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Modeling and Designing Direct Inverse Control Using Back-propagation Neural Network for Skid Steering Boat Model

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Abstract – This paper discusses about designing a direct inverse control based back-propagation neural network for a skid steer model boat. The boat is modeled into a MIMO system, with port side and starboard propeller as input, while yaw, surge velocity and sway velocity as output. The inverse plant model was created for the controller and tested with an identification model of the plant. The simulation result is the plant output follows the desired output value that is fed to the inverse controller with the normalized mean sum square error for yaw 0.1203, surge velocity 0.4459 and sway velocity 0.1723.

Keywords: boat model, direct inverse control, back-propagation neural network

I. Introduction

In marine survey sector, surveyor found several areas that can't be reached by a survey vessel due to a shallow and narrow areas. Therefore, engineers try to design a small boats (mini boats) that equipped with several survey instruments which can be operated in that areas. One of the small boat design is a small boat (mini boats) with a double propeller system (twin propellers), equipped with batteries and able to operate both autonomous and manually using the remote control. This type of mini boat is classified into an unmanned water surface vehicle.

The boat model requires a control system to be able to operate properly. The control system will maintain the stability of the boat model in the desired degree of freedom-DOF. There are some difficulties of controlling an autonomous unmanned surface vehicle because it runs on the waters that affected by nonlinear factors such as water currents, waves, and winds [1].

Because of the non-linear properties, couplings, and gyro effects on the boat model, it makes its own challenge in making an accurate models. While the disturbance that ussually occurs on the ship model is the wind or the surface water currents. This problem makes the design of the boat control become more difficult. Proportional Integral Derivative (PID) control system is used for angular stabilization and speed of the boat model. With PID, the boat model is assumed to be a linear system. The superiority of PID control is a simple and robust control structure for system characters that are linear.

To minimize the use of various assumptions in mathematical models, control systems are modeled using artificial neural networks that have been widely studied [2]. Some examples of the use of artificial neural networks for unmanned surface vehicle control systems include back-propagation control [3], [4], back-stepping control [5], self-organizing maps control [6], radial-base function control [7]. But from these examples, the neural network-based control system that is the simplest structure and uses a direct learning system is back-propagation neural networks (BPNN).

back-propagation is one of the NN learning methods that is classified as supervised learning. It means that the input and output data pairs are needed to train the NN until the appropriate weight is obtained. This algorithm has a simple training process, if the output gives the wrong result, then the weight is corrected based on the error so that the error is getting smaller [2]. Generally, the back-propagation structure of NN consists of three layers, namely the input layer, hidden layer, and output layer. The number of neurons in the input layer states the number of input dimensions. The number of neurons in the hidden layer can be chosen as needed, while the number of neurons in the exit layer, according to the number of output dimensions. Each neuron in the input layer has a special activation function, namely 1 (this neuron only functions to transmit input data), while the neurons in the hidden layer and output layer have certain activation functions. The input layer and hidden layer are associated with weights, while between the hidden layers and the output layer are connected by weights. Besides weight, there is also bias, and which is a special weight for neurons that have input 1.

In this study, the use of BPNN-controllers under the direct inverse control (DIC) scheme to control the skid steer boat model will be evaluated.

II. Hardware Design For Boat Model

This study use a boat model with a skid steering drive system or uses two independent propellers on the port side and starboard in the astern. For a straight motion, the two propellers rotate at the same speed. While to make a turn

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left, the starboard propeller rotates faster than the port side propeller and vice versa for turn right.

The controller using Pixhawk autopilot which is installed the Ardurover firmware. This autopilot controller use 32-bit STM32F427 Cortex M4 core with FPU, 168 MHz/256 KB RAM/2 MB Flash and The 32-bit STM32F103 failsafe co-processor. Also equipped with ST Micro L3GD20 3-axis 16-bit gyroscope, ST Micro LSM303D 3-axis 14-bit accelerometer/magnetometer, Invensense MPU 6000 3-axis accelerometer/gyroscope, MEAS MS5611 barometer sensor, GPS and magnetic compass sensor.

The output from autopilot is a PWM signal that is forwarded to the electronic speed controller (ESC) to drive the motor according to the desired speed rotation. The boat can be operated manually using the remote control or automatically following the programmed lane. The boat model construction and whole electronic schematic shown on Fig. 1 and Fig. 2.

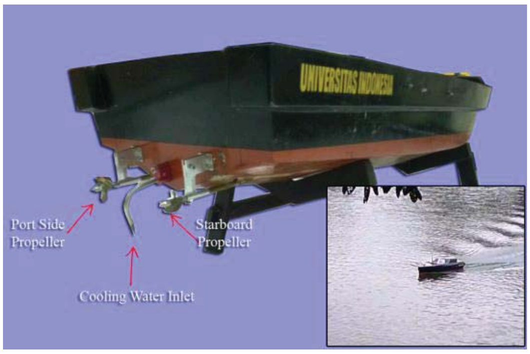

Fig. 1 Boat Model Construction

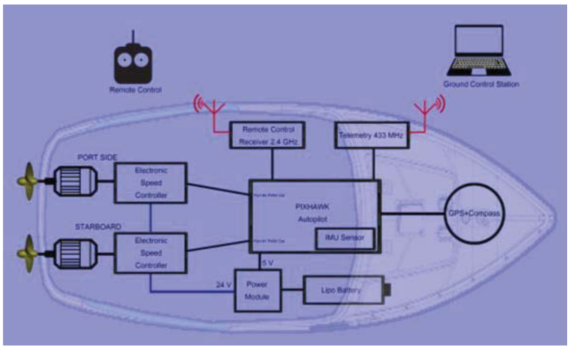

Fig. 2 Electrical Schematic

TABLE I. BOAT MODEL TECHNICAL SPECIFICATIONS

PHYSICAL	
Boat length	150 cm
Boat width	52 cm
Boat height	37 cm
Weight of base boat	7.25 kgs
Hull material	Fiberglass(glass-fiber reinforced plastic)
Propulsion	Dual brushless DC motor 1200Kv

ELECTRICAL	
Navigation remote	FUTABA Remote Control PCM FP-T8SGA-P
Navigation remote frequency	2.4 GHz
Data telemetry	3D Robotic Telemetry 433 Mhz 500mW
Controller	Pixhawk, Processor 32-bit ARM Cortex M4 core with FPU
GPS+Compass	U-blox M8 GNSS modules, 72 channel receiver, Velocity accuracy 0.05m/s, Heading accuracy 0.3deg.
ESC	Seaking 180A
IMU Sensor	MPU6000 and ST Micro 14-bit Accelerometer/compass

III. DATA ACQUISITION

To get varied data, the boat is run with a winding track. When sailing, boat data can be observed directly through a ground control station that communicates via radio telemetry. The controller will store all cruise data that will be used to make identification and inverse plant modeling. The log data is downloaded using ground control station software.

The movement of the boat can be modeled with the MIMO system, where the input are the port side and starboard propeller rotational speed. The propeller rotational speed data is represented by the PWM value that is fed to ESC. While the output are surge velocity, sway velocity, and yaw [8]. The movement of the boat model is affected by the thrust forces of the port side and starboard propeller which are generated by BLDC motors. They rotate independently, same or difference speed of rotation. Vector of the boat movements consists the surge velocity, the sway velocity, both in the body-fixed frame, and the heading angle (yaw), in the inertial frame [9]. This MIMO modeling is illustrated by Fig. 3.

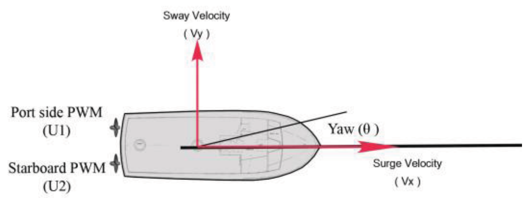

Fig. 3 MIMO Boat Modeling

Following is the specification of the recorded data.

TABLE 2. DATA SPECIFICATIONS

Data Name	Units	Update Rate
X Acceleration	m/s^2	50 Hz
Y Acceleration	m/s^2	50 Hz
Yaw	degree	50 Hz
Port side PWM	microsecond	10 Hz
Starboard PWM	microsecond	10 Hz

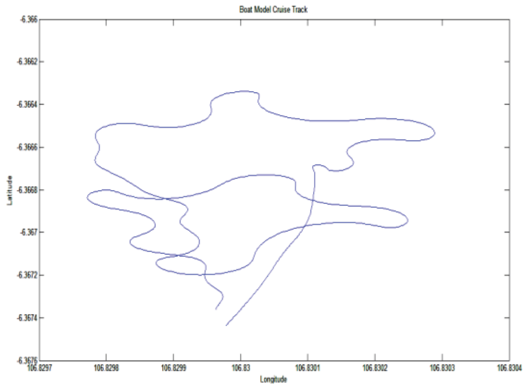

Fig. 4 Cruise Track to Generate Data Model

Fig.4 shows the cruise track of the boat according to latitude and longitude from the log data. Because of the difference in update rate data as shown in Table 2, it must be uniformed by filtering it to the lowest update rate of 10 Hz to get the same amount of data.

To get the speed value of both surge velocity (Vx) and sway velocity (Vy) must be derived from the acceleration value from sensor and time value from the controller using the following formula :

$$v(t) = \int_{t=0}^{t} a\,.dt \quad \text{.......................................} (1)$$

Or

$$v(t) = v(0) + \sum a \times dt \quad \text{.......................................} (2)$$

As explained earlier, the plant is modeled in the form of MIMO that consisting of two inputs and three outputs. Fig. 5 shows data from the plant model. The yaw value is converted from the inertial frame to body-fixed frame value.

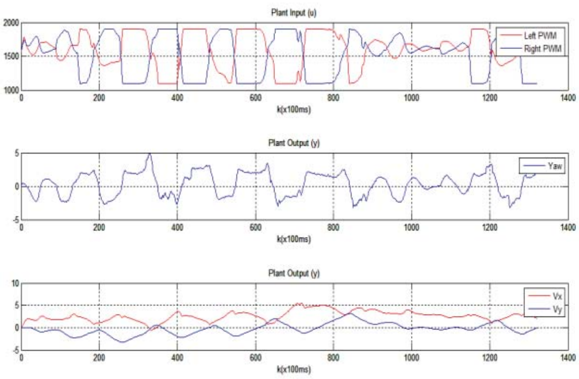

Fig. 5 Input and Output Plant Data For Training The Neural Networks

IV. Neural Network Based System Identification

Nonlinear autoregressive exogenous model (NARX) is used to approach plant model identification. The NARX formula is represented as follows:

$$y[k]=f(y[k-1],\dots,y[k-n_y],u[k-1],\dots,u[k-n_u]) \quad .....(3)$$

Where y is the plant output, u is the input and n_y dan n_u are the memory or delay operators. The identification of plants using artificial neural networks in this study was to use multi layer neurons, 12 input neurons, one hidden layer with 24 neurons and 3 output neurons. All the neurons use bipolar sigmoid activation function.

Artificial neural networks, as shown in Fig. 6 for identify a boat model plant operated using back-propagation techniques. Training is carried out with a learning rate of 0.3 and a momentum of 0.05. After reaching 2,000,000 iterations, the training gets a normalized mean square error of 1.7477×10^{-4}. The MSSE record graph during training is shown in Fig. 7. The testing result of the artificial neural network identification (ANN-Identification) are yaw 0.0205, surge velocity 0.0355 and sway velocity 0.0516 in a normalized training mean square error. The output value of the plant identification uses artificial neural networks compared to the output of the boat model can be seen in Fig. 8.

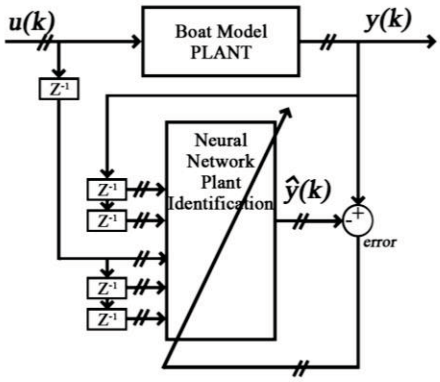

Fig. 6 Neural Networks for Boat Model Indentification

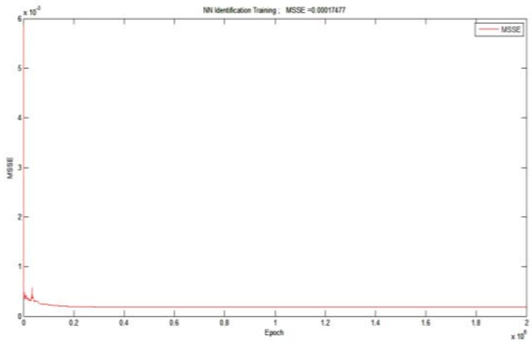

Fig. 7 MSSE during Idenfication Training

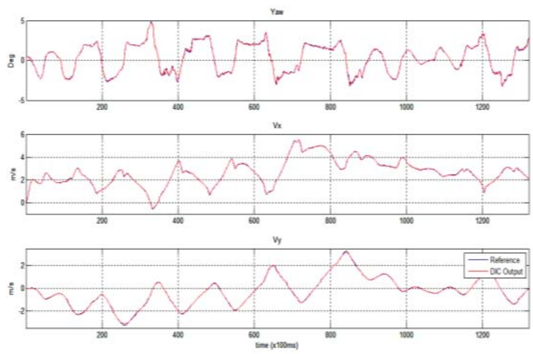

Fig. 8 Output Comparison, Plant vs NN Identification (Normalized MSSE = 1.7477×10^{-4})

It can be seen that the values of Vx, Vy, and yaw produced by NN-Identification are near similar to the original data from the model boat plant. A small total error implies that the identification of an artificial neural network plant has successfully modeled the transfer function of the plant boat model.

V. Neural Network Based Inverse Control System

Nonlinear inverse control techniques are an excellent control method technique among most existing nonlinear control approaches [10], [11]. As in the plant identification modeling process, the inverse plant modeling also uses nonlinear autoregressive exogenous model (NARX) and written in the following formula :

$$y[k]=f^{-1}(u[k-1],\ldots,u[k-n_u+1],y[k+1],\ldots,y[k-n_y+1]) \quad \ldots(4)$$

Where y is the plant output, u is the input and n_y dan n_u are the memory or delay operators. Just as in plant identification, this modelling also uses artificial neural networks to replace the inverse function of the plant, f^{-1}. The artificial neural network structure used is 13 input neurons, one hidden layer with 26 neurons, and 2 output neurons, as illustrated in Fig. 9. This inverse modeling training also uses back-propagation techniques with a learning rate of 0.3 and momentum 0.05. All neurons use the bipolar sigmoid activation function. Before entering into training, all data is normalized into vulnerable values -1 to 1.

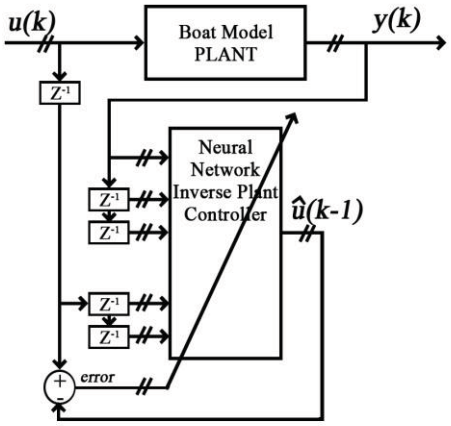

Fig. 9 Neural Networks for Plant Inverse Controller

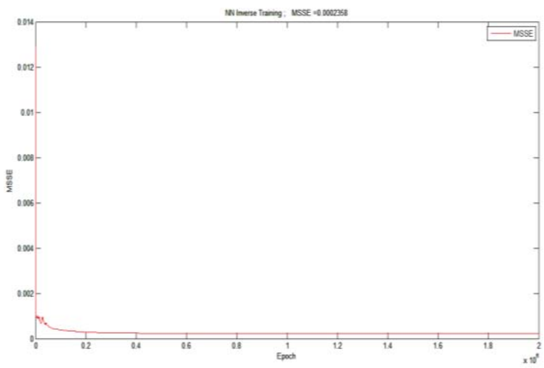

Fig. 10 MSSE during Plant Inverse Training

The training iteration of inverse plant model was carried out up to 2,000,000 epochs and produced a normalized training mean square error of 2,358x10^{-4} as seen in Fig. 10 which shows the trend of decreasing errors during training. Then the artificial neural network structure of the training was tested and produced an MSSE for portside propeller 0.1226 while for starboard propeller it was 0.1499. The graph in Fig. 11 shows a comparison between the plant data and the NN-Inverse output data, which means that inverse plant modeling uses artificial neural networks to succeed satisfactorily.

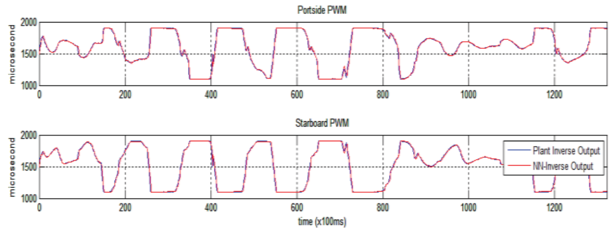

Fig. 11 Output Comparison, Plant vs NN Inverse (Normalized MSSE = 2,358x10^{-4})

VI. Neural Network Based Direct Inverse Control

Direct inverse control neural network (NN-DIC Neural Network Direct Inverse Control) is an artificial neural network controller (ANN) which is considered good to be used for the control of a non-linear system. NN-DIC is used because its characteristics are simple and easy to apply. The architecture of the open loop NN-DIC system can be seen on Fig. 12.

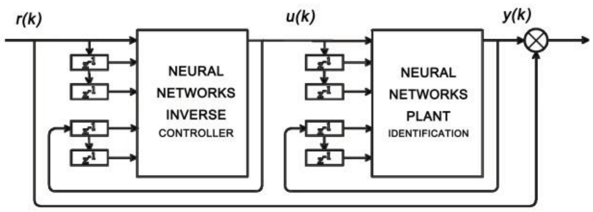

Fig. 12 Neural Network Based Direct Inverse Control

Fig. 12 shows that the NN-DIC control system is designed by compiling cascade of two parts of the NN block, namely the Neural Network Inverse System (NN-INV) which acts as the system controller and Neural Network Identification System (NN-ID) which acts as a controlled system or plant.

Back-propagation neural network (BPNN) controller was tested using the open-loop Direct Inverse Control (DIC) scheme. Testing data is used in this test.

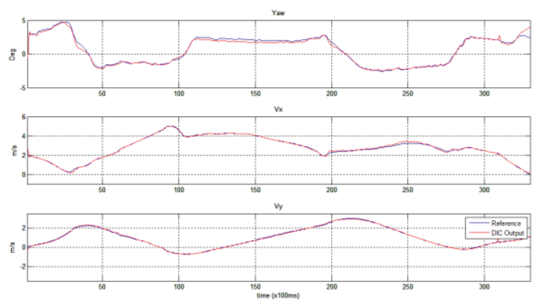

Fig.13 Un-normalized NN-DIC Test Result

Normalized MSSE error was obtained from the test are yaw: 0.1203, surge velocity (Vx) 0.4459 and sway velocity (Vy) 0.1723 as indicated by Fig 13. These results show that simulation inversion-based direct neural network control can be done. However, it is necessary to have an iteration and an appropriate neural network structure to produce a smallest error.

VII. CONCLUSIONS AND COMMENTS

The use of artificial neural networks in skid steer boat model plant identification modeling, inverse plant modeling (inverse control) and direct inverse control (DIC) has been described. The results show that the use of back-propagation artificial neural networks is very satisfying to nonlinear transfer functions modeling. The output plant follows the references value that is fed to the inverse controller. In this research there was no simulated interference with the control system or plant, so that further research is expected to add interference and analyze the performance of the control system.

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