Research of an Autonomous Path Planning Algorithm in the Dynamic Target Tracking

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Abstract—Path planning has made great progress in recent years, for which more and more autonomous algorithms are proposed. Dynamic target tracking plays very important role in path planning, but most research of whom are related to the hardware that to realize it. There is very few research focus on the dynamic target autonomous tracking. Based on our previous work, this paper tries to research on an autonomous path planning algorithm in the task of dynamic target tracking. The algorithm is redesigned according to operant conditioning principle, and its rationality is proved. Different simulations are done, and the characteristics of our algorithm in dynamic target tracking are analyzed.

Keywords—dynamic target tracking; autonomous path planning; mobile robot; operant conditioning; intrinsic motivation

I. INTRODUCTION

Path planning is one of the core contents of mobile robot research. With the rapid development of computer science, sensor technology and artificial intelligence, path planning technology has been further studied. In order to make up for the shortcomings of traditional path planning algorithms, many scholars have proposed intelligent path planning algorithms by optimizing complex computational processes and inference methods, including genetic algorithms [1], neural network algorithms [2], fuzzy logic algorithms [3], and etc. For all of the intelligent algorithms above, very few of them are used to achieve dynamic target tracking.

Dynamic target tracking [4] is an intersection of computer vision and artificial intelligence. Zhang pointed out in the literature [5] that the basic problem form is to select dynamic obstacle targets in image sequences or video streams, and actively search and track targets in successive image frames to obtain their specific states, positions and running trajectories. At present, the tracking methods for moving targets are mainly divided into optical flow based, motion estimation based, and target tracking based [6], and is widely used in the fields of visual navigation, intelligent monitoring, human-computer interaction and so on. Although as early as in the twentieth century, moving target detection, recognition and positioning technology has achieved greater development, but in the face of the incomplete collection images, images of the complex trajectory and noise pollution, visual dynamic target tracking method in the treatment of target motion on the video and image sequence frame remains a great challenge. In order to obtain a complete and clear image, Oxford University developed the Robot Car UK automatic driving system to obtain map data and surrounding dynamic target motion through the camera mounted on the front end of the vehicle [7]. Reference [8] also stated that dynamic targets must be well visible and close enough to the camera to provide sufficient information for accurate shape detection. It can be seen that the dynamic target tracking research mainly focuses on visual research or visual hardware, but does not pay attention to the dynamic target tracking autonomic algorithm itself.

Based on our work before as in [9], this paper studied the implementation of an autonomous path planning algorithm in the realization of dynamic target tracking. Firstly, we redesigned the algorithm, and proved its rationality. Then different simulation experiments are conducted and analyzed. Conclusions are given at the end of the paper, and the future works are proposed.

II. AUTONOMOUS PATH PLANNING ALGORITHM

Aiming at the realization and application of path planning algorithm in dynamic target tracking, and based on an existing autonomous path planning algorithm [9], this paper redesigns its orientation learning algorithm and curiosity algorithm according to the operant conditioning and intrinsic motivation principle.

The model of the algorithm after redesigned can be defined as a nine-tuple computing model called NCM. NCM=\{t, S, A, N, E, O, C, P, H\}, the meaning of each part can be found in the [9].

A. Algorithm redesigned

Orientation is an important concept introduced from the psychology. It shows the preference degree of the mobile robot for different actions’ selection. In general, when the agent has a low selection orientation for an action in a certain state, the selection orientation of other actions in this state will be high. At the same time, if the result of the selected action is the expected result, then the orientation of the agent to select this action at the next moment will increase, while the orientations of other actions will decrease, and vice versa. It can be seen that the agent's self-learning process in the environment is guided by the operating conditioning principle.

Therefore, this paper redesigns the orientation mapping update algorithm of NCM as follows:

Assuming that at time , NCM selects action \( a \), according to the intrinsic motivation under the perceptual state \( s \). At this
time, the orientation map set is \( o_i \), then at time \( t+1 \), the orientation map sets \( o_i(t+1) \) and \( o_i(t+1) \) are updated as equations (1), (2) and (3):

\[
o_i(t+1) = o_i(t) + \Delta \times (1 - o_i(t))
\]

\[
o_i(t+1) = o_i(t) - \Delta \times (1 - o_i(t)) \times \frac{o_i(t)}{\sum_{j\neq i} o_j(t)}
\]

\[
\text{If } E(t+1) > E(t),\quad \text{then at time } t+1,
\]

\[
\text{if } E(t+1) = E(t),\quad \text{then at time } t+1,
\]

\[
\text{if } E(t+1) < E(t),\quad \text{then at time } t+1.
\]

From the biological point of view, when the number of times an agent learns for a certain action increases in a certain state, the degree of curiosity about the action in that state will reduce. So NCM’s curiosity function is designed as equation (4):

\[
c_j = e^{-|a_j - c|}
\]

where, \( k \) and \( \epsilon \) are curiosity parameters.

B. Proof of Algorithm Rationality

First of all, the orientation learning algorithm should guarantee throughout all of the learning process that:

\[
0 \leq o_i(t) \leq 1 (i = 1, 2, \ldots, n_i) ;
\]

\[
\sum_{j=1}^{n_i} o_j(t) = 1 (i = 1, 2, \ldots, n_i).
\]

Take state \( s_i (i = 1, 2, \ldots, n_i) \) as an example, at the initial learning time, the conditions can be satisfied according to the definition \( o_i(0) = 1/n_i \);

(1) Suppose that at time \( t \), the NCM state is \( s_i(t) \), according to the intrinsic motivation, a certain action \( o_i(t) \) is selected, at time \( t+1 \):

If \( E(t+1) > E(t) \), the orientation is updated according to the formula (1). For \( o_i(t+1) \), based on the assumption \( 0 \leq o_i(t) \leq 1 \), we can get that

\[
0 \leq 1 - o_i(t) \leq 1 , \quad 0 \leq \Delta = 1 - e^{-|E(t+1) - E(t)|},
\]

as \( 0 \leq 1/n_i \), therefore \( 0 \leq o_i(t) \times \Delta \leq 1 - o_i(t) \), so

\[
0 \leq o_i(t) \leq o_i(t+1) = o_i(t) + (1 - o_i(t)) \Delta \leq o_i(t) + (1 - o_i(t)) = 1
\]

For \( o_i(t+1) \), there is \( 0 \leq \Delta = 1 - e^{-|E(t+1) - E(t)|}/n_i \), so

\[
0 \leq o_i(t+1) \leq o_i(t) - (1 - o_i(t)) \Delta \leq o_i(t) \leq 1
\]

If \( E(t+1) < E(t) \), the orientation is updated according to the formula (3), the condition can also be established through the same analysis process as the situation \( E(t+1) > E(t) \).

If \( E(t+1) = E(t) \), the orientations do not change according to formula (2), and the condition can be established.

To sum up, in any case, as long as \( 0 \leq o_i(t) \leq 1 \) is true, \( 0 \leq o_i(t+1) \leq 1 \) is also true. According to mathematical induction, the initial learning time satisfies condition \( 0 \leq o_i(t) \leq 1 \), and it can be concluded that NCM orientation satisfies \( 0 \leq o_i(t) \leq 1 (i = 1, 2, \ldots, n_i, j = 1, 2, \ldots, n_j) \) in the whole learning process.

(2) First, at the initial learning moment, according to the definition \( o_i(0) = 1/n_i \), NCM’s orientation satisfy \( \sum_{j=1}^{n_i} o_j(0) = 1 \).

Suppose that at time \( t \), sets \( \sum_{j=1}^{n_i} o_j(t) = 1 \) and \( \Delta = 1 - e^{-|E(t+1) - E(t)|} \), then at time \( t+1 \):

If \( E(t+1) > E(t) \), the orientations updated according to the formula (1), then:

\[
\sum_{j=1}^{n_i} o_j(t+1) = o_j(t+1) + \sum_{j=1}^{n_i} o_j(t+1) = o_j(t) + \Delta \times (1 - o_j(t)) + \sum_{j=1}^{n_i} o_j(t) \leq 1
\]

If \( E(t+1) < E(t) \), the orientations updated according to the formula (3), then:

\[
\sum_{j=1}^{n_i} o_j(t+1) = o_j(t+1) + \sum_{j=1}^{n_i} o_j(t+1) = o_j(t) + \Delta \times (1 - o_j(t)) + \sum_{j=1}^{n_i} o_j(t) \leq 1
\]
\[
\sum_{j=1}^{\hat{\mathbf{m}}} \theta_j(t+1) = \hat{\mathbf{m}}(t+1) + \sum_{j=1}^{\hat{\mathbf{m}}} \theta_j(t) \quad (8)
\]

If \( E(t+1) = E(t) \), the orientations updated according to formula (2), then:

\[
\sum_{j=1}^{\hat{\mathbf{m}}} \theta_j(t+1) = \hat{\mathbf{m}}(t+1) + \sum_{j=1}^{\hat{\mathbf{m}}} \theta_j(t) = 1 \quad (9)
\]

In summary, in any case, if \( \sum_{j=1}^{\hat{\mathbf{m}}} \theta_j(t) = 1 \) is established, then \( \sum_{j=1}^{\hat{\mathbf{m}}} \theta_j(t+1) = 1 \) can be established. According to the mathematical induction method, at the learning initial time \( \sum_{j=1}^{\hat{\mathbf{m}}} \theta_j(0) = 1 \) satisfies the condition, so the NCM orientation satisfies \( \sum_{j=1}^{\hat{\mathbf{m}}} \theta_j = l (l = 1,2,\cdots,n) \) throughout the learning process.

III. DYNAMIC TARGET TRACKING SIMULATION EXPERIMENT

The simulation experimental environment that the mobile robot learns is shown in FIGURE I. The yellow circle represents the mobile robot. The target point is the triangle and the green squares represent the obstacles. 10 obstacles are set between the robot and the target point.

In the dynamic target tracking experiment, the robot randomly selects a target point and reaches it, and then uses this target as new starting point to move to the next randomly target point. During this process, the position and size of the obstacle are unchanged. For our experiment, the dynamic target setting must be realized first. Since the state energy function of the mobile robot is fixed in this method, so the dynamic target selected in this paper is distributed on the distribution axis of the state energy function value, which means that the selection of the next dynamic target is randomly generated in the region where the energy value is higher than the previous target.

In this part, three dynamic target tracking experiments are carried out to explain the influence of target position changing on the state energy function value axis. Details are as follows.

In dynamic target tracking experiment 1, starting from (0.25m, 0.25m), the horizontal and vertical coordinates are randomly increased between 0.1m-2m, resulting in five target points, which are (1.3m, 1.8m), (2.5m, 2m), (2.9m, 3.2m), (4m, 3.2m), (4.6m, 4m). In order to more clearly and intuitively reflect the process of robot’s tracking on dynamic targets, the experiment decomposes the process, and the results of different tracking path segment are shown in FIGURE III. From the results we can see that, based on the free learning results, the robot quickly completes the tracking of five random target points, and the path is smooth. It can be seen that the mobile robot can track the dynamic target point whose state energy function value increases.

The state energy function in the NCM is used to determine the learning direction of the mobile robot and the energy distribution is shown in FIGURE II. It can be seen that starting from the (0.25m, 0.25m) to the target point (4.75m, 4.75m), the distribution of the state energy function value tends to increase, except around the obstacles. The closer to the obstacle, the smaller the energy function value is. For the state energy function value from the starting point to the target point, the energy function value keep increasing, and we name it state energy function value distribution axis.

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Next, dynamic target tracking experiment 2 is performed. The five target points in the experiment 2 are set according to the state energy function value distribution. The state energy function value of the next target point is bigger than the previous target point. On the distribution axis of the energy function value from the starting point to the target point, the symmetrically unobstructed objects on both sides of the axis can be regarded as with equal energy values, which means that the value of the horizontally selected next target point is greater than the previous target point. The five randomly selected target points are (1m, 2m), (2.5m, 1m), (2.8m, 3.5m), (4m, 2m), (4.5m, 4.5m), and the results are shown in FIGURE IV.

The difference between experiment 2 and experiment 1 is that the dynamic target point in experiment 1 moves along the step shape, while the target point in experiment 2 moves along the zigzag shape. In experiment 1, the next target point’s horizontal and vertical coordinates must not be smaller than the previous target point, while in experiment 2, the horizontal and vertical coordinates of the next target point are not necessarily bigger than the previous target point. The common point of experiment 1 and experiment 2 is that the state energy function value of the next target point must be greater than the previous target point.

Finally, dynamic target tracking experiment 3 is carried out. The five target points in experiment 3 are set as follow: the first target point is randomly selected in, and then the other four target points are sequentially incremented by 0.8m on the abscissa and 0.9m on the ordinate. The five target points in experiment 3 are finally selected as (1.5m, 1m), (2.3m, 1.9m), (3.1m, 2.8m), (3.9m, 3.7m), (4.7m, 4.6m). We can see in this set, the targets are distributed in the obstacles. The results are shown in FIGURE V. The difference between experiment 1 and 3 is that the dynamic targets in experiment 3 moves along the straight line.
It can be seen from all the three experiments that the robot’s dynamic target tracking is independent of whether the target point position is on an established path, but related to the state energy function value. The collision-free motion of the robot from the starting point to the target point is established by increasing the value of the state energy function.

IV. CONCLUSION

In this paper, an autonomous path planning algorithm is applied to the dynamic target tracking task through simulation experiments. The results show that the dynamic target tracking of the robot is independent of whether the target point position is on an established path, but related to the state energy function value. So with such an autonomous path planning algorithm [9], the dynamic targets should be distributed along the increasing axis of the state energy function. It can be found that the learning effect of the robot is closely related to the design of state energy function, which not only affects the update of the orientation learning algorithm, but also directly determines the learning direction of robot. A good state energy function can enable the model to achieve effective cognitive learning and generally adapt to a variety of unknown environments. On the contrary, if there is any deviation in the design of state energy function, the learning will be deviated from the target. Therefore, designing a dynamic state energy function which can constantly update according to the environment’s changes will be our next work.

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