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Potential field aided navigation path planning algorithm

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Abstract – In potential field aided navigation, optimal trajectories is an important task. The decision system is a key component of optimal trajectories. Designing the way in which decisions are taken and the path length in decision making will influence the whole performance. When classical algorithm need complete and precise models of the working space, and in many real scenarios their application is not available. Thus, model free methods for path planning under uncertainty are favorable choice. This paper uses Dyna-H algorithm in potential field aided navigation. The Dyna-H algorithm chooses branches more likely to produce good outcomes than other branches. and it is also a model free online reinforcement learning algorithm. The result of simulation shows that the navigation error of the planned path is less than that of arbitrary path. Improved A* path plan algorithm could enhance the performance of gravity aided.

Keywords – Path-planning, Heuristic-search, Potential field aided inertial navigation

1.Introduction

There has been an increasing interest in the areas of path planning. A number of approaches have been developed that focus on such problem.The main focus of this research is to compute collision-free shortest-paths as quickly as possible.

Path plan is a key technology in potential field aided navigation which determined the navigation accuracy. Because the potential field is a field of random amplitude, the performance of potential aided navigation is different at different path using the same match method in the same match area. After careful path plan, the performance of potential correlation match will be enhanced even in the area with relatively poor gravity information. It is necessary to research path plan in gravity aided navigation. Literature on the algorithm of path plan or route plan is abundant, such as voronoi map, A* algorithm [1, 3], reinforce learning [3, 4], fuzzy logic [5], neural network [6], anti colony algorithm [7] and particle swarm algorithm [8]. Such algorithm was applied in UAV [9], hypersonic airplane vehicle path plan because of little calculation amount, available and global optimum solution. Research paper on path plan in potential field aided navigation is scarcity. To adaptive to path plan in potential aided navigation, heuristic algorithms need to be proposed.

The organization of the paper is described as follows. Firstly, the way to generate a local gravity anomaly map and its stochastic model are described in section 2. Section 3 focuses on the key parameters setting of Dyna-H, in which potential field feature is taken as heuristic factor. Then, the results of numerical simulation and four typical planned paths are presented in section 4. Finally, conclusion is presented in section 5.

2.Model and simulation of potential field map

The potential field aided navigation needs local potential field map. There are many methods to simulate potential field. Two-dimensional potential field model is presented in following section.

2.1. The algorithm for local potential field

Local potential peak use two-dimensional model [10] as follows:

$$P(x,y)=P_0+\sum_{i=1}^{n}P_i exp\left\{-\left[\frac{x-x_{0i}}{x_{li}}\right]^2-\left[\frac{y-y_{0i}}{y_{li}}\right]^2\right\} \tag{1}$$

where P_0 is potential chart datum level, P_i is the amplitude of potential peak value, for i=1,2,3…, x_{0i}, y_{0i} are the coordinates of the potential peaks, for i= 1,2,3…, x_{li}, y_{li} are relative to gradient of potential value in the direction of X and Y axis. Local hollow could be simulated by the minus of the potential peak.

It is supposed that the statistical character of local potential is a stationary two-dimension stochastic process. Potential value fluctuation can be viewed as random series of Gauss distribution. The correlations are decaying as exponential function of distance. The correlation function is defined as:

$$\begin{aligned}R(\tau_x,\tau_y)&=E\left\{P(x,y)P(x+\tau_x,y+\tau_y)\right\}\\&=Aexp\left\{\frac{\tau_x}{\tau_{xl}}-\frac{\tau_y}{\tau_{yl}}\right\}\end{aligned} \tag{2}$$

Where τ_x, τ_y are the distance between two specified nodes. τ_{xl}, τ_{yl} are correlation distance. For a specified potential field, the longer correlation distance is, the smoother the potential value fluctuation is. The potential value recursion formula is defined as:

$$P(x,y) = a_1 P(x-1,y) + a_2 P(x,y-1) + a_3 P(x-1,y-1) + W(x,y) \quad (3)$$

where $P(x,y)$ is the value of the potential value in (x,y). $W(x,y)$ is the sequence of zero-mean Gaussian white noise, with the variance δ_w^2.

$$a_1 = exp\left[\frac{-1}{\tau_{xl}}\right] \quad (4)$$

$$a_2 = exp\left[\frac{-1}{\tau_{yl}}\right] \quad (5)$$

$$a_3 = -exp\left[\frac{-1}{\tau_{xl}}\right] \cdot exp\left[\frac{-1}{\tau_{yl}}\right] \quad (6)$$

$$\delta_w^2 = S^2(1-a_1^2)(1-a_2^2) \quad (7)$$

Where S is the RMS of the two-dimensional stochastic series. τ_{xl} , τ_{yl} are correlation distances in x and y directions, the correlation equation is defined as:

$$R_{ij} = exp\left\{\frac{-i}{\tau_{xl}} + \frac{-j}{\tau_{yl}}\right\} \quad (8)$$

In the path plan for potential field aided navigation, the effect of potential field chart datum level could be negligible. Therefore, it is supposed that potential field value mean amplitude is zero.

2.2. Simulation results

Three potential value peaks are set in the simulation; the positions of the peak points (x_{0i} , y_{0i}) are (25, 25), (10, 10) and (20, 25); Potential field value amplitudes are 60, 60, 45;

$\tau_{xl} = 1000$, $\tau_{yl} = 1500$ and S = 20; Sample interval is 250 ;

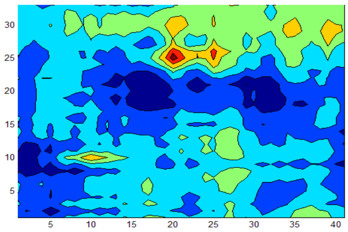

Figure1.Simulation results of the potential field

Simulation results of potential field are shown in Fig.1.The upper picture is a three-dimensional potential field map; the lower picture is a contour map of potential field.

Sample interval between two nodes in the potential field map is distant. The vehicles can easily turn between the nodes in traveling. Therefore, the algorithm takes the vehicles as a particle. The following simulations are based on above map.

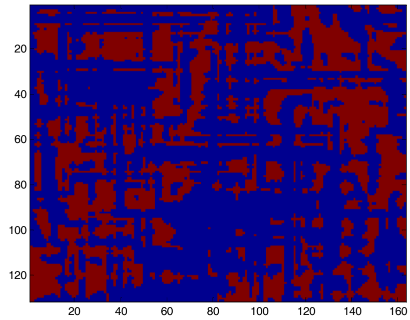

Figure2.Results of obstacles in the environment

Calculation of gradient has been done, and threshold has been set. Points of potential gradient under the threshold are viewed as obstacles.Figure2 depicts the result. Red points are the obstacles.

3. Potential field aided navigation path planning algorithm

The paper incorporates a heuristic planning strategy into a Dyna agent, in order to find the desire paths in potential aided navigation environments. Instead of producing all available solution choices, a heuristic method tends to get profitable selections than others. It is selective at each decision point. The method incorporates the ability of heuristic search with the ability of reinforcement. The characteristic of the method is that it could run without complete model of the environment before search.

3.1. Sampling from bad trajectories

The sampling strategy relies on using a learned model of the environment, using the worst trajectories with respect to some priori knowledge of the domain, receiving the worst rewards. Only in this way, it will get desire solution faster than using a priori better approach.

Sampling from “bad” paths looks like random behavior. Different trajectories use this sampling strategy. The bad trajectories present some discontinuities or abrupt jumps and sometimes traverse the barriers, which means the result fail to avoid the obstacle; things that are very common in practice before perfect.

H function is related to the value-systems of human, which mold their behavior. Indeed, there is much research about value-systems in robotics and autonomous agents to make robots possess self-learning ability, because values systems maybe the right path for robots to work autonomously through self-generated activity. There are different kinds of value systems based on human behavior related to motivation such as intrinsic motivated and curiosity driven. While there is little publication about the study of value-systems with the Reinforcement Path planning field.

3.2. The Core algorithm

In potential field aided navigation path planning scenario, it is custom to use the distance of real mean as an effective heuristic. In this simulation, the Euclidian distance is used for the heuristic (H) planning unit. But H(s; a) represents a general function that gives an estimate of the performance about the taken action in state s. The formula is defined as:

$$H(n,b) = \|n' - goal\|^2 \tag{9}$$

Where the n' state is the result of the model query: $n' = Mod(n,b)$. Given the parameter H, the heuristic action $h_b(n,H)$ is defined as:

$$h_b(n,H) = \underset{b}{argmax}\, H(n,b) \tag{10}$$

Where $h_b(n,H)$ is the worst action following (H).That means the action that yields the higher distance from the goal.

3.3 Experimental scenario depiction

To study path planning problem in the context of reinforcement learning, it is viewed as a Markov decision process, and there is a series of available states and a series of actions. Obstacle avoidance is a key topic in path-planning. New approach to this problem is to ignore obstacles until traverse them. This method is straightforward and it needs few demands: all that it requires is the relative position of the entity and its goal, and whether the neighbor area is barred. However there are occasions where the only smart method that could be used to plan the entire path in advance.

In this paper, the working space is represented with square fields as a 131*163 grid (figure 2). The obstacles are walls that are set according the characteristic of potential field. The state is the position where the entity is located. Neighboring states would vary depending on the local potential field situation. The cost of travelling represents some heuristic information:

it is computed as the Euclid distance between the two points, which in RL terminology is equivalent to set t =-1 for all non-terminal state transitions, searching an optimal path. The grid is represented as a two dimensional matrix of 131 rows and 163 columns. This matrix establishes the relationship between nodes or states;

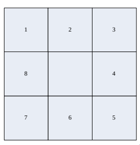

Figure 3.The expandable neighbor grids of path planning algorithm

The potential field is nonstationary and irregular, so in search space there are several isolate expandable areas which are not connective. Path may traverse several areas; the result path of 4neighbor expandable grids may be hard to follow. Algorithm uses the shortest step to search first. When the neighbor grids of current grid are not expandable, the action fails. Pic1 depicts Dyna-H algorithm of 4 neighbor grids that are expandable. The expandable grids are up (2), down (6), left (8) and right (6).

4. Simulation

The concrete steps of path plan algorithm are depicted as follows:

1. Calculation of potential field characteristic.
2. Determine the obstacle points.
3. Initialize Q(n; b), Mod(n; b) $\forall n \in N, b \in \mathrm{B}$.
4. repeat {for each episode}
5. n ← current state; b ← ε -greedy(n; Q)
6. execute b; observe n' and r
7. $Q(n,b) \leftarrow Q(n,b) + \alpha[r + \gamma \max_{b'} Q(n',b') - Q(n,b)]$; $Mod(n,b) \leftarrow n', r$
8. for i = 1 to N do
9. $b \leftarrow h_b(n,H)$
10. if n, b ∉ Mod then
11. n ← random previously observed state; b ← random action previously taken in s
12. end if
13. n'; r ← Mod(n, b)
14. $Q(n,b) \leftarrow Q(n,b) + \alpha[r + \gamma \max_{b'} Q(n',b') - Q(n,b)]$
15. $n \leftarrow n'$
16. end for
17. until n' is terminal

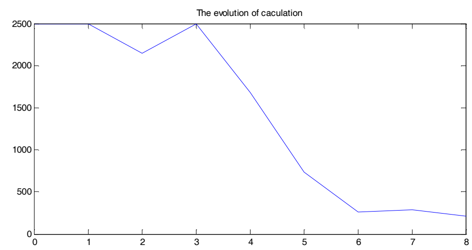

Figure 4. Performance of planned path

The performance of paths planning at each episode is depicted in Fig.4. The method used in the paper could search out several paths that attain the aim of short length and low potential field correlation coefficient. The curve shows that the paths that posses rich gravity navigation information could be searched gradually after 5 tries. Solution of early tries could be heuristic models of later calculations. The performance curves of the planned paths fluctuate at first, and it declines to less than 500steps afterward. The heuristic factors used in the algorithm bring forth the results analyzed above.

The trend of planned paths represents itself in a zigzag shape. The planned path in Fig.5 goes left firstly; the path then follows the contour of potential field. It successfully avoids the area lack of potential information, and turn down. Next, the path goes back to the nearest route between the start point and end. The planned path passes an area of low potential field correlation coefficient on the nearest route. The path then traverses several edges of contours. The contour lines could provide rich potential aided navigation information; The simulation results show that the paths could satisfy the requirements of path plan for potential field aided navigation. The validation of path plan algorithm is proved by the simulation.

The characteristic of paths planned is analyzed above. Following the planned path, the vehicle could obtain rich potential aided navigation information. The paths above represent typical resultant paths the algorithm planned. Similar topologic configuration in the above paths exposes the feature of potential field configuration itself. The simulation needs no more than two minutes to obtain all expected solutions. In view of long distance between two nodes in the potential field map, the method could resolve the problem of real-time path planning fast and effectively.

5. Conclusion

The paper studies path plan for potential field aided navigation using Dyna-H. Attention is given to path length and gravity navigation feature. The method takes gravity anomaly correlation coefficients as heuristics factors. Simulation of path plan for potential field aided navigation is carried out based on the local map. The results show that the convergence velocity of algorithm is fast. The planned paths meet short requirements, and the nodes the planned paths passed posses relative low potential field correlation coefficient.

6. Reference

[1]Bayili S, Polat F. Limited-damage A*: A path search algorithm that considers damage as a feasibility criterion [J]. Knowledge-Based Systems. 2011, 24(5): 501–512.

[2]Lu Zeyuan,Cai Tijing.Gravity aided navigation path plan research based on A* algorithm[J].Journal Of Chinese Inertial Technology . 2010,18(5):556-560

[3]Iglesias A, Mart´ınez P, Aler R, Fern´andez F. Reinforcement learning of pedagogical policies in adaptive and intelligent educational systems[J]. Knowledge-Based Systems.2009, 22(4): 266 – 270

[4]Alvarez, C., Santos, M., L´opez, V. Reinforcement learning vs A* in a role playing game benchmark scenario. In: Ruan, D., Li, T., Xu, Y., Chen,G., Kerre, E. (Eds.), Computational Intelligence, Foundations and Applications. 2010, 3: 644–650.

[5]Lopez, V., Santos, M., Montero, J. Fuzzy specification in real estate market decision making. International Journal of Computational Intelligence Systems. April 2010, 3 (1), 8–20.

[6]Zhang Y D, Wu L N, Wei Geng, Wang S H. A novel algorithm for all p airs shortest path problem based on matrix multiplication and pulse couple d neural network [J]. Digital Signal Processing. 2011, 21(4): 517-521

[7]Zeyuan Lu,Tijing Cai,Zhuopeng Yang.Path Plan in Gravity Aided Inertial Navigation Based on Ant Colony Algorithm[C]. WRI Global Congress on Intelligent Systems, Xiamen, 2009, 19-21 May GCIS '09: 193 – 198

[8]Zhang Y D, Yan J, Wei G, Wu L N. Find Multi-objective paths in stoch astic networks via chaotic immune PSO [J]. Expert-Systems with Applicat ions. 2010, 37: 1911-1919

[9]Zhang Y D, Wu L N, Wang S H. UCAV path planning based on FSCA BC [J]. Information-An International Interdisciplinary Journal. 2011, 14(3) : 687-692

[10] L. Ping, "Research on route planning and terrain contour mapping techniques based on ascertain missile", [D] China, University of Aeronautics and Astronautics, 2007

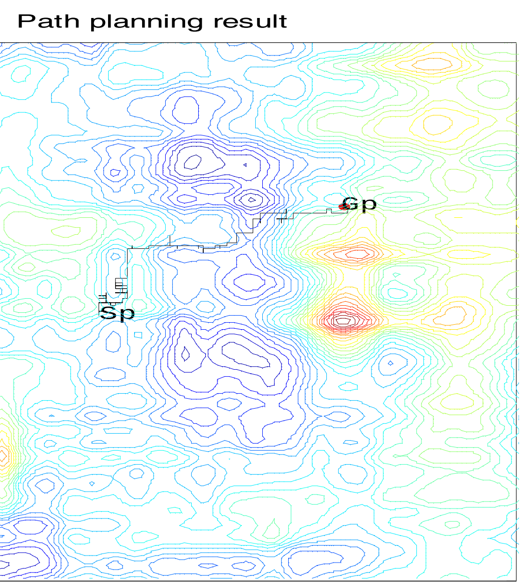

Figure 5.Paths planned by Dyna-H algorithm