25(292):306–19.

[12] Zhang X, Zou Z. Identification of Abkowitz model for ship maneuvering motion using ϵ-support vector regression. J Hydrodyn 2011; 23(3):353–60.

[13] Perera PL, Oliveira P. Dynamic parameter estimation of a nonlinear vessel steering model for ocean navigation. In: Proceedings of the 30th international conference on ocean, offshore and arctic engineering, Rotterdam, The Netherlands, 2011.

[14] Rajesh G, Bhattacharyya SK. System identification for nonlinear maneuvering of large tankers using artificial neural network. Appl Ocean Res 2008; 30:256–63.

[15] Herrero ER, González FJV. Two-step identification of nonlinear manoeuvring models of marine vessels. Ocean Eng 2012;53:72–83.

[16] Abkowitz MA. Lectures on ship hydrodynamics steering and manoeuvrability. Report Hy-5. Denmark: Hydro- and Aerodynamics Laboratory; 1964.

[17] Liu Y, Ding F, Shi Y. An efficient hierarchical identification method for general dual-rate sampled-data systems. Automatica 2014;50:962–70.

[18] Jia X, Yang Y. Ship motion mathematical model. Dalian, China: Dalian Maritime University Press; 1999.

[19] Araki M, Hosseini HS, Sanada Y, Tanimoto K, Umeda N. Estimating maneuvering coefficients using system identification methods with experimental, system-based, and cfd free-running trial data. Ocean Eng 2012;51:63–84.

[20] Ding F, Chen T. Hierarchical least squares identification methods for multivariable systems. IEEE Trans Autom Control 2005;50(3):397–401.

[21] Perera LP & Guedes Soares C. (2013). Lyapunov and hurwitz based controls for input–output linearisation applied to nonlinear vessel steering. Ocean Engineering, 66(Complete), 58-68.

[22] Yoon HK, Rhee KP. Identification of hydrodynamic coefficients in ship maneuvering equations of motion by estimation-before-modeling technique. Ocean Eng 2003; 30:2379–404.

[23] Perez T, Fossen T. Time-domain models of marine surface vessels based on seakeeping computations. In: the 7th IFAC conference on manoeuvring and control of marine vessels MCMC, Portugal, 2006.

[24] Ross A. Nonlinear manoeuvring models for ships: a Lagrangian approach[Ph.D. thesis]. Norway: Norwegian University of Science and Technology; 2008

[25] Herrero E. R. and Francisco J. G. Two-step identification of nonlinear manoeuvring models of Marine vessels. Ocean Engineering, 2012, 53(10): 72-82.

[26] Motoki Araki, Hamid Sadat-Hosseini, Yugo Sanada, et al. Estimating maneuvering coefficients using system identification methods with experimental, system-based, and CFD free-running trial data. Ocean Engineering, 2012, 51(9): 63-84.

[27] Ding Feng. Coupled-least-squares identification for multivariable systems. IET Control Theory and Application, 2013, 7(1): 68-79.

[28] Liu Yanjun and Ding Feng. Convergence properties of the least squares estimation algorithm for multivariable systems. Applied Mathematical Modelling, 2013, 37(2): 476-483.

[29] Moustafa K A F. Identification of stochastic time-varying systems. IEEE Proceeding, Part D:Control Theory and Applications, 1983, 130(4): 137-142.

[30] Ding F, Liu X P, Liu G. Multi-innovation least squares identification for system modeling. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 2010, 40(3): 767-778.

[31] Ding F, Chen T. Performance analysis of multi-innovation methods. Automatica, 2007, 43(1): 1-14.

[32] Ding F. Several multi-innovation identification methods. Digital Signal Processing, 2010, 20(4): 1027-1039.

[33] Ding F, Xiao Deyun, Ding Tao. Multi-innovation stochastic gradient identification method. Control theory and application，2003, 20(6): 870-874.

[34] Han H Q, Xie L, Ding F, et al. Hierarchical least squares based iterative identification for multivariable systems with moving average noises. Mathematical and Computer Modelling, 2010, 51(9-10): 1213-1220.

[35] Zhang Z N, Ding F, Liu X G. Hierarchical gradient based iterative parameter estimation algorithm for multivariable output error moving average systems. Computer& Mathematics with Applications, 2011, 61(3):672-682.

[36] Li Dianpu. Ship Movement and Modeling [M]. National Defense Industry Press, 2008.

[37] Bolzern P, Colaneri P and De Nicolao G .Optimal robust filtering with time-varying parameter uncertainty .Int. J. Control, 1996, 63(3):557 -576

[38] Jia Xinle, Yang Yansheng. Mathematical model of ship motion -- Mechanism modeling and identification Modeling [M]. Dalian: Dalian Maritime University Press, 1999.

[39] Luo Weilin. Research on ship Maneuvering Motion Modeling based on Support Vector Machine [D]. Shanghai Jiao Tong University, 2009.

[40] Yuan Yuan, Cheng Zhijun. Six degrees of freedom nonlinear coupling equations of ship motion in waves [J]. Journal of Shanghai Jiao Tong University, 2001(04): 57-59.

[41] Tu Quanzhao. Research on control System of physical Simulation Platform of 2-DOF Parallel Mechanism [D]. Xiamen University, 2013.

[42] Liu Chuan. Robust Neural network control for responsive Nonlinear ship Model [D]. Dalian Maritime University, 2004.

[43] BAI Weiwei, REN Junsheng. Multi-Innovation Gradient Iterative Locally Weighted Learning Identification for A Nonlinear Ship Maneuvering System. China Ocean Engineering, 2018,32(3):288-30.