Situation Information Fusion Assessment for Underwater Robots

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Abstract

Situation information is very important for the underwater robots. With the situation information, the underwater robots could make the right decision to complete their works. Situation assessment is the process to translate the environment information collected by sensors into the situation information. Hence, situation assessment is very significant for underwater robots. However, problems of poor objectivity, low accuracy, etc. always existing in evaluation methods of the electrical systems attract interests of many researchers. This paper puts forward a situation information fusion assessment method for the underwater robots. The multi-agent situation assessment factors are designed in the first to build the data set and model input for the next step. The BP neural network is then utilized for train the map relationship from the evaluation factors to the situation information. The results of experiments in the underwater robot platform demonstrate that the proposed method has better properties in efficiency than the competing methods.

Keywords

Underwater robot, Situation assessment, Situation information, Fusion assessment.

1. Introduction

1.1 State model

At present, in the field of underwater robots [1]-[3], underwater vehicles have become a common research direction in the initial stage of underwater robots, such as the “Blue Flag Tuna”-21 underwater autonomous vehicle used by the US Navy, China Weifu Intelligent The CCROV underwater vehicle developed by the company. However, these underwater robots have some significant drawbacks: the system is very complicated, the volume is quite large, the operation control flexibility is not high, and the price is expensive. In recent years, the intelligent bionic robot fish model based on bionics theory has been gradually studied by scholars because of its high efficiency, low noise, high speed and high maneuverability. In addition, the development of materials science, institutional science, 3D printing technology and composite technology in recent years have also provided the basis for the development of bionic robot fish.

Intelligent decision-making (Intelligence Decision, ID) is a combination of artificial intelligence (AI) and decision-making system (Decision System, DS) [4]-[7]. It is a computer-implemented technology that mimics human thinking. Inferential and logical judgments on decision-making problems, and then can make certain decision-making assistance or guidance to decision-makers, even in a certain field and under certain circumstances, instead of human beings to make independent decisions and formulate plans to achieve accurate and rapid decision-making purposes, reducing Decision-making mistakes or deviations caused by human's own objective emotions and physical reasons. In recent years, in order to adapt to the increasingly complex and dynamic environment, adaptive decision-making technology that can continuously improve its decision-making performance and improve decision-making level over time has emerged.

As a single intelligent agent, the underwater robot can sense the surrounding scene information, and then the process of judging and deciding according to certain rules can be called the single intelligent decision of the underwater robot. This is of great significance for realizing autonomous operation and autonomous operation of robots in water. Without intelligent decision-making technology, underwater robots are equivalent to no "brains" and cannot reflect the characteristics of robot autonomy. In addition, for the case of Multi Intelligent Agent, information exchange and information sharing between agents, and multi-agent coordinated distribution and cooperative action group intelligent decision-making technology based on more comprehensive information are also necessary. For each different agent, the tasks that can be completed and the tasks it specifies may be different. In this case, consider multi-agents from the whole, avoid conflicts between each other, and improve the group. Job efficiency, improved group system (GS) parallelism, robustness, etc. are very important.

In summary, research on the relevant decision-making of underwater robots has achieved phased research results both at home and abroad. However, due to the complex and variable robotic operating environment in real water, the applicability and versatility of various decision-making schemes are poor. In the single water robot decision-making and multi-water robot coordination, a lot of in-depth research is still needed.

2. Multi-agent Situation Assessment Factor Selection

Situation assessment is a process of judging situational understanding information based on multi-factor selection. It is necessary to consider the number of influencing factors and the types of influencing factors selected: if the selection factor is too small, the information to be evaluated is incomplete; if too much Will cause the algorithm to be too complicated and cumbersome, affecting real-time. And there are many kinds of factors affecting the situation, they will affect the formulation of the strategy to different extents, especially the effectiveness of the implementation strategy is different, so it is necessary to reasonably match the selected quantity and type, and select the evaluation that can highlight the performance situation. factor.

Therefore, considering the complexity of the scene state space, the real-time nature of the whole model, the information capacity, and the complexity of the algorithm, combined with the domain expert knowledge and the actual scene verification, the objective of the multi-water robot control environment situation is finally objectively formulated. The six main factors. They are: the remaining time ratio, the gap between the two sides against the score, the real-time position against the target, the real-time information of the robot in our water, the real-time information of the robot in the other party and our field control ability.

2.1 Remaining time ratio

In the multi-water robot confrontation, the remaining time against the game is one of the main reasons that influence the situation analysis. This is similar to the human race. The remaining number of games will directly lead to changes in the specified strategies against the two sides. For example, when the current game time is nearing the end, we have achieved a clear advantage. The confrontation strategy we adopt should focus on defense, that is, the current situation can be defined as a defensive favorable situation; when the game is about to end, our game is slightly behind. At this time, we should actively attack and strive for the final time to overtake the score, so the current situation can be defined as a favorable offensive situation.

Suppose a total time for a match is T, and the current time is tc, then the remaining time ratio is

$$r_r = \frac{T - t_c}{T} \tag{1}$$

Therefore, as the game progresses, the remaining time ratio has been decreasing.

2.2 Against the score gap between the two sides

The gap between the two sides can directly reflect the state we are in, and it also reflects the advantages of opposing the two sides in deploying follow-up strategies. To put it simply, in the case of our low score, we must focus on offense; when our score is high, we are mainly defensive.

Real-time scores are obtained through the multi-water robot confrontation platform. Assuming that the opponent scores at the current time, and the real-time score difference is

$$s = s_1 - s_0 \tag{2}$$

2.3 Operation target real-time location

Take the water polo confrontation as an example, and the two sides need to obtain the position of the water polo in real time to carry out strategy and formation. Simply put, if the water polo is closer to our goal, then we should quickly return to the defense and enter the defensive strategy; if the water polo is stronger than the opponent's goal, we should attack it with all our strength.

Objects of a specified shape, color, and size can be identified, and the position against the target can be obtained by conversion and translation of standard graphics. In particular, when there are more targets, a set of targets against the target will be obtained. Recorded as $\{(x_0^o, y_0^o), (x_1^o, y_1^o), (x_2^o, y_2^o)...\}$. Among them, (x_i^o, y_i^o) represents the real-time location of the ith target.

2.4 Real-time information of our underwater robot

The real-time location of our underwater robots is also a very important factor influencing decision making. Simply put, if our underwater robot is far away from our goal and close to the ball, we should actively attack and score goals; if our underwater robot is closer to our goal and closer to the ball, Explain that the ball is out of our goal. Therefore, we should adopt a defensive strategy to take the ball away from the goal and isolate the danger.

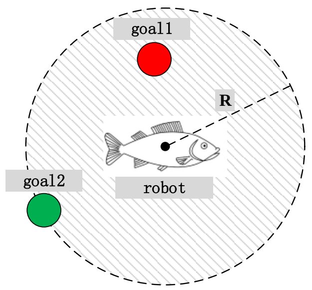
With the position and angle information of the underwater robot, in the multi-water robot confrontation system, the underwater robot information acquired by the computer in real time is not unique, but it is one of us. Underwater robot information collection, Recorded as $\{(x_0^0, y_0^0, \alpha_0^0), (x_1^0, y_1^0, \alpha_2^0), (x_2^0, y_2^0, \alpha_2^0)...\}$. Among them, (x_i^0, y_i^0) indicates the real-time position of the ith underwater robot, α_0^0 indicates the real-time declination of the ith underwater robot.

2.5 Real-time information of the robot in the other party

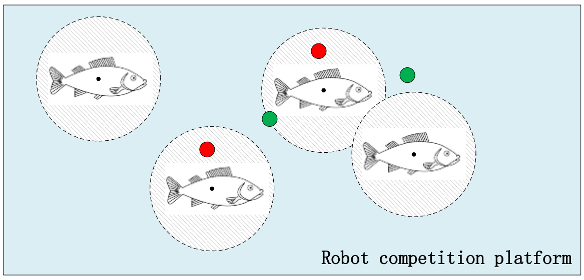
The real-time position of the robot in the other water is also a very important factor affecting decision making. Simply put, if the opponent's underwater robot is far away from our goal and is closer to the ball, we should actively return to the defense; if the other party's underwater robot is far away from our goal and is closer to the ball, we should actively attack, try to score the ball into the opponent's goal.

With the position and angle information of the underwater robot, in the multi-water robot confrontation system, the underwater robot information acquired by the computer in real time is not unique, but is a counterpart. Water robot information collection, recorded as $\{(x_0^1, y_0^1, \alpha_0^1), (x_1^1, y_1^1, \alpha_2^1), (x_2^1, y_2^1, \alpha_2^1)...\}$. (x_i^1, y_i^1) indicates the real-time position of the ith underwater robot. α_0^1 indicates the real-time declination of the robot in the ith counterpart.

2.6 Our field control ability



(a) Single-water robot field control



(b) Group water robot field control

Fig. 1 Schematic diagram of field control of multi-water robots against platform.

For the judgment of whether we have on-site control, set a circle with a radius of R centered on a single underwater robot, indicating the field control range of one of our underwater robots, as shown in Fig. 1. Among them, the value of R is set according to the size and flexibility of the robot in the water, combined with the experience of the game.

As shown in Fig. 1 (a), the number of operating targets in the field control range of the underwater robot is recorded as the description of the field control capability of the underwater robot. At the current time, the field control ability of our n underwater robots is expressed as

$$FC_t^0 = \sum_{i=1}^{n} {}^0TN_i^t \tag{3}$$

Among them, TN_i^0 indicates the number of operational targets that our ith underwater robot can detect at time t.

Therefore, it can be calculated that the field control ability of the robot in our water is pushed from the current time before the start of the current time.

$$AFC_t^0 = \sum_{j=}^{K} \sum_{i=1}^{n} {}^0TN_i^t \tag{4}$$

According to the same method, it is possible to calculate the field control ability of the other n underwater robots to push K time slices before the current time starts.

$$AFC_t^1 = \sum_{j=}^{K} \sum_{i=1}^{n} {}^1TN_i^t \tag{5}$$

From this, we can calculate the percentage of our field control ability:

$$u^t = \frac{AFC_t^0}{AFC_t^1 + AFC_t^0} = \frac{\sum_{j=}^{K} \sum_{i=1}^{n} {}^0TN_i^t}{\sum_{j=}^{K} \sum_{i=1}^{n} {}^1TN_i^t + \sum_{j=}^{K} \sum_{i=1}^{n} {}^0TN_i^t} \tag{6}$$

It can be seen that the larger u^t is, the higher the field control power in a certain period of time, the greater the field control power in a certain period of time, we can judge that we are in a favorable position.

3. Design of situational fusion algorithm based on BP neural network model

Due to the complexity and change of the actual anti-scene environment information, the multivariate regression analysis after the extraction of key factors does not necessarily meet the needs of situational integration. The relationship between situational outcomes and key factors is not necessarily linear, and the most likely is the nonlinear relationship. However, considering the uncertainty and difficulty of nonlinear fitting, the traditional nonlinear fitting method is not suitable [8]-[9]. Therefore, this paper designs a set of nonlinear situational potential fusion evaluation based on BP neural network model. method.

3.1 BP algorithm steps

Step 1: Initialize the weight.

Assign a small portion of the non-zero sample value to $w_{mi}(0)$, $w_{ij}(0)$, $w_{mj}(0)$, and $w_{jp}(0)$ randomly.

Step 2: Determine the BP neural network structure.

Let $X_k=\{x_{k1},x_{k2},...,x_{km}\},k=1,2,...,N$ be the input vector and N be the number of training samples. $Y_k(n)=\{y_{k1}(n),y_{k2}(n),...,y_{kp}(n)\}$ is the output of the nth iteration and $d_k=\{d_{k1},d_{k2},...,d_{kp}\}$ is the desired output.

Step 3: Enter the training sample.

Train the sample set and learn the sample as $X=\{X_1,X_2,...,X_K,...,X_N\}$.

Step 4: Forward delivery.

The output of the BP network is calculated according to the set function, and the training error value of the sample X_k is calculated.

Step 5: Reverse delivery.

Referring to the error value, the weights and thresholds of each layer are updated according to the function. If the condition of K>N is satisfied, the process proceeds to Step6, otherwise, the process proceeds to Step3.

Step 6: Compare the total error.

If the final accuracy requirement is reached, the training ends, otherwise go back to Step 3 and continue learning.

Situational Fusion Evaluation Algorithm Based on BP Neural Network Model

According to Chapter II, the real-time evaluation factors are: the ratio of remaining time r, the difference between the two sides against the score s, and the real-time position of the $\{(x_0^o,y_0^o),(x_1^o,y_1^o),...,(x_{n_o-1}^o,y_{n_o-1}^o)\}$ targets. n^0 our underwater robot information data $\{(x_0^0,y_0^0,\alpha_0^0),(x_1^0,y_1^0,\alpha_2^0),...,(x_{n^0-1}^0,y_{n^0-1}^0,\alpha_{n^0-1}^0)\}$ 、 n^1 counterpart water robot information data $\{(x_0^1,y_0^1,\alpha_0^1),(x_1^1,y_1^1,\alpha_2^1),...,(x_{n^1-1}^1,y_{n^1-1}^1,\alpha_{n^1-1}^1)\}$. Our field control ability u.

Then the real-time evaluation factor set is $\{r,s,x_0^o,y_0^o,x_1^o,y_1^o,...,x_{n_o-1}^o,y_{n_o-1}^o,x_0^0,y_0^0,\alpha_0^0,x_1^0,y_1^0,\alpha_1^0,...,x_{n^0-1}^0,y_{n^0-1}^0,\alpha_{n^0-1}^0,x_0^1,y_0^1,\alpha_0^1,x_1^1,y_1^1,\alpha_1^1,...,x_{n^1-1}^1,y_{n^1-1}^1,\alpha_{n^1-1}^1,u\}$ .Dimension is $O(3+2n_o+3n^0+3n^1)$.

Then the number of independent variables of the corresponding BP neural network model is $(3+2n_o+3n^0+3n^1)$.

At the same time, each dimension is normalized. We can get $\{\hat{r},\hat{s},\hat{x}_0^o,\hat{y}_0^o,\hat{x}_1^o,\hat{y}_1^o,...,\hat{x}_{n_o-1}^o,\hat{y}_{n_o-1}^o,\hat{x}_0^0,\hat{y}_0^0,\hat{\alpha}_0^0,\hat{x}_1^0,\hat{y}_1^0,\hat{\alpha}_1^0,...,\hat{x}_{n^0-1}^0,\hat{y}_{n^0-1}^0,\hat{\alpha}_{n^0-1}^0,\hat{x}_0^1,\hat{y}_0^1,\hat{\alpha}_0^1,\hat{x}_1^1,\hat{y}_1^1,\hat{\alpha}_1^1,...,\hat{x}_{n^1-1}^1,\hat{y}_{n^1-1}^1,\hat{\alpha}_{n^1-1}^1,\hat{u}\}$.

These values are used as input parameters for the BP neural network model.

After performing the above processing according to the scene information, the training data set can be obtained.It is $\{(x_1^1,x_2^1,...,x_{3+2n_0+3n^0+3n^1}^1,f_1),(x_1^2,x_2^2,...,x_{3+2n_0+3n^0+3n^1}^2,f_2),...,(x_1^K,x_2^K,...,x_{3+2n_0+3n^0+3n^1}^K,f_K)\}$,among them, $f_i\in\{F_1,F_2,...,F_n\}$.

Finally, the training of the neural network can be carried out according to the training process of the BP neural network model. In particular, since the situation evaluation result obtained by the data through the neural network model is not an integer, the rounding of the decimal is also performed by rounding off the algorithm to obtain the final situational label.

4. Simulations and Experiments

4.1 Case Verification of Situation Assessment Technology Based on BP Neural

There is a red water polo, a black bionic robot fish, a black bionic robot fish, and then a water polo confrontation. The real-time data has 11 dimensions $\{r,s,x_o,y_o,x_0,y_0,\alpha_0,x_1,y_1,\alpha_1,u\}$. A total of three types of labels are described for the current situation: favorable situation (1), unfavorable situation (2), and intermediate situation (3).

The real-time data acquisition of the multi-water robot confrontation platform is performed within a certain period of time, and then for each set of data, according to the expert experience, each situation data can be given a status label. A total of 1000 experimental data were selected in the experiment, and the BP neural network model was established to simulate the simulation under matlab. Set the network learning rate $\eta = 0.05$; training error $E = 0.01$. The training results of the BP neural network are shown in Fig. 2.

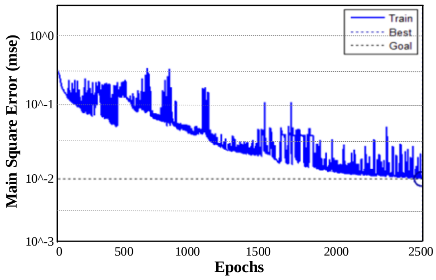
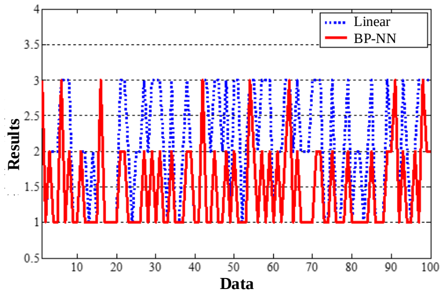


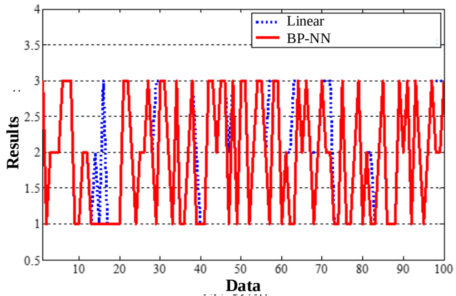
Fig. 2 Convergence Diagram of BP Neural Network.

It can be seen from the figure that after 2500 iterations, the error of the situational fusion evaluation model based on the BP neural network model is less than 0.01, that is, the training is completed.

4.2 Situation assessment prediction accuracy comparison



(a) Comparison of linear fit results with standard results



(b) Comparison of fitting results

Fig. 3 Comparison of prediction results of two situational fusion assessment methods.

According to the training network results in Chapter III, the cross-validation method can be used to perform linear fitting regression analysis and the prediction accuracy comparison of nonlinear situation assessment based on BP neural network model. Sorting and selecting 100 sets of new data for data accuracy comparison. The 100 arrays are all manually indexed by the situational information as the reference situation information, and then the two fusion situation assessment results are compared respectively. The results are shown in Fig. 4.

According to Fig. 4, the nonlinear situational potential fusion evaluation results based on the BP neural network model are more accurate than the linear fitting, which proves the superiority of the method for the situation assessment. And practicality.

5. Conclusion

For the situation assessment problem of the scene, this chapter first analyzes the commonly used situation assessment methods based on expert experience and linear fitting, and then proposes a method for the dynamic complex scenes of multi-water robots studied in this paper. Nonlinear situational potential fusion evaluation method based on BP neural network model. First, the evaluation factors extracted in Section 3 are normalized, and then used as input nodes of the neural network model to perform nonlinear fitting training, and finally a reasonable BP network model can be obtained. In the experimental part, the experimental results also show the superiority of the nonlinear situation assessment based on BP neural network model.

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