Intelligent obstacle avoidance algorithms for autonomous underwater vehicle

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Abstract. Real-time obstacle avoidance is the basis to ensure the safe operation of the autonomous underwater vehicle (AUV), and it also represents the intelligent level of AUV. The main factors that affect AUV obstacle avoidance are environment perception ability, obstacle avoidance decision-making ability, and trajectory tracking control ability. This paper starts from the perspective of obstacle avoidance decision-making ability, that is, obstacle avoidance algorithm. Firstly, we summarized the structure and influencing factors of AUV real-time obstacle avoidance. Then, we introduced in detail the research progress of AUV intelligent obstacle avoidance algorithms, including fuzzy logic algorithms, neural network algorithms, and reinforcement learning algorithms. And we analysed the improvement methods of each algorithm from three-dimensional underwater environment, ocean current, AUV motion characteristics, and dynamic obstacles. Finally, we prospected the development of the AUV intelligent obstacle avoidance algorithm.

1. Introduction

There are abundant resources in the ocean. The rational exploitation and utilization of marine resources are of great significance to the sustainable development of mankind. The emergence of an autonomous underwater vehicle (AUV) provides a powerful tool for the human to explore the ocean [1]. AUV has many advantages, such as a wide range of activities, high mobility and autonomy, good concealment and safety [2]. It has been widely applied in both civil and military fields [3]. An embodiment of AUV's autonomy is that AUV can interact with the external environment and avoid unknown obstacles in real-time. Due to the complexity, unpredictability, and randomness of the underwater environment, AUV cannot obtain complete environmental information of the task in advance in the actual underwater operation and may encounter unknown obstacles. Therefore, AUV must have real-time obstacle avoidance ability to ensure its safety and improve the success rate of task completion.

2. AUV Real-time Obstacle Avoidance

AUV real-time obstacle avoidance can be used as a local path planning. Under the guidance of global path planning, AUV online detects the surrounding environment to obtain obstacle information based on sensors (such as sonar), and then adopts an obstacle avoidance algorithm to avoid unknown obstacles [4], as shown in Fig.1(a). The structure of AUV real-time obstacle avoidance includes three parts: environmental perception, obstacle avoidance planning, and obstacle avoidance control, as shown in Fig.1(b).
In the underwater environment, AUV obstacle avoidance depends not only on AUV’s motion characteristics but also on environmental factors, such as obstacles, ocean currents, etc.

(1) Motion characteristics: The essence of obstacle avoidance is to control AUV to make appropriate actions to avoid obstacles, so obstacle avoidance is closely related to AUV’s motion control [5]. This requires that the motion characteristics of AUV, i.e. kinematic and dynamic constraints, should be considered in the process of obstacle avoidance.

(2) Ocean current: Ocean current has a great impact on the obstacle avoidance movement of AUV, especially the low-speed AUV [6], which makes the actual obstacle avoidance effect inconsistent with theoretical planning.

(3) Obstacles: AUV obstacle avoidance is affected by the characteristics of obstacles, such as shape, size, motion state, relative position, and density.

3. Intelligent Obstacle Avoidance Algorithms

In recent years, intelligent obstacle avoidance algorithms have been widely used in AUV real-time obstacle avoidance. AUV intelligent obstacle avoidance algorithm mainly includes fuzzy logic algorithms, neural network algorithms, and reinforcement learning algorithms. The comparison between them is shown in Table 1.

| Algorithms | Advantages | Disadvantages |
|------------|------------|---------------|
| FL (Zadeh, 1965) | 1. Simple structure; 2. Easy to implement; 3. Low calculation; 4. Strong real-time performance; 5. Suitable for unknown environments. | 1. Difficult to summarize fuzzy rules in complex underwater environment; 2. Difficult to adjust online; 3. Poor environmental adaptability and generalization ability; 4. Incomplete experience and limited input. |
| NN (McCulloch, Pitts, 1943) | 1. High parallelism; 2. Strong learning ability and adaptability; 3. Suitable for nonlinear problem; 4. High research heat. | 1. Large calculation; 2. Difficult to obtain representative samples; 3. Difficult to set the weight; 4. Difficult to predict points outside the sample. |
| RL (Minsky, 1954) | 1. Strong self-learning ability; 2. Strong adaptability; 3. Suitable for complex and unknown underwater environment; 4. High research heat. | 1. High computational cost; 2. Long learning time; 3. Slow convergence speed; 4. Difficult to deal with continuous state space; 5. Improper setting of reward function can easily lead to learning failure. |
3.1. Fuzzy logic algorithms

The fuzzy logic (FL) algorithms simulate the uncertainty judgment and reasoning thinking mode of the human brain and do not require an accurate mathematical model to deal with the complex and dynamic underwater environment [7]. FL is suitable for solving the AUV real-time obstacle avoidance in an unknown environment. The structure of the fuzzy obstacle avoidance planner designed according to the FL is shown in Fig. 2.

Fig. 2 Structure diagram of fuzzy obstacle avoidance planner

In general, the inputs of the fuzzy logic method are the distance and orientation of obstacles relative to AUV [8], which is suitable for static obstacles. To avoid collision between AUV and moving obstacles, Li et al. proposed a three-input fuzzy logic method considering the moving speed of obstacles. The method adds the distance change between AUV and obstacle as input and realizes dynamic obstacle avoidance in a two-dimensional environment [9]. However, this method is based on the premise that the velocities of AUV and obstacle are constant. For AUV with different forward speeds, Galarza et al. designed a reactive obstacle avoidance system based on fuzzy logic. The system takes the actual forward speed of AUV as one of the inputs, and the output variables are forward speed and yaw angle. Although the calculation amount and complexity of the algorithm are increased, it effectively solves the impact of AUV’s speed on obstacle avoidance [10].

Chen et al. extended fuzzy logic to the three-dimensional (3D) underwater environment and designed a fuzzy controller with three inputs and two outputs. The controller also integrates the behavior selection strategy that can select the more efficient obstacle avoidance behaviour (horizontal steering or vertical heave) as the output based on the environment information obtained by sonar, which makes AUV obstacle avoidance faster and more intelligent [11]. To realize continuous obstacle avoidance in 3D space, Xu et al. introduced event feedback monitoring into the fuzzy controller. By adding depth and heading holding states, the controller can guide the AUV to smoothly and effectively bypass multiple continuous static obstacles [12]. For obstacle avoidance in a 3D dynamic environment, Sun et al. developed a fuzzy-inference system with an accelerate/brake module, which realized AUV’s automatic obstacle avoidance to dynamic obstacles [13]. However, the choice of the fuzzy boundary is highly subjective, and the generated obstacle avoidance path cannot be guaranteed to be optimal. Using the particle swarm optimization algorithm or quantum particle swarm optimization algorithm to optimize the membership function value in fuzzy logic rules can effectively reduce the dependence on expert experience knowledge [14].

In order to make AUV adjust the obstacle avoidance strategy in real-time according to the change of ocean current, Lu increases the size and direction of the current as the input of the fuzzy planner and takes the AUV’s steering angle increment as output. The planner can adjust the central value of the membership degree of the steering angle increment online according to the real-time ocean current changes. This method not only considers the impact of ocean currents on AUV real-time obstacle avoidance but also effectively reduces the complexity of the fuzzy rule base [15]. Chen designed a hierarchical multi-rule set fuzzy planner to realize real-time obstacle avoidance in a complex marine environment [16]. The planner can select different input and control rulesets according to the current velocity and consider the dynamic characteristics of AUV. The fuzzy logic method pays attention to
safety and often ignores the energy consumption in the process of obstacle avoidance. Yu used a genetic algorithm to optimize the membership function of the fuzzy controller, which improves the energy utilization rate of AUV and the environmental adaptability of the algorithm [17].

3.2. Neural network algorithms

The main idea of the neural network method is to simulate the organizational structure and behaviour characteristics of the biological neural system. The neural network method has strong learning ability and adaptability, which is very suitable for the uncertain and highly nonlinear control object, such as AUV [18]. Generally, there are three ways to apply the neural network method to AUV real-time obstacle avoidance.

The first way is to obtain training samples directly in the AUV’s operating environment, that is, the sensor data is taken as the network input, and the expected position and attitude of AUV are taken as the network output. Dong et al. proposed a 3D real-time obstacle avoidance method based on BP neural network [19], which divides the 3D obstacle avoidance into horizontal obstacle avoidance and vertical obstacle avoidance. Taking horizontal obstacle avoidance as an example, the output information of the distance sensor is transformed into the danger degree as the input of the BP neural network, and the output is the heading that AUV needs to adjust, as shown in Fig.3(a). The second way is to combine neural network with fuzzy logic. Xu added a fuzzy layer between the input layer and the output layer of the BP neural network (Fig. 3(b)) and used fuzzy rules to construct the neural network. The fuzzy neural network combines the logical reasoning ability of the fuzzy method with the self-learning ability of neural network efficiently and enhances the adaptability of AUV obstacle avoidance [20]. However, it is not easy to obtain a large number of representative and non-contradictory training data. Considering the safety of AUV and the particularity of the working environment, the learning difficulty of the algorithm is greatly increased.

The third way is the bio-inspired neural network (BNN), as shown in Figure 4. BNN model has a simple structure, good real-time performance, and no need for sample learning and training. The Underwater Robot and Intelligent Systems Laboratory of Shanghai Maritime University has conducted extensive research on the application of the BNN model in AUV obstacle avoidance [21, 22]. Yan [21] and Zhu [23] matched the neural network with the 2D grid map one-to-one, as shown in Fig.4(a), and the obstacle avoidance path of AUV was planned based on the dynamically changing neural activity landscape in the neurodynamic model. The model can effectively avoid both static and moving obstacles in an unknown environment. However, the traditional BNN algorithm may encounter a problem, that is, AUV moves along the edge of the obstacle when avoiding obstacles, which affects the safety of AUV. Wu et al. added the lateral inhibition of obstacles in the neural network to solve this problem, which greatly improved the safety and rationality of obstacle avoidance [24]. Zhu et al. extended BNN to 3D obstacle avoidance [25, 26]. The neurons in the 3D BNN model correspond to the cell grids in the 3D grid map (Fig.4(b)), and the weight influence of adjacent neurons is added to the excitation item of the model, and then the navigation direction of AUV is determined according to the maximum activity output value of adjacent neurons. The improved model is suitable for dealing
with 3D underwater environment and sudden obstacles and improves the autonomy and safety of obstacle avoidance.

![Bio-inspired neural network model](Image)

For obstacle avoidance in a complex current environment, Zhu et al. added an ocean current model to the glasius BNN model. The improved model adds the current factor to the activity output value of neurons to adjust the activity value in the AUV neighbourhood, which reduces the influence of dynamic time-varying current and saves energy consumption [27].

3.3. Reinforcement learning algorithms

Reinforcement learning is an intelligent obstacle avoidance algorithm suitable for the complex and unknown underwater environment, which conducts online learning through continuous interaction between AUV and the environment [28]. Reinforcement learning technology can improve the self-learning ability and intelligence level of AUV.

Huang et al. designed the appropriate environment state set and the obstacle avoidance behaviour set based on the obstacle information obtained by sensors and then used the reinforcement learning method to select the optimal state-action combination suitable for autonomous obstacle avoidance of AUV to ensure safety of AUV Navigation [29]. Q-learning is a commonly used reinforcement learning method [30, 31]. However, the reinforcement learning method has some problems, such as dimension disaster, difficult to deal with continuous state space, and long learning time. The neural network has powerful nonlinear processing ability and function approximation ability, which can be used to solve these problems. Liu [32], Li [33], et al. used the BP neural network to enhance the generalization of the Q-learning algorithm. The output of the neural network corresponds to the Q value of the action (Fig.5), and then the optimal obstacle avoidance action of AUV adapted to the environmental state is determined. The hybrid method improves the autonomous ability and environmental adaptability of AUV and realizes the obstacle avoidance movement of AUV in a complex and uncertain environment. Sun used the CMAC neural network to approximate Q function and state-space to solve the problem that it was difficult to store continuous state space in Q-learning. This method improved the obstacle avoidance performance of AUV in the two-dimensional plane [34].

![BP neural network generalizes Q learning](Image)

Vibhute et al. designed a real-time obstacle avoidance system based on reinforcement learning. The system takes into account the kinematics and dynamics of AUV and can generate an optimal action that can reduce the local cost to the lowest under the obstacle avoidance constraint. And it performs well in real-time obstacle avoidance of static obstacles [35]. Yao analysed the forces of AUV in the ocean current environment and constructed a 6-DOF spatial motion model of AUV. Then the Q-learning mechanism is introduced to adjust the fuzzy rule strategy, and the influence of ocean current on AUV is also considered in the design of the reinforcement signal. In this way, the adaptive ability
of AUV is effectively improved [36]. For the case of unknown current velocity, Yao proposed an obstacle avoidance method based on the current prediction model. Firstly, the current prediction model is used to predict the current velocity, which is used as the input of the motion model to obtain the real-time pose of AUV. Then, the Q (λ) learning algorithm is used to plan the obstacle avoidance path, and the heading angle of AUV is corrected in consideration of the ocean current. This method improves the adaptability and safety of AUV in the time-varying current environment [37].

4. Conclusion
With the intelligent and autonomous development of AUV, the underwater environment faced by AUV is more complex. The 3D obstacle avoidance algorithm that introduces the motion characteristics of AUV is still one of the focuses of future research. In addition, there are many problems to be discussed to improve the practicability of the obstacle avoidance algorithms and apply them to the actual marine environment, such as time-varying ocean current, energy constraint, irregular or flexible obstacles.

Acknowledgments
This article was funded by the National Natural Science Foundation of China, grant number 61471224 and the Shandong Key Research and Development Program, grant number 2018GHY115022.

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