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Dynamic model identification of unmanned surface vehicles using deep learning network

Joohyun Woo[a], Jongyoung Park[a], Chanwoo Yu[b], Nakwan Kim[c,*]

[a] Department of Naval Architecture and Ocean Engineering, Seoul National University, 1, Gwanak-ro, Gwanak-gu, Seoul, 08826, South Korea
[b] The 6th R&D institute – 3rd Directorate, Agency for Defense Development, Dong-eup, Uichang-gu, Jinhae, Changwon, 51698, South Korea
[c] Department of Naval Architecture and Ocean Engineering, Research Institute of Marine Systems Engineering, Seoul National University, 1, Gwanak-ro, Gwanak-gu, Seoul, 08826, South Korea

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ABSTRACT

In this paper, a deep learning–based dynamic model identification method is proposed. The proposed method is designed to capture higher-order dynamic behaviors that result from the coupling of hydrodynamics and actuator dynamics. By adopting recent advancements in deep learning, our model addresses problems such as the regression problem in machine learning. Among various deep learning algorithms, long short-term memory (LSTM)–based recurrent neural network was used to deal with the hidden latent state of the USV dynamic model. The model validation was performed using free running test data of a USV. Analysis result shows that proposed model reduces surge speed prediction error by 76.9%, yaw rate prediction error by 60.7% and sway velocity prediction error by 27.9% over the conventional linear dynamic model.

1. Introduction

Over the last few decades, research on unmanned surface vehicles (USVs) has attracted considerable attention. USVs have significant advantages over conventional manned systems as they can operate in dangerous and extreme environments. Concerning commercial applications, USVs can be adopted to conduct missions such as environmental monitoring [1], resource exploration [2] or shipping [3]. For military applications, USVs are expected to perform missions such as mine countermeasures [4], anti-submarine warfare [5] and reconnaissance [6]. Although the different types of USVs have various purpose and missions, it is common that they need a robust and effective maneuvering controller for successful operation during their missions.

There have been a number of studies on the control of an USVs or ship such as [7–11]. Regarding the controller design for an unmanned system, one of the most important aspects is to understand the vehicle's dynamic behavior. Designing the controller based on its dynamics can increase both dynamic performance and stability of the vehicle. In practice, controllers of unmanned vehicles are often constructed based on identified dynamics as stated in Refs. [12,13], and [14]. To build the system's dynamic model, a method called system identification is frequently used. The system identification method finds a model that best describes input-output data relationships. In general, parameters in the system are identified through the minimization of the error between predicted output states and target output states for a given input.

Several applications of system identification methods in both time and frequency domain have been published (mostly about linear time invariant system). In the time domain approach, various system estimation methods such as maximum likelihood [15], Kalman Filter [16,17], recursive least squares [18] and particle swarm optimization (PSO) [13] have been suggested. In addition, a frequency domain approach has been suggested by Selvam et al [19].

Neural network and deep learning are also well known tools that are used for vehicle dynamic system identification. Rajesh et al [20]. proposed the black box approach, a method that uses a feed forward neural network to map the dynamical relationship between the state variable (input variable), the hydrodynamic force and moment data (output variable). Ghosh et al [21]. proposed the "delta method," which uses a feed forward neural network similar to the one adopted in Ref. [20], but in this case, the neural network is used to extract the first-order force and the moment coefficient. By making a small variation in one of the input variables, its effect on the control force or moment was calculated. Punjani et al [22]. used a rectified linear unit (RELU) based on deep neural networks, for identifying small scale helicopters. In this work, multi-layered feedforward RELU network estimated the acceleration component corresponding to the input states. Similar to aerial vehicles, there are substantial works which use neural network as a tool

* Corresponding author.
E-mail address: nwkim@snu.ac.kr (N. Kim).

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for modeling of a surface vehicle. This work includes [23,24] and [25]. Although such neural network–based approaches showed effective dynamics approximation capability, the methods present some limitations. Since the methods use a feed forward neural network architecture, the models cannot grasp sequential information contained in input-output history data. For example, yaw rates at time steps t and $t-1$ are strongly coupled and correlated. However, the feed forward network considers the data as independent data.

In this context, in order to grasp sequential information, a recurrent neural network (RNN)–based model was proposed for the approximation of USV dynamics. In this paper, a RNN model for predicting USV dynamics is proposed. Due to the feed-back structure of the RNN, the model has an ability to "memorize" past data pattern and able to capture the sequential information in test data. Since dynamic state at time steps t is strongly coupled to that of at time step $t-1$, such sequential information can help the model predicting its dynamics more accurately. This is one of the main contributions of this paper. Although previous works in system identification [23–25] used neural network to model dynamics, they used conventional feed-forward structure neural network. Feedback structure of RNN will increase its effectiveness by nature of ship dynamics. In addition, this paper contains a structured procedure for constructing and analyzing the dynamic modeling of a USV based on deep learning. For collecting the data set for deep learning, a free running of a USV test was conducted on a USV. For identifying the ship dynamic model, several maneuvering tests such as a turning test, zigzag test, and 3-2-1-1 input test have been performed. Using experimental data, simplified maneuvering parameters of the USV were extracted and a RNN model was used to describe the remaining terms of the USV dynamics that the simplified model cannot describe.

The remainder of this paper is organized into four main sections. In Section 2, a review of a non-linear dynamic model and a number of simplified models for USV maneuvering are presented. In Section 3, background and detailed information of RNN-based model is described. Section 4 contains the procedures for the system identification and a detailed description of the USV water test. The system identification results will be presented here, and the performance of the suggested method will be compared with the performance of other methods. In Section 5, the main conclusions and a further discussion are presented.

2. USV dynamic system

According to previous research related to USV system identification, researchers tend to choose simplified linear dynamic models such as Nomoto's model [12,13] or first-order linearized steering models [14] as a target model, because these models can be easily identified using collected free running test data. Although identified linear models are often directly used to design the controller of the USV (as in [12] and [13]), remaining non-linear parts of the dynamics of USV are important as well. In order to predict dynamic states more accurately, an additional model that considers the nonlinear parts of the dynamics has been constructed.

For this reason, the proposed dynamic model is composed of two parts. The first part is based on a simplified dynamic model of a USV. For this part, the model is identified through the same approach that Sonnenburg et al [12]. suggested. The other part of the dynamic model concerns the non-linear terms of the USV dynamic model. These terms are highly coupled and complex, due to convoluted hydrodynamics and actuator dynamics. Therefore, we decided to use a data-driven approach rather than a physics-based approach for developing this model. With high approximation and pattern extraction capability of deep neural networks, non-linear parts of the dynamic model can be extracted.

2.1. WAM-V USV

The wave adaptive modular vessel (WAM-V) is a catamaran-shaped boat platform produced by Marine Advanced Research, Inc. WAM-V platform has two inflatable pontoons, a deck, and two supporting arches [14]. One of the main characteristics of the platform is that it has two suspensions between the pontoons and vehicle's deck, which can dissipate the motion induced by waves [26,27]. The length of the WAM-V platform is 4.88 m (16 ft) and that of the beam overall is 2.44 m (8 ft). The vehicle is equipped with two electric propulsion modules (Minn Kota RT EM160) at the stern side of each hull. The maximum speed of the vehicle is approximately 4.5 knots. Because there is no rudder or gimbaled thruster (e.g., an outboard motor) as in Refs [12]. and [13], our vehicle can generate steering motion by creating RPM (revolutions per minute) differences in the two main thrusters. Because of this characteristic, there is no direct sway force acting on the vehicle, produced by the main thrusters.

Various sensors are attached to the vehicle as well. For navigation purposes, two dual frequency Novatel GPS sensors are installed to collect position, velocity and heading angle information. An AHRS sensor is mounted in the center of the deck, which provides attitude information as well as turn rate information. National Instrument cRIO-9024 model is used to collect navigational sensor data and to calculate the control command of the USV. In addition, sensor data and control input histories are logged in the computer during maneuvering tests.

2.2. USV dynamic model

In order to depict the motion of the WAM-V USV, we have derived an equation of motion for rigid hull with a differential thruster. For simplicity, we consider only three degrees of freedom (surge, sway and yaw) in the horizontal planar motion. The notation developed by Fossen was adopted [28,29]. Fig.1 shows a schematic description of the USV and its coordinate frame, where x_i and y_i represent, respectively, the north and east directions of the vehicle in the inertial frame while u, v and V represent the surge, sway and total speed of the vehicle in a body fixed frame, respectively. The heading angle of the vehicle is represented as ψ, while the side slip angle and the course angle are defined by χ and β, respectively. The side slip angle can be calculated by the expression $\beta = \arcsin(\frac{v}{V})$ and the course angle can be defined using the heading angle and the side slip angle as $\chi = \psi + \beta$.

The kinematic model of the USV can be expressed by the following equation.

$$\dot{\boldsymbol{\eta}} = \boldsymbol{R}(\boldsymbol{\eta})\boldsymbol{\nu} \tag{1}$$

where $\boldsymbol{\nu}$ is the velocity vector, $\boldsymbol{\eta}$ is the position vector and $\boldsymbol{R}(\boldsymbol{\eta})$ is a rotation matrix that maps vectors from a body fixed frame to an inertial frame.

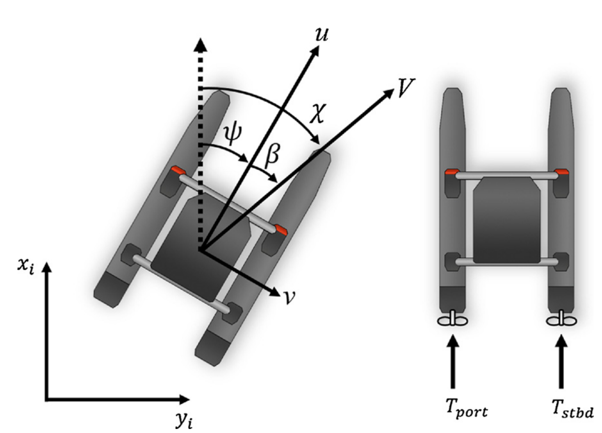

Fig. 1. Schematic description of the diffrential thrust of the USV.

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