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A Fuzzy Adaptive Rapid-Exploring Random Tree Algorithm

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ABSTRACT: In view of the deficiency of the traditional RRT algorithm parameters setting, a fuzzy adaptive RRT algorithm is proposed based on the analysis of RRT realization mechanism. According to the number of random nodes and the total nodes in tree, a fuzzy inference system is designed, which can adaptive update selection probability p_g and step length ε. Chaotic sequence is adopted to generate initial random node position. The simulation results show that new strategy can set parameters more reasonable; improve the efficiency and the success rate obvious, especially for complex task environment.

1 INTRODUCTION

Rapidly-exploring Random Tree (RRT) is a sampling based algorithm for path planning, has been shown to be probabilistically complete and computationally efficient for many path planning problems (LaValle, 1998, 2001). RRT traditionally focused on finding collision free paths, without considering their quality. Compared with the path planning methods based on cost function, RRT algorithm has the disadvantage in smoothness and optimality, but RRT algorithm has simple structure, less algorithm parameters, and high calculated efficiency (David, 2006). So RRT can be widely used in UAV route planning, robot motion planning, etc (Moon, 2015; Juan, 2015).

The present research on RRT mainly focuses on new node sampling methods, random node expansion methods. Parameters of the RRT algorithm have not been explicitly set, generally on the basis of experience and trial and error.

Fuzzy inference system base on the fuzzy set theory and fuzzy reasoning method, and has the ability to deal with fuzzy information. Fuzzy inference system can realize complex nonlinear mapping relationship, and its input and output are accurate numerical. Fuzzy inference system widely uses in the controller design, information processing, and other fields (Wang, 2006; Atefeh, 2012).

Parameters are important part in RRT, directly affect the algorithm performance. Parameters setting principles of traditional RRT algorithm is not clearly. In this paper, based on the analysis of the realization mechanism, a method of fuzzy parameters setting for RRT algorithm is proposed. In the process of path planning, based on the number of random nodes and the number of total nodes in current tree, fuzzy inference system adaptive adjust the selection probability and step length of the RRT. Chaotic sequence is adopted to generate initial random node position. Paper firstly introduces the basic principle of RRT algorithm, and then proposes the fuzzy parameter design method. Finally the simulation test is carried out.

2 PRINCIPLE OF BASIC RRT ALGORITHM

Assumes that C is the search space. C_{free} denote the feasible region, C_{obs} denote the obstacle region, C_{free} and C_{obs} are subset of C, and satisfies $C = C_{free} \cup C_{obs}$, $C_{free} \cap C_{obs} = \varnothing$. $q_{init} \in C_{free}$ and $q_{target} \in C_{free}$ represent the initial position and target position. The mission is to find out a feasible path from initial position to target position.

Using RRT algorithm for path planning is divided into two procedures which are tree growth and feasible path search. First, the initial position is selected as the root node of the tree. The target position q_{target} is selected as the random node q_{rand} with the probability p_g.Choosing the q_{rand} from the search space with the probability $1-p_g$. The nearest node from the tree to q_{rand} is selected as the near node q_{near}. Then, a candidate new node q_{new} is obtained by extending the distance ε with the direction from q_{near} to q_{rand}. In the extension process, judging whether the pathway is conflict with the known obstacle, if there is no confliction, then the candidate new node will be accepted as a part of the tree nodes, else reject this candidate new node and renew one. With the constant extension, the construction process of tree is complete if any of the nodes in the tree is close enough to the target position. From the closest node with the target position, to search its parent node step by step. Then a feasible path is obtained from initial position to target position. The node expansion process of the basic RRT algorithm in a two-dimensional space is shown in figure 1.

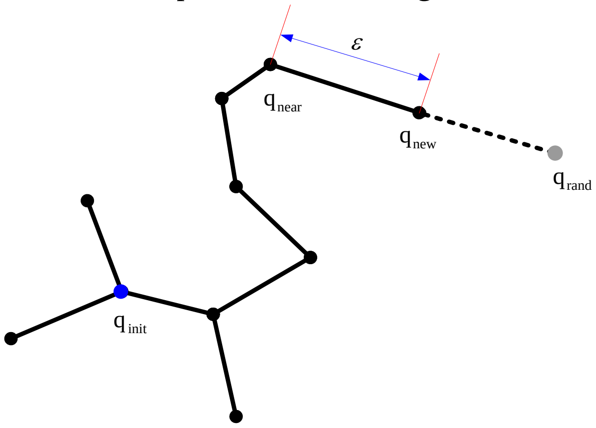

Figure 1. Nodes extension of the RRT in 2D space.

3 ALGORITHM IMPROVEMENT

Selection probability p_g and step length ε are mainly parameters in RRT algorithm, which are lack of theoretical method for the choice of them. According to the real-time condition of path planning, dynamic adjust parameters and obtain the better optimization performance, which is the starting point of this paper.

The procedure of looking for q_{near} spends the most time in RRT algorithm. This is because each q_{rand} needs to traverse all the nodes in the tree, and calculate the corresponding distance. Each produces a q_{new}, the required number of q_{rand} is called N_r. N_r has important influence on the speed of algorithm. Therefore, N_r is selected as a basis for adjusting parameter p_g and ε.

In the process of building RRT, on the one hand, nodes growth is hoped tend to target, to reach the target as soon as possible, which belongs to the longitudinal extension. On the other hand, RRT need to avoid obstacles. This requires algorithm must have lateral extension ability. Nodes growth needs to keep balance between longitudinal extension and lateral extension. In the different stages of path planning, RRT's extension has different requirements. In the early planning stage, RRT should tend to broader lateral extension. In the late planning stage, algorithm should strengthen the extension to the target position. So define N_s, the number of total nodes in the RRT is selected as another basis in parameters adjustment.

3.1 *Fuzzy parameter design*

As shown in figure 2, external precise inputs are fuzzified by fuzzy inference system, and transform into fuzzy sets on the domain. According to the fuzzy rules, appropriate fuzzy inference will be adopted. Then fuzzy inference results obtain. Finally defuzzification gets the precise output.

When the input, output and membership function of the system are discrete, the limited number of inputs corresponds to limited number of outputs. Thus we can obtain a fuzzy inference table, which indicate the relation between inputs and outputs. Discrete fuzzy inference table can be generated offline and used online, particularly suitable for the occasion of high real-time requirements.

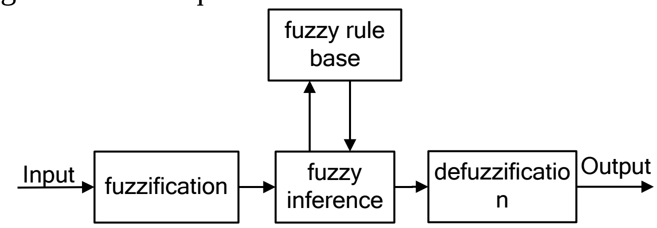

Figure 2. Fuzzy inference system.

Based on the fuzzy theory, two inputs two outputs discrete fuzzy inference system is established. The input variables are N_r and N_s, and the outputs are p_g and ε.

In the planning process, too excessive frequent change of algorithm parameters, also will lead to the decline optimization efficiency. Therefore, setting threshold N_r^*, when the N_r is an integer multiple of N_r^*, then lookup discrete fuzzy inference table and update algorithm parameters. Thus it can reduce the number of calls, and further improve the timeliness of the algorithm.

$T(N_r) \in \{PS, PM, PB\}$ is the fuzzy set of N_r, respectively "positive small", "positive middle" and "positive large". The number of total nodes in the tree is used to characterize the progress of the planning process. $T(N_s) \in \{PS, PM, PB\}$ is the fuzzy set of N_s. According to the range of p_g, its fuzzy set is $T(p_g) \in \{PS, PM, PB\}$. The fuzzy set of step ε is $T(\varepsilon) \in \{PS, PM, PB\}$.

Two inputs and two outputs discrete fuzzy inference system can be divided into double two inputs single output system. In the process of extend q_{new}, when N_r is small, large p_g can be used to enhance the trend of longitudinal extension. At the same time, the step length is increased to accelerate extension. Large N_r means that q_{rand} has been repeatedly generated, and the q_{new} has not been expanded. At this time, smaller p_g is needed to enhance the exploration ability, and reduce the step size to avoid the obstacles. When N_s is small, it is needed to enhance the ability to explore the unknown region. In the later stage of planning, we should strengthen the extension to the target. Based on the above analysis, the fuzzy rules are established, as shown in table 1 and table 2.

Table 1. Fuzzy rules of p_g.

N_s \ p_g / N_r	*PS*	*PM*	*PB*
PS	PB	PM	PM
PM	PM	PM	PS
PB	PS	PS	PS

Table 2. Fuzzy rules of ε.

N_s \ ε / N_r	*PS*	*PM*	*PB*
PS	PB	PB	PM
PM	PB	PM	PS
PB	PM	PS	PS

3.2 *Chaos initialization*

Under deterministic excitation, the motion state of the chaotic system has approximate random performance. When solving the optimization problem, chaotic system can be used to generate chaotic sequence, as the initial value of the algorithm.

Chaotic sequence can be used to generate the position of q_{rand} in the RRT, which can guarantee the randomness. This method can make full use of the ergodicity and regularity of chaos system, to make the position of q_{rand} cover the entire task environment. The position of q_{rand} is generated by two Logistic mapping sequences.

3.3 *Fuzzy adaptive RRT algorithm procedure*

The parameters of the algorithm are changed dynamically by using the fuzzy inference system, and the random nodes are generated by chaotic sequences. According to the above analysis, the implementation steps of fuzzy adaptive RRT algorithm, as shown flow.

1） Initialization algorithm;

2） Query fuzzy inference table, update p_g and ε;

3） Whether reach the target position? No reach then turn to step 4), else turn to step 9);

4） Judge random number $p < p_g$? Turn to step 5), else turn to step 6);

5） Set q_{target} as q_{rand}, choose q_{near} and extend q_{new};

6） Logistic mapping is used to generate q_{rand} in the search space, and the candidate q_{new} are calculated accordingly;

7） Whether exist obstacle between q_{new} and q_{near} ? if there is no obstacle, q_{new} will be added to the tree, then turn to step 3), else turn to step 8);

8） If $\mathrm{mod}(N_r, N_r^*) = 0$, turn to step 2), else turn to step 4);

9） The path from the initial position to the target position is obtained by backward search.

4 SIMULATION

The fuzzy adaptive RRT (faRRT) and the basic RRT (bRRT) are carried out the path planning. Three kinds of task environment is used, respectively, the number of obstacles is $N_T = 100, N_T = 50, N_T = 20$. Task environment is 2D area, which length of side is 100, and regardless of the unit. The initial position coordinates is (0, 0). The target position coordinates is (100, 100). Each kind environment randomly generates 100 maps, the average of 100 path planning as the final simulation results. In the basic RRT algorithm, set $p_g = 0.5$ and $\varepsilon = 8$. The parameters of faRRT algorithm are obtained by the fuzzy inference table.

Set $N_r^* = 5$, $N_r \in \{0, 5, 10, 15, 20\}$. The number of obstacles in the task environment is use to characterize the obstacle intensity. The domain of N_T is $N_T \in \{20, 35, 50, 70, 85, 100\}$ .The membership degrees of N_r and N_T are shown in table 3 and table 4 respectively.

Table 3. Membership degrees of N_r.

$\mu(N_r)$ \ N_r / $T(N_r)$	0	5	10	15	20
PS	1	0.7	0.1	0	0
PM	0	0.6	0.8	0.1	0
PB	0	0	0.3	0.6	1

Table 4. Membership degrees of N_T.

$\mu(N_T)$ \ N_T / $T(N_T)$	*20*	*35*	*50*	*70*	*85*	*100*
PS	1	0.7	0.1	0	0	0
PM	0.1	0.4	0.9	0.4	0.1	0
PB	0	0	0	0.3	0.8	1

According to the range of p_g, its domain is set to $p_g \in \{0.3, 0.4, 0.5, 0.6, 0.7\}$. According to the range of step length ε, its domain is set to $\varepsilon \in \{4, 8, 12\}$. The membership degrees of p_g and ε are shown in table 5 and table 6 respectively.

Table 5. Membership degrees of p_g.

$\mu(p_g)$ \ p_g / $T(p_g)$	0.3	0.4	0.5	0.6	0.7
PS	1	0.6	0.1	0	0
PM	0	0.3	1	0.3	0
PB	0	0	0.1	0.6	1

Table 6. Membership degrees of ε.

$\mu(p_g)$ \ p_g / $T(p_g)$	4	8	12
PS	1	0.3	0
PM	0.1	0.7	0.1
PB	0	0.3	1

Fuzzy operation adopts single fuzzy set. Weighted average method is used to defuzzification. In the practical application, the corresponding outputs can be obtained according to inputs by query fuzzy inference table, and parameters of the RRT algorithm can be adjusted dynamically. Pay attention to the mean time of program running T_{mean}, the mean length of path L_{mean}, the total nodes number N_{sum}, the number of failure time s N_{fail}. Simulation results are shown in table 7.

Table 7. Simulation results.

N_T	Algorithm	T_{mean}	L_{mean}	N_{sum}	N_{fail}
100	bRRT	3.05	201.25	162.25	22
	faRRT	2.11	197.66	164.25	13
50	bRRT	0.31	176.51	83.23	3
	faRRT	0.26	173.90	67.98	2
20	bRRT	0.05	159.86	43.11	0
	faRRT	0.04	158.47	33.18	0

According to table 7, we can see that faRRT is better than the bRRT algorithm for different types of task environment. For 100, 50 and 20 obstacles task environment, the runtime of faRRT decrease by 30.9%, 16.6% and 23.6% respectively. This shows that using fuzzy inference table online update algorithm parameters, will not increase the extra burden of the algorithm, but will be more reasonable settings through the parameters adjust, so that the timeliness of the algorithm improve. In the case of different obstacles, the difference of path length between two algorithms is not obvious, and faRRT is only slightly less than bRRT. The faRRT algorithm can significantly improve the success rate of planning in complex task environment.

As shown in Figure 3, for the case of $N_T = 100$, the value of p_g and ε are dynamically adjust according to the extension of tree.

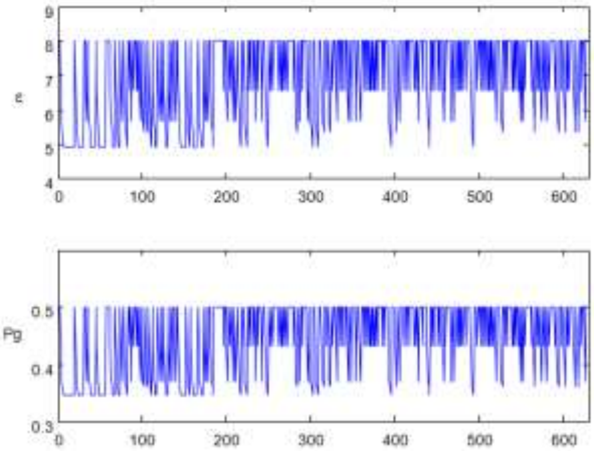

Figure 3. Dynamic change curve of RRT parameters.

On the whole, faRRT algorithm could significantly improve the planning performance in complex task environment, improve planning success rate and reduce planning time obviously. The faRRT algorithm could reduce the runtime and the total nodes in the simple and medium task environment. In the simple task environment, without need for a larger number of N_r, the new node q_{new} can be obtained, which unnecessary frequently updates p_g and ε. The more complex environment, the more difficulty to get q_{new}, and need more frequently to update parameters.

5 CONCLUSION

RRT algorithm is an efficient path planning method. It has a broad application prospect in the field of robot motion planning, UAV path planning and so on. In view of the shortcomings of traditional RRT algorithm parameter setting, according to the node expansion, the fuzzy inference table is designed and used to dynamic adjust algorithm parameters. Chaotic sequence is used to generate initial random nodes. Simulation results show that the fuzzy strategy can set the parameters more reasonably, shorten planning time, improve success rate. In future research, fuzzy strategy can be combined with advanced random node sampling method and advanced new node extension method.

6 ACKNOWLEDGEMENT

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