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Analysis of control algorithms for water quality testing robots

Yiran Luo

School of Control Engineering, Northeastern University (Qinhuangdao Campus), Qinhuangdao, China

202013749@stu.neuq.edu.cn

Abstract. The research background of the water quality detection robot lies in effectively monitoring and assessing the quality of water bodies to address the increasingly severe issue of water pollution. This technology, employing advanced sensors and machine learning algorithms, facilitates automated acquisition of water quality data, enabling real-time analysis and reporting of various indicators in the water bodies. Consequently, it provides crucial evidence for safeguarding the environment and human health. This article investigates the problem of posture control in water quality detection robots operating in complex underwater environments. It compares three control algorithms: the traditional PID fuzzy control algorithm, and a BP neural network-based PID algorithm. Through experimental simulation, these algorithms are evaluated based on their differences in system dynamic performance. The results indicate that the utilization of the BP neural network PID algorithm significantly enhances both stability and control precision of the robot when dealing with non-linear environments characterized by uncertainties. This algorithm combines traditional PID control with neural network technology, allowing for adaptive optimization of PID controller parameters through training the neural network. As a result, it overcomes limitations associated with traditional PID and fuzzy control algorithms while improving overall performance.

Keywords: PID Control, fuzzy control, BP neural network

1. Introduction

This article delves into the critical issue of posture control for water quality inspection robots operating in intricate underwater environments. A comparison is made between two prominent approaches: the PID fuzzy control algorithm, common in traditional settings, and the BP neural network PID algorithm, both evaluated through simulation experiments to spot their disparities in system dynamic performance.

The research findings demonstrate that employing the BP Neural Network PID algorithm can significantly enhance the stability and accuracy of the robot's operations in nonlinear, uncertain environments. An upgrade from the conventional PID fuzzy control algorithm, this study efficiently tackles its limitations by introducing an adaptive approach to optimize PID controller parameters through neural network training. Noteworthy is the ability of the proposed algorithm to autonomously learn the nonlinear characteristics of the system and adjust the parameters real-time to adapt effectively to environmental changes.

As opposed to the traditional manual parameter adjustments, the BP neural network PID algorithm has proven to yield superior real-time responsiveness and robustness. These groundbreaking results

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pave the way for advancing the control methodologies used in water quality inspection robots, offering solid theoretical guidance and bearing significant implications for further developments in underwater robotics. By enhancing its stability, accuracy, and anti-interference capability, this control method profoundly improves the efficiency and precision of water quality detection in complex underwater environments. Moving forward, exploration can be intensified on how the BP neural network PID algorithm can be applied to other spheres of underwater robotics application, consequently promoting intelligent underwater vehicle technology's evolution.

An earthquake with a magnitude of 9.0 occurred in the Pacific Ocean region of northeastern Japan on the eleventh of March in 2011, was followed by a tsunami that had a devastating effect on the Fukushima Daiichi and Fukushima Daiichi nuclear power reactors. The Japanese government declared on August 22, 2023, that the first batch of 7,800 tons of radioactively contaminated water from Fukushima would be released within 17 days if the concentration is confirmed to have dropped to the anticipated level. The nuclear contaminated water release from Fukushima would begin on August 24, 2023. About 31,200 tons of tritium are anticipated to be released in the year 2023, for an aggregate tritium amount of five trillion becquerels. This is 20% of TEPCO's top limit of scheduled annual discharges, which is 22 trillion becquerels. The proposal calls for the release of Fukushima's radioactively contaminated water into the ocean for a minimum of 30 years [1]. Harmful substances in the nuclear effluent can cause great harm to humans and marine organisms when they enter the ecology of the marine environment. In recent years, the types of robots for water quality inspection tend to be diversified, and many control methods for robots under the interference of underwater complex environments have emerged. By continuing to propose innovative solutions, it is possible to better understand the potential adverse effects in the oceans while protecting the well-being of humans and marine life.

As a very important part of environmental engineering, water quality monitoring plays a key role in the process of ecological environmental protection [2]. The accuracy of water quality detection directly affects the assessment of water quality conditions and the decision to take effective management measures. By studying the control methods of water quality inspection robots, the motion accuracy and attitude control of robots in complex underwater environments can be improved, which in turn improves the accuracy and reliability of water quality inspection. Traditional water quality inspection methods are often limited by human resources and time costs, and cannot flexibly respond to various types of water environments. The emergence of water quality inspection robots can realize autonomous and remote operation, and can be used in a variety of complex underwater environments, including the deep sea, lakes, rivers, etc., thus broadening the application field of water quality inspection. Water quality testing often needs to be carried out in hazardous environments or in areas that are difficult to reach, such as chemical pollution zones, toxic wastewater discharges and so on. By using water quality testing robots, personnel can be placed in safer environments, reducing potential risks and hazards and improving work safety. Research on control methods for water quality testing robots can promote the development of intelligent water quality monitoring technology. By training neural networks, innovative control methods can make the robot adaptive, real-time and robust, and show better performance when dealing with complex water quality environments and various types of perturbations.

2. Experimental program

2.1. Underwater robot design

The design uses Arduino Mega 2560 as the main board with sensors such as MS5837, JY901 and RW10. A comparison analysis of the standard PID control algorithm, the PID fuzzy control algorithm, and the BP neural network PID will be carried out in order to compare various control algorithms. The underwater robot is designed to realize underwater navigation operations and underwater observation functions. The RS-485 communication connection is established between the robot and the mother ship by data transmission through USB to 485 module and TTL to RS485 module.

The underwater control system is centered on the Arduino Mega 2560 control board, which contains components such as electronic speed controller, thrusters, lights, and sensors. The robot utilizes the RS485 serial port to transmit water quality monitoring data to the mother ship. The underwater control system is responsible for driving the 28GM-2838 motors to rotate and generate thrust, thus realizing the robot's forward, steering, traversing, lifting and other movements. At the same time, the robot's camera system and lighting system are also controlled by the water surface control system.

2.2. Research method

Simulation: through the establishment of the system model of the water quality inspection robot, and the use of computer software for simulation. According to different scenarios and control algorithms, it can simulate the robot's motion characteristics, attitude adjustment and water quality sampling in the underwater complex environment.

Neural network training: when it comes to the BP deep learning PID control method, the researcher needs to design and train the neural network model. Using the existing dataset, combined with appropriate deep learning algorithms to train the neural network, so that it has the ability to adapt and optimize the PID controller parameters.

Comparative analysis: different control methods will be compared and analyzed on the water quality testing robot. Through the experimental results or simulation output data, the performance of different control methods in attitude adjustment accuracy, stability and robustness is compared, and their advantages and disadvantages are evaluated.

3. Experimental procedure

3.1. Design robots and sensor systems

3.1.1. Mobile platform. The mobile platform of the water quality detection robot uses four 28GM-2838 motors as power to drive four propellers, of which two propellers face upward to provide forward propulsion, and the other two propellers face backward to provide reasoning force. The four propellers can rotate the robot as a whole by rotating in different directions. In addition, the robot is equipped with a buoyancy chamber, which can control the depth of its floating and sinking to adapt to different underwater environments. The robot shape is shown in Figure 1.

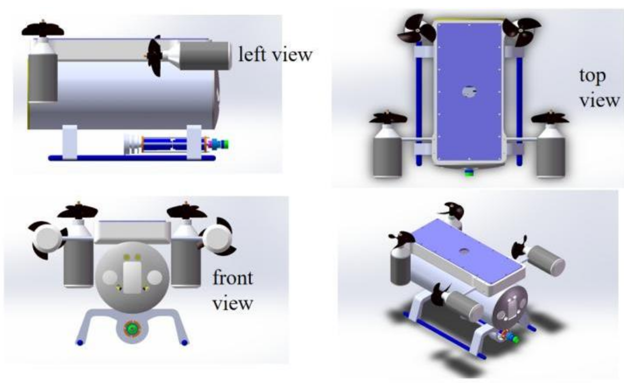

Figure 1. Robot appearance (photo credited: original)

3.1.2. Sensor. The water quality detection robot uses a variety of sensors to obtain data. These include the MS5837 underwater pressure sensor, the JY901 inertial navigation sensor and the RW10 mounted water quality sensor. The integrated application of these sensors enables the robot to conduct accurate and comprehensive monitoring and analysis of water pressure, attitude and water quality.

MS5837 underwater pressure sensor is a barometric depth sensor with a measuring depth of 0-300m and a measuring accuracy of 0.2%FSR [3]. It can accurately measure the water depth and convert the measured pressure value into the corresponding depth information. Such sensors are widely used in underwater detectors, diving equipment and underwater robots.

The JY901 Inertial Navigation sensor provides accurate attitude and navigation information. It consists of nine-axis (acceleration + gyroscope + magnetometer) quaternions, of which the three-axis magnetometer is implemented by on-chip integration AK8963, the baud rate is set at 4800-921600, the IIC rate can reach 400K, the return rate is 0.1~200Hz, and the attitude measurement accuracy is 0.05 degrees static and 0.1 degrees dynamic [4]. Therefore, the use of JY901 sensors in water quality detection robots can obtain important data such as robot positioning, tilt Angle and yaw.

RW10 Hanging water quality sensor for monitoring water quality parameters. It can measure key water quality indicators such as temperature, dissolved oxygen, turbidity, and electrical conductivity in water bodies. When used in conjunction with other sensor data, the RW10 sensor can provide a detailed assessment of the environmental quality of a water body to help judge the level of water pollution and ecological health.

3.1.3. Control module. The water quality detection robot uses an Arduino Mega 2560 control board as the core control module, which is an ATmega-based microcontroller chip programmed using the Arduino IDE environment [5]. Several components such as electronic speed controller, thrusters, lights and sensors are integrated. Through this control module, the robot is able to realize a variety of functions, including the speed and direction control of the propellers, the switching and brightness adjustment of the lights, and the acquisition and processing of sensor data.

3.1.4. Communication module. The communication module of the water quality inspection robot uses a USB to 485 module and a TTL to RS485 module in order to establish an RS-485 communication connection and to realize data transmission between the robot and the mother ship. The module is resistant to common-mode interference and greatly improves the reliability of communication with high sensitivity and anti-interference [6]. Through the cooperation of these two modules, the robot is able to transmit the acquired water quality data, attitude information, etc. to the mother ship via RS-485 protocol. This communication method is stable and reliable, and can support longer distance data transmission, providing a reliable remote data transmission solution for water quality monitoring.

3.2. Control algorithm experiment

The Simulink function in Matlab is utilized in this design to compare the first order and second order transfer function under step input signal, as well as the first order transfer function under ramp, sine wave, and sawtooth wave input signals, with the dynamic performance of PID control algorithm, PID fuzzy control algorithm, and BP-PID control algorithm. The dynamic response signals are imported into the workspace and processed by a signal processing program.

For the first-order and second-order transfer function responses under step input signals, the rise time, peak overshoot, and regulation time are used experimentally as their dynamic performance metrics. For the first-order transfer function response under a ramp input signal, the steady state error and the regulation time of the rise rate of each signal are used as indicators. For the first-order transfer function response under a sine wave signal, the rise time, peak-to-peak and phase delay are used as indicators. For the first-order transfer function response under a sawtooth wave signal, the experiment uses rise time, peak-to-peak value, and peak time as indicators. In this paper, the rise time is defined as the time used for the output response from 0.1 to 0.9 y_{ref} [7].

3.2.1. Design PID controller. Simulink’s auto-tuning feature is used to tune the PID settings after modeling the PID controller. In order to achieve good control effect, the auto-tuning parameter can automatically search for the ideal PID parameters based on the supplied performance indexes, such as overshooting amount, peak time, or steady state error, etc. In Figure 2, the PID controller model is displayed.

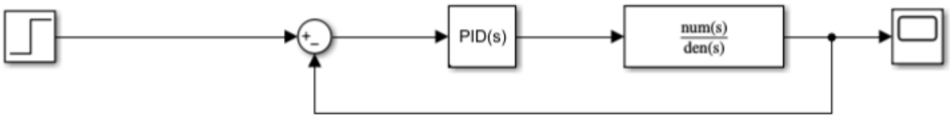

Figure 2. PID controller (photo credited: original)

3.2.2. Design PID fuzzy controller. The PID fuzzy controller model is constructed using Simulink and consists of a fuzzy logic controller in addition to a PID controller, the steps of designing fuzzy logic controller are 1) selecting the input-output fuzzy set, 2) defining the affiliation function of the inputs and outputs, 3) building the table of fuzzy control rules, 4) building the fuzzy control rules, 5) performing fuzzy inference, 6) defuzzification [8].

The fuzzy rules for PID parameters are shown in Table 1, Table 2 and Table 3.

Table 1. Fuzzy rule of Kp [9]

e \ ec	NB	NM	NS	Z	PS	PM	PB
NB	PB	PB	PM	PM	PS	Z	Z
NM	PB	PB	PM	PS	PS	Z	NS
NS	PM	PM	PM	PS	Z	NS	NS
Z	PM	PM	PS	Z	NS	NM	NM
PS	PS	PS	Z	NS	NS	NM	NM
PM	PS	Z	NS	NM	NM	NM	NB
PB	Z	Z	NM	NM	NM	NB	NB

Table 2. Fuzzy rule of Ki [9]

e \ ec	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NM	NM	NS	Z	Z
NM	NB	NB	NM	NS	NS	Z	Z
NS	NB	NM	NS	NS	Z	PS	PS
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PS	PM	PB
PM	Z	Z	PS	PS	PM	PB	PB
PB	Z	Z	PS	PM	PM	PB	PB

Table 3. Fuzzy rule of Kd [9]

e \ ec	NB	NM	NS	Z	PS	PM	PB
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NM	NM	NS	Z
NS	Z	NS	NM	NM	NS	NS	Z
Z	Z	NS	NS	NS	NS	NS	Z
PS	Z	Z	Z	Z	Z	Z	Z
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PS	PB

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Figures 3 and 4 display the PID fuzzy controller model.

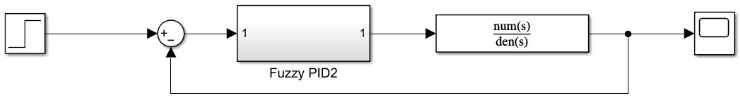

Figure 3. PID fuzzy controller (photo credited: original)

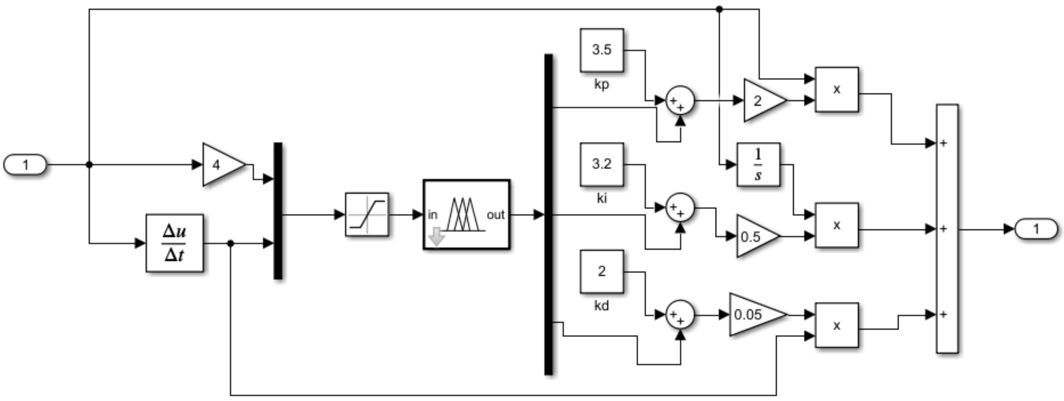

Figure 4. PID fuzzy controller subsystem (photo credited: original)

3.2.3. Design BP-PID controller. The BP-PID control algorithm consists of two parts: the BP neural network and the PID controller, in which the BP neural network is responsible for regulating the PID control parameters, and the PID control is responsible for outputting the position control signals According to the neural network model and experimental objectives [10]. Figures 5 and 6 display the PID controller for the BP neural network.

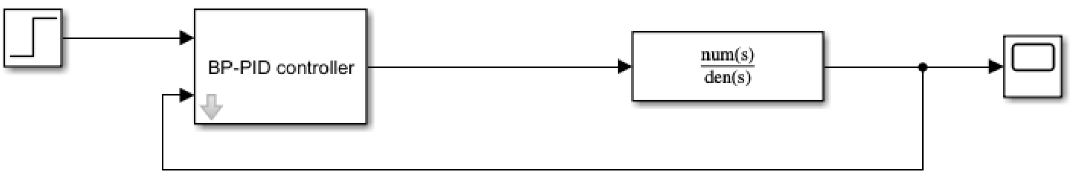

Figure 5. BP-PID controller (photo credited: original)

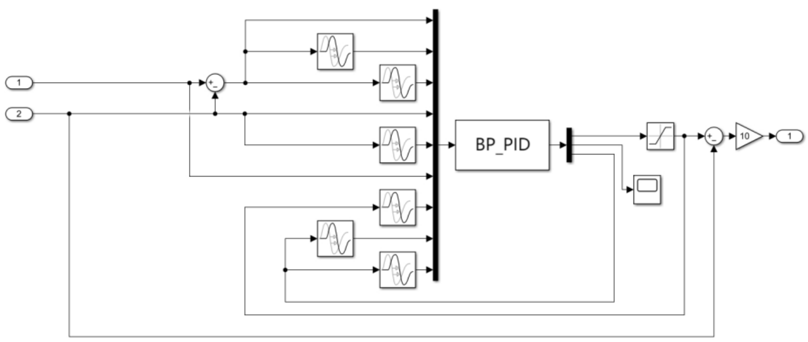

Figure 6. BP-PID controller subsystem (photo credited: original)

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3.2.4. Design input signal. This experiment uses step, ramp, sine wave and sawtooth wave as input.

3.2.5. Design the object to be controlled. Five first-order and second-order transmission function models are randomly selected as objects to be controlled.

The selected first and second order transfer functions are shown in Figure 7.

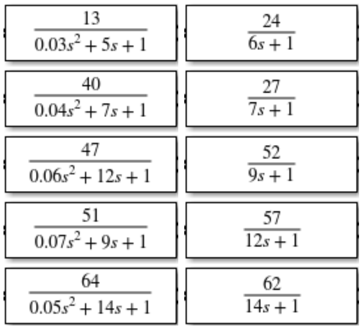

Figure 7. The selected transfer function (photo credited: original)

3.2.6. Run the experiment. The connected Simulink model is shown in Figure 8. The responses of PID control algorithm, PID fuzzy control algorithm and BP-PID to the input signals of step, slope, sine wave and sawtooth wave were observed respectively.

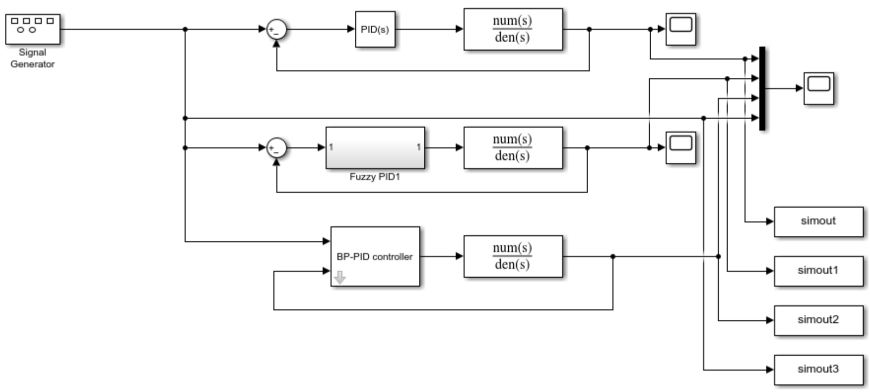

Figure 8. Simulink model (photo credited: original)

3.2.7. Results of the experiment. The Dynamic performance is displayed in Figures 9 to 13.

Step response:

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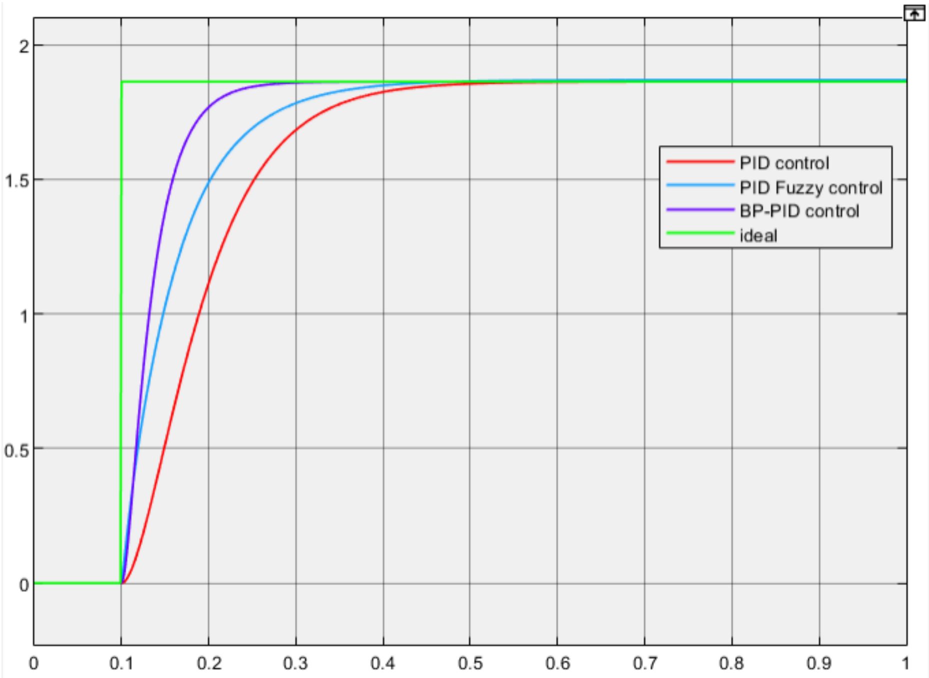

Figure 9. Second-order system step response (photo credited: original)

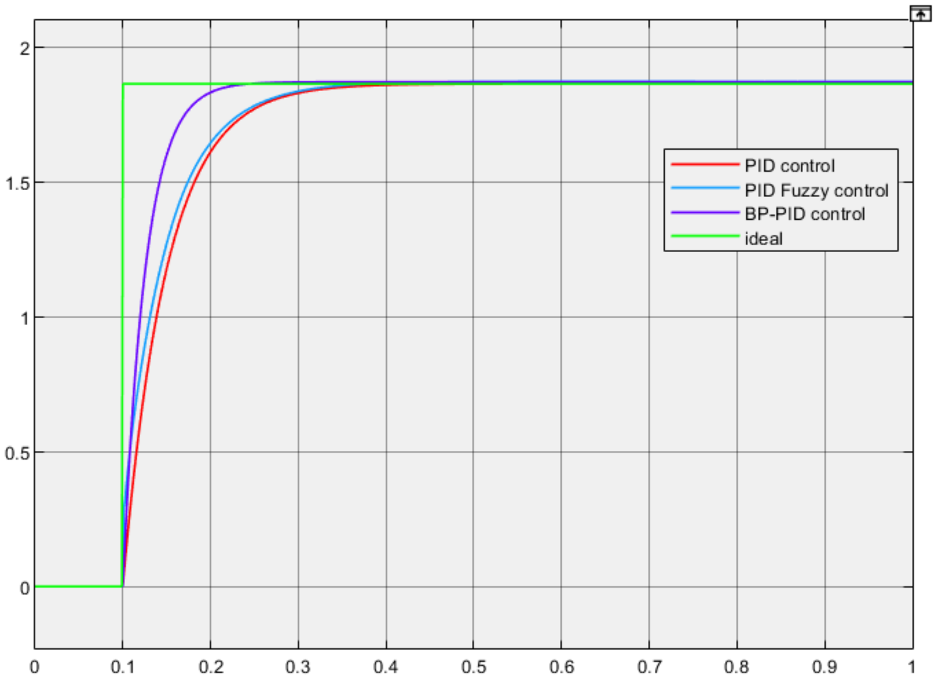

Figure 10. First-order system step response (photo credited: original)

Ramp response:

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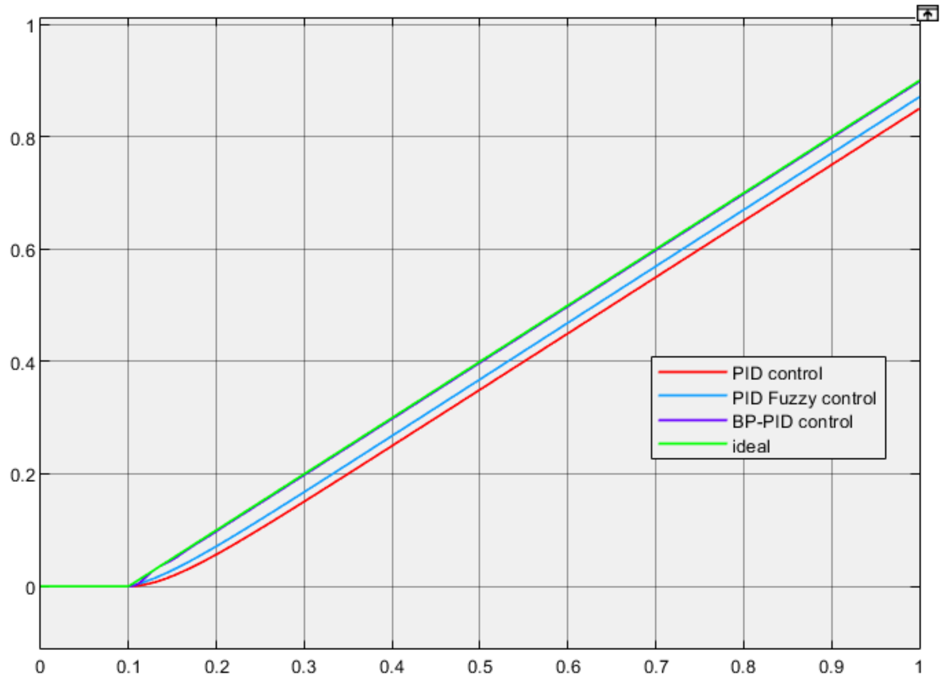

Figure 11. First-order system ramp response (photo credited: original)

Sine-wave response:

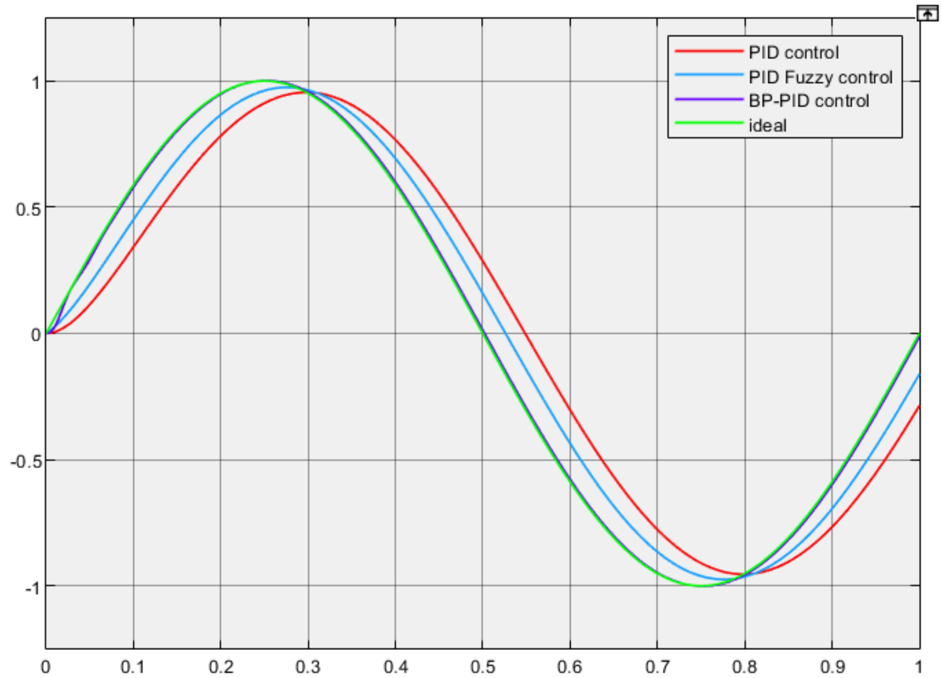

Figure 12. First-order system sine-wave response (photo credited: original)

Sawtooth response:

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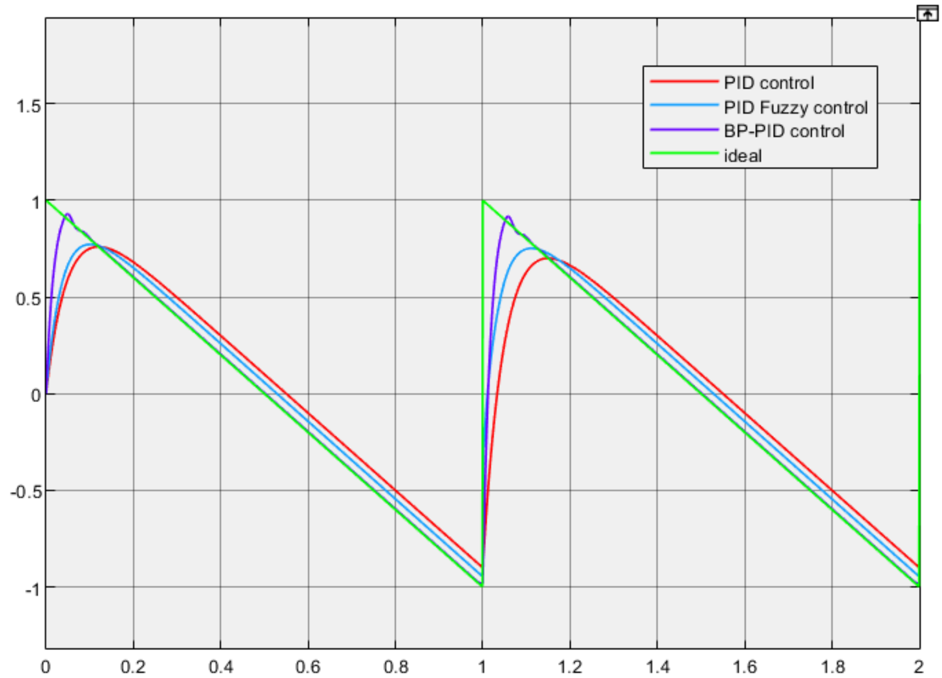

Figure 13. First-order system sawtooth response (photo credited: original)

3.3. *Performance Comparison Analysis*

The dynamic curves of the three control algorithms are compared with the ideal curves to obtain the dynamic performance indexes of the three control algorithms, and the performance indexes are displayed in Tables 4 to 8.

Step response:

Table 4 displays the reaction times, overshoots, and stabilization times for the three distinct algorithms used in the second order system with step signal inputs. The BP-PID control outperforms the other two algorithms in terms of response time, and the PID fuzzy control outperforms the traditional PID control as well, according to the statistics. Second, although overshoot occasionally occurs in both PID fuzzy control and BP-PID control, it usually stays within acceptable bounds, with overshoot in the PID control seldom exceeding 5%. In summary, the BP-PID shows better dynamic performance in second order systems with step signal inputs, with faster response times, smaller overshoots and the shortest stabilization times.

Table 4. Dynamic indicator of second-order system step response

Indicator Algorithm Transmission function		$\frac{13}{0.03s^2+5s+1}$	$\frac{40}{0.04s^2+7s+1}$	$\frac{47}{0.06s^2+12s+1}$	$\frac{51}{0.07s^2+9s+1}$	$\frac{64}{0.05s^2+14s+1}$
Risetime (s)	PID control	0.211	0.096	0.099	0.207	0.102
	PID fuzzy control	0.140	0.073	0.100	0.070	0.091
	BP-PID control	0.071	0.028	0.045	0.029	0.040

Table 4. (continued).

Overshoot (%)	PID control	0.090	0	0	0	0
	PID fuzzy control	0.140	0.180	0.32	0.05	0.30
	BP-PID control	0	0.350	0	2.79	0
Settling time (s)	PID control	0.391	0.237	0.239	0.388	0.242
	PID fuzzy control	0.193	0.101	0.136	0.098	0.123
	BP-PID control	0.101	0.039	0.065	0.037	0.058

Table 5 displays the response time, overshoot amount, and stabilization time of the three distinct methods for the first order system with step signal input. Compared to the PID control and the fuzzy PID control, the BP-PID control has a substantially lower rise time. In terms of the amount of overshoot, there is no overshoot in both the conventional PID control and BP-PID control, while the fuzzy PID control's, which is less resistant to interference in practical applications, has a higher amount of overshoot [11]. The stabilization time of the conventional PID control was 0.15 seconds in all five sets of experiments, the stabilization time of the fuzzy PID control varied between 0.103 seconds and 0.146 seconds, whereas the stabilization time of the BP-PID control ranged between 0.052 seconds and 0.078 seconds. Thus, the BP-PID control has the lowest stabilization time. In conclusion, BP-PID control is the most desirable choice of algorithm in first order systems with step signal inputs because it possesses faster response time, no overshoot and shorter stabilization time.

Table 5. Dynamic indicator of first-order system step response

Indicator Algorithm Transmission function		$\frac{24}{6s+1}$	$\frac{27}{7s+1}$	$\frac{52}{9s+1}$	$\frac{57}{12s+1}$	$\frac{62}{14s+1}$
Risetime (s)	PID control	0.110	0.110	0.110	0.110	0.110
	PID fuzzy control	0.106	0.110	0.175	0.192	0.097
	BP-PID control	0.054	0.057	0.038	0.046	0.050
Overshoot (%)	PID control	0	0	0	0	0
	PID fuzzy control	0.16	0.20	0.16	0.26	0.29
	BP-PID control	0	0	0	0	0
Settling time (s)	PID control	0.150	0.150	0.150	0.150	0.150
	PID fuzzy control	0.142	0.146	0.103	0.122	0.130
	BP-PID control	0.075	0.078	0.052	0.064	0.068

Ramp response:

The response time, overshoot and stabilization time of the three different algorithms for the first order system with a ramp signal input are shown in Table 6. First of all, both the fuzzy PID control and normal PID control have very significant and highly fluctuating steady state errors. On the other hand, the BP-PID control's steady state errors are extremely tiny. This indicates that the steady state error is extremely near to zero and that the BP-PID control method is capable to align the output more accurately with the target value. Secondly, the stabilization time of the conventional PID control is always 0.151 seconds, the stabilization time of the fuzzy PID control varies between 0.109 and 0.150 seconds, while the stabilization time of the BP-PID control is between 0.064 and 0.099 seconds, which is significantly shorter than both the traditional PID control and the PID fuzzy control. In summary, the BP-PID control algorithm has the best dynamic performance.

Table 6. Dynamic indicator of first-order system ramp response

Indicator Algorithm Transmission function		$\frac{24}{6s+1}$	$\frac{27}{7s+1}$	$\frac{52}{9s+1}$	$\frac{57}{12s+1}$	$\frac{62}{14s+1}$
Steady-state error	PID control	-0.0500	-0.0500	-0.0503	-0.0500	-0.0500
	PID fuzzy control	-0.0346	-0.0345	-0.0217	-0.0251	-0.0263
	BP-PID control	-0.0020	-0.0020	-0.0020	-0.0020	-0.0020
Settling time (s)	PID control	0.151	0.151	0.152	0.151	0.151
	PID fuzzy control	0.146	0.150	0.109	0.126	0.133
	BP-PID control	0.096	0.099	0.064	0.085	0.090

Sine-wave response:

The response times, overshoots and stabilization times of the three different algorithms for a first order system with a sinusoidal signal input are shown in Table 7. From the data, it can be seen that the response times of the various algorithms are relatively close to each other, with the BP-PID response time being a little shorter than that of the PID fuzzy control and the conventional PID. Secondly, the peak-to-peak values of BP-PID control are relatively high while the peak-to-peak values of PID and fuzzy PID control are somewhat different in comparison. The BP-PID control also has the minimum phase delay while the PID and fuzzy PID control are relatively high. In conclusion, the BP-PID control algorithm performs best in terms of dynamic performance of first order system with sinusoidal signal input.

Table 7. Dynamic indicator of first-order system sine-wave response

Indicator Algorithm Transmission function		$\frac{24}{6s+1}$	$\frac{27}{7s+1}$	$\frac{52}{9s+1}$	$\frac{57}{12s+1}$	$\frac{62}{14s+1}$
Risetime (s)	PID control	0.180	0.181	0.181	0.179	0.181
	PID fuzzy control	0.182	0.182	0.167	0.179	0.180
	BP-PID control	0.160	0.160	0.162	0.165	0.165
Peak-to-peak value	PID control	1.9132	1.9096	1.9096	1.9194	0.9095
	PID fuzzy control	1.9108	1.9077	1.9492	1.9346	1.9282
	BP-PID control	2.0361	2.0380	2.0243	2.0305	2.0321
Phase delay (π)	PID control	0.093	0.096	0.096	0.090	0.092
	PID fuzzy control	0.072	0.075	0.052	0.064	0.066
	BP-PID control	0.004	0.005	0.004	0.004	0.004

Sawtooth response:

The response time, overshoot and stabilization time of the three different algorithms for the first order system with a sawtooth wave signal input are shown in Table 8.According to the data, the BP-PID control has the shortest response time, which is a significant advantage over the PID control and fuzzy PID control. It has a relatively high peak-to-peak value, which is closer to the input signal. In addition, BP-PID control has the shortest peak-to-peak time, while PID and fuzzy PID controls are relatively high. In conclusion, the BP-PID control algorithm performs best in terms of dynamic performance of the first order system with sawtooth wave signal input.

Table 8. Dynamic indicator of first-order system sawtooth response

Indicator Algorithm Transmission function		$\frac{24}{6s+1}$	$\frac{27}{7s+1}$	$\frac{52}{9s+1}$	$\frac{57}{12s+1}$	$\frac{62}{14s+1}$
Risetime (s)	PID control	0.063	0.065	0.065	0.065	0.065
	PID fuzzy control	0.064	0.064	0.052	0.058	0.060
	BP-PID control	0.040	0.041	0.030	0.035	0.037
Peak-to-peak value	PID control	1.6775	1.6600	1.6602	1.6602	1.6600
	PID fuzzy control	1.6586	1.6533	1.7188	1.6916	1.6805
	BP-PID control	1.8843	1.8815	1.9151	1.9009	1.8954
First peak time (s)	PID control	0.117	0.120	0.120	0.117	0.120
	PID fuzzy control	0.119	0.121	0.101	0.110	0.114
	BP-PID control	0.063	0.065	0.049	0.056	0.059

3.4. Analysis of the results

In step input for both first-order and second-order systems, BP-PID control demonstrates superior performance. When compared to fuzzy PID control and conventional PID control, it exhibits shorter rise time, adjustment time and appropriate overshoot. This implies that BP-PID control can respond more rapidly to the input signals and attain the target state with increased stability.

Moreover, in ramp input for a first-order system, BP-PID control is capable of swift following while maintaining minimal steady-state error. In sine wave and sawtooth wave inputs for a first-order system, the response of BP-PID flaunts the greatest peak-to-peak value among the three control algorithms, indicating commendable following ability and outstanding dynamic performance in contrast to the other two control techniques.

Thus, based on the experimental outcomes, employing the BP-PID control algorithm for the control of the designed water quality inspection robot would be advantageous for operations in complex underwater disturbance environments since it shows superior performance and adaptability under different types of inputs. Nonetheless, these experiments were carried out in a simulated environment, therefore, their conclusions may be affected by factors such as parameter settings and model assumptions. For real-world applications, parameter adjustments and further validation are necessary in order to achieve optimal control effects.

4. Conclusion

In this paper, a water quality inspection robot is designed, using Arduino Mega 2560 as the main board, four 28GM-2838 motors are selected as the power, the sensors are equipped with MS5837, JY901 and RW10, and the 485 module is used to establish communication with the mother ship. In the selection of control algorithms, this paper designs comparison experiments for three algorithms: traditional PID control, PID fuzzy control and BP deep learning PID control. Five systems—first-order transfer function with step input, second-order transfer function with step input, first-order transfer function with ramp input, first-order transfer function with sinusoidal input, and first-order transfer function with sawtooth wave input—are used to compare the performance indices of the three algorithms. In terms of dynamic performance, the study of the experimental data indicates that the BP-PID control algorithm works well. It has a faster and more accurate response time, along with a larger peak-to-peak value and the shortest stabilization time. Therefore, the BP-PID control algorithm is the optimal choice for the algorithm selection of the water quality detection robot, which can realize more efficient, accurate and stable system control in the underwater complex interference environment.

This design based on BP neural network PID control system can achieve the dynamic performance requirements of underwater vehicles in the underwater complex interference environment, but there

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are still some problems to be solved and need to further improve the design: (1) This design has not yet involved the control of automatic cruise of underwater robots during underwater operation, which can be researched in this direction next. (2) Due to the limitation of experimental conditions, the actual test of underwater vehicle sailing cannot be realized, and only simulation analysis is carried out.

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