The control of four-track underwater mining vehicle based on NNPID

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Abstract

The article introduces a novel control algorithm for an underwater four-track mining vehicle utilizing NNPID, which effectively tackles the issue of unstable speed control in challenging underwater conditions that traditional fixed parameter algorithms struggle to overcome. The algorithm was evaluated through simulation utilizing RecurDyn software, showcasing its effectiveness in achieving precise speed and directional control of the vehicle.

Keywords

control strategy, BP network, PID, underwater track vehicle

1. Introduction

The ocean floor abounds with valuable minerals, including cobalt-laden crusts and manganese nodules [1], both of which serve as vital suppliers of rare earth elements essential for contemporary technological applications, from smartphones to electric vehicles. As the demand for these elements surges, driven by the rapid advancement of technology and the push towards sustainable energy solutions, the exploration and exploitation of underwater mineral resources have gained significant interest. The mining of submarine metal resources is more difficult than that on land, which requires underwater mining vehicles to complete the mining of submarine metal. However, the pursuit of these resources is fraught with challenges. Unlike terrestrial mining operations, where heavy machinery can operate with relative ease on stable ground, underwater mining presents a unique set of difficulties. The harsh underwater environment, characterized by high pressure, low visibility, and unpredictable seabed conditions, demands specialized vehicles capable of navigating and working effectively in these conditions.

In the 1960s and early 1970s, the extraction of underwater minerals was primarily conducted through the bucket mining system and the shuttle vessel mining system [2-4]. In the late 1970s, several consortia, including OMI (Ocean Mining Inc), OMA (Ocean Mining

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Associates), and OMCO (Ocean Minerals Company-Lockheed), began the extraction of underwater minerals for the first time using underwater mining vehicles [5]. Afterwards, various countries have also conducted sea trials at different depths for key equipment such as underwater mining vehicles. Japan conducted a 2,000-meter water depth mineral collector test in 1997 [6], India carried out a 400-meter-class partial system sea trial in the 2000s [7] and a seabed walking test for a mining vehicle in 2021, South Korea conducted a simulated polymetallic nodule collection test at 1,370 meters water depth in 2013 and a mineral lift pump and intermediate storage test at 1,200 meters water depth in 2015 [8], and the European Union performed an operational and disturbance test for a mining vehicle at 300 meters water depth in 2022, among others. However, there is a current absence of a well-defined and mature model for the development of marine mineral resources on a global scale, and the commercial extraction of these resources has not yet been achieved.

To enhance the mobility of track vehicles over the challenging sea floor topography, certain subsea mining machines are equipped with a four-track configuration, which significantly bolsters their capability to overcome obstacles. The track design is instrumental in optimizing the operational performance of these vehicles within the demanding environment of deep-sea mining operations. However, due to the complex condition of the seabed bottom [9], the four-track mining vehicle often cannot guarantee that it can walk in accordance with the predetermined path, and it may be unable to walk in a straight line due to skidding. The complex condition of the seabed, including its irregular surfaces and varying consistencies, can lead to deviations from the predetermined path, causing the vehicle to skid or veer off course. Moreover, maintaining a consistent speed is crucial for the efficiency of ore collection, as fluctuations in speed can affect the overall yield and success of the mining operation. At the same time, it is necessary to ensure that the vehicle can travel at a constant speed, so as to ensure the ore collection rate control. The conventional PID controllers are used widely in the field of underwater vehicle control. However, the underwater conditions are changing, so PID with fixed parameters cannot solve the control problem well [10].

The paper introduces a novel control method for an underwater four-track vehicle utilizing Neural Network PID (NNPID), designed to address the instability issues encountered when employing fixed-parameter control algorithms in the complex underwater setting. This approach uses neural network adaptability to dynamically adjust parameters, ensuring robust and reliable vehicle operation across varying underwater conditions. The paper is organized as follows: Part 2 introduces the dynamics model of four-track mining vehicle; Part 3 introduces a control algorithm for four-track mining vehicle. In Part 4, the proposed algorithm is verified by using RecurDyn software. Part 5 presents the conclusion.

2. Vehicle dynamic model

Underwater track vehicles mainly work on the two-dimensional plane of the seabed, thus the vehicles only moves on the horizontal plane and have three degrees of freedom [11]. The dynamic model of track vehicles is shown as Figure 1.



Figure 1: Dynamic model of track vehicles

O is the steady state steering center of the track vehicle, and the vehicle dynamic model is established with *O* point as the coordinate origin [12]. R_s is the turning radius of the mining vehicle, and *B* is the distance between the left and right tracks. ω_0 is the angular speed of the vehicle. O_1 and O_2 are the intersection points of *x* axis with the center line of the left and right tracks. O_1' and O_2' are the instantaneous rotation centers of the inner and outer tracks respectively. The distance from O_1 to O_1' is C_1 , the distance from O_2 to O_2' is C_2 . The velocity of point O_2 to the ground is

$$V_{oo_2} = \omega_0 \left(\frac{B}{2} + R_s\right) \tag{1}$$

The projection of point 0 on the track junction with respect to the speed of the track frame is

$$U_{o_2} = \omega_{out} \cdot r \tag{2}$$

 ω_{out} is the angular speed of the outer track motor, and r is the radius of the track drive wheel.

The speed of the track ground point relative to the ground is

$$V_{o_{2}o_{2}} = V_{o_{2}} - U_{o_{2}} = -\omega_{2}c_{2}$$
(3)

The steering radius of the track vehicle can be obtained from the above formulas [13]

$$R_{s} = \frac{\omega_{out}(\frac{B}{2} + c_{2}) + \omega_{in}(\frac{B}{2} + c_{1})}{\omega_{out} - \omega_{in}}$$
(4)

3. Control strategy

Because it is difficult to establish the mechanical model of underwater vehicles, especially for underwater tracked vehicles, the ground soil mechanical parameters are difficult to measure. Thus, PID has become one of the most commonly used control algorithms in underwater vehicle control [14]. To enhance adaptability to fluctuating soil environments, this paper proposes the implementation of a Neural Network PID (NNPID) control strategy for underwater vehicles.

The structure of NNPID controller is shown as Figure 2. On the basis of the basic PID, a neural network module is added to adjust the three parameters, K_p , K_i , K_d . The paper adopts the incremental PID control algorithm, so

$$u(k) = u(k-1) + \Delta u(k) \tag{5}$$

$$\Delta u(k) = K_p(e(k) - e(k-1)) + K_i \cdot e(k) + K_d(e(k) - 2e(k-1) + e(k-2))$$

$$u(k) = u(k-1) + \Delta u(k)$$
(6)



Figure 2: The structure of NNPID controller

As shown in Figure 3, the network has 3 layers, and it has 4 input-layer nodes, 5 hiddenlayer nodes, 3 output-layer nodes. The input layer nodes include system states and error, while the output layer nodes are three PID parameters, K_p , K_i , K_d .



Figure 3: The structure of the network

The cost function is shown below:

$$E(k) = \frac{1}{2}(r(k) - y(k))^2$$
(7)

The network refreshed the weight coefficient of nodes by using the gradient descent method [15].

$$\Delta \omega_{il}^{(3)}(k) = -\eta \frac{\partial E(k)}{\partial \omega_{il}^{(3)}} + \alpha \omega_{il}^{(3)}(k-1)$$
(8)

 η_{-} is the learning rate and $|\alpha_{-}|$ is the momentum factor. And according to the chain rule, there is

$$\frac{\partial E(k)}{\partial \omega_{il}^{(3)}} = \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial u(k)} \cdot \frac{\partial u(k)}{\partial o_i^{(3)}} \cdot \frac{\partial o_i^{(3)}}{\partial net_i^{(3)}} \cdot \frac{\partial net_i^{(3)}(k)}{\partial \omega_{il}^{(3)}(k)}$$
(9)

And

$$\frac{\partial net_i^{(3)}(k)}{\partial \omega_{il}^{(3)}(k)} = o_i^{(2)}(k)$$
(10)

$$\frac{\partial E(k)}{\partial y(k)} = -e(k) \tag{11}$$

Finally, the weight coefficients of output layer can be derived as shown below [16].

$$\Delta \omega_{li}^{(3)}(k) = \alpha \Delta \omega_{li}^{(3)}(k-1) + \eta \delta_i^{(3)} O_i^{(2)}(k)$$
(12)

$$\delta_i^{(3)} = e(k) \cdot \operatorname{sgn}(\frac{\partial y(k)}{\partial u(k)}) \frac{\partial u(k)}{O_l^{(3)}(k)} g'(net_l^{(3)}(k))$$
(13)

And, the weight coefficients of hidden layer are

$$\delta_i^{(3)} = e(k) \cdot \operatorname{sgn}(\frac{\partial y(k)}{\partial u(k)}) \frac{\partial u(k)}{O_i^{(3)}(k)} g'(net_i^{(3)}(k))$$
(14)

$$\Delta \omega_{ij}^{(2)}(k) = \alpha \Delta \omega_{ij}^{(2)}(k-1) + \eta \delta_i^{(2)} O_j^{(1)}(k)$$
(15)

$$\delta_i^{(2)} = f'(net_i^{(2)}(k)) \sum_{l=1}^3 \delta_l^{(3)} w_{li}^{(3)}(k)$$
(16)

Where

$$g'(x) = \frac{2}{(e^x + e^{-x})^2}$$
(17)

$$f'(x) = \frac{4}{\left(e^x + e^{-x}\right)^2}$$
(18)

4. Simulation

The paper uses RecurDyn to build the dynamic model of the track vehicle to verify the control algorithm. The model built in the RecurDyn is shown as Figure 4, and main parameters of the vehicle are shown as table 1 [17].



Figure 4: The model of the track vehicle built in RecurDyn

Table 1

Main Parameters of Vehicle

Parameter	Data
Vehicle mass in water(kg)	1000
Ground length of the front track(m)	0.6
Distance between front and rear tracks(m)	1.7
Ground length of the rear track(m)	0.6
Track guage(m)	1.5
Track width(m)	0.46

The walking of track vehicle on soft ground are closely related to the parameters of the seabed soil [18], such as cohesion, shearing resistance angle, etc. In this paper, the parameters of the real seabed soil are selected as the simulation parameters in RecurDyn, as shown in table 2.

Table 2

The Parameters of The Real Seabed Soil

Parameter	Data	Parameter		Data
Terrain Stiffness	1.27×10-2	Shearing Angle(°)	Resistance	1
Exponential Number	0.7	Shearing Modulus	Deformation	25
Cohesion(c)	10-3	Sinkage Ration 0		0.05

The control system is built using Simulink as shown in Figure 5, and co-simulation is performed on Simulink and RecurDyn [19]. The RecurDyn model has 4 inputs, including motor speed of four tracks, and 2 outputs, including the speed and heading of the vehicle. After comparing the output speed and the set speed, the output heading and the set heading, the control system calculates the track motor speed that the vehicle needs according to the error of the speed and heading [20].



Figure 5: The model of the control system built in Simulink

Table 3

Parameters of NNPID

Parameter	Data
Learning rate	0.5
Momentum factor	0.1
Sample time(S)	0.001

The model of neural network PID is shown as Figure 6, which has 2 inputs including r(k) and y(k), and 4 outputs including the k_p , k_i , k_d and the output of the PID.



Figure 6: The model of the neural network PID in Simulink

The simulation time is set to 10 seconds, and the sample time is set to 0.001 seconds. As shown in Table 3, the learning rate and the momentum factor of the neural network are set to 0.5 and 0.1. By employing the dynamic vehicle model and control system, simulations yield data on vehicle speed and heading, which are depicted in Figure 7 through a co-simulation process. The proposed control technique is evaluated against both traditional PID control and an uncontrolled direct drive approach.





(c)The evolutions of the parameters of NNPID controller

Figure 7: The simulation data through co-simulation on Simulink and RecurDyn

As shown in Figure 6(a) and Figure 6(b), the newly introduced NNPID control algorithm demonstrates superior performance in managing both speed and heading in comparison to traditional PID and uncontrolled direct drive approach. Figure 6(c) illustrates how the NNPID parameters, namely K_p , K_i and K_d , have the capacity to self-adjust in response to changes in the desired signal and converge towards a stable set of values.

5. Conclusions

The research presented in this paper successfully demonstrates the feasibility and effectiveness of the NNPID algorithm for controlling underwater tracked vehicles. The proposed control method has the potential to enhance the performance and operational capabilities of underwater tracked vehicles, thereby expanding the possibilities for underwater exploration, resource collection, and environmental monitoring. Furthermore, the research opens up opportunities for future studies to explore the application of the NNPID algorithm in other domains of unmanned underwater vehicles and robotics. The significance of the NNPID algorithm lies in its ability to adapt to the complex and dynamic underwater environment, which is a key advantage over traditional PID control methods. By incorporating neural networks, the NNPID algorithm can learn from the changing conditions and adjust the control parameters accordingly, resulting in improved speed and heading control. This adaptability makes the NNPID algorithm particularly well-suited for underwater operations where the environment is unpredictable and constantly changing. The research also highlights the importance of using collaborative simulation tools like RecurDyn and Simulink to evaluate the performance of control algorithms. By integrating the multi-body dynamics simulation capabilities of RecurDyn with the control system design features of Simulink, the research was able to provide a comprehensive assessment of the NNPID algorithm's effectiveness. This approach allows for a more realistic representation of the underwater vehicle's behavior and its interaction with the environment, leading to more accurate and reliable results.

In conclusion, the research presented in this paper makes a significant contribution to the field of underwater vehicle control. The introduction of the NNPID algorithm and its successful evaluation through collaborative simulation provide a valuable framework for future research and development in this area. As underwater operations continue to grow in importance, the enhanced control capabilities offered by the NNPID algorithm have the potential to drive advancements in underwater exploration, resource extraction, and environmental monitoring.

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