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The Application of Adaptive Ant-colony A* Hybrid Algorithm Based on Objective Evaluation Factor in RoboCup Rescue Simulation Dynamic Path Planning

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Abstract. This paper proposed an adaptive A* Hybrid algorithm combining the advantages of ant colony and A* algorithm. Improvements of the traditional ant-colony algorithm was suggested, and the Target Evaluation Factor based on global dynamic information was introduced to promote the performance of ant path decision. In addition, an adaptive pheromone updating strategy was designed to balance and speed up the convergence rate. Test results showed that this algorithm can effectively guide agents to get an optimal path to ensure the efficient completion of tasks.

1. Introduction
Since the first invention of industrial robots in 1959, over the past 6 decades, robots have been widely used, especially in the new field of disaster relief. In order to improve and optimize the robot, especially the efficiency of cooperative working method and intelligence control techniques in multi-agent systems[1], many researchers focused on the development of the robot application simulation system and have launched a simulation platform for simulating robot rescue, such as the RoboCup Rescue Simulation System(RCRSS)[2]. In RoboCup rescue simulation, due to agents' limited perception, poor communication and the complexity, timeliness and dynamics of the surrounding environment, this is a collaborative problem in an unknown environment[3].

Unlike previous studies, this paper focuses on how to combine the A* heuristic path planning with ant colony algorithm, which is a kind of swarm intelligence algorithm, to realize the local optimization of intelligent coordination and obstacle removal under the condition of limited awareness, lack of global information and complete the analysis of the global trend of estimation and the optimization of group decision through the local information. At the same time, it also ensures the rapid response speed and high executive ability under various sudden changes.
2. Hybrid Ant Colony and A* Algorithm

As mentioned above, in RCRSS, there are many dynamic changing factors. This paper combines the advantages of the two algorithms to find a more ideal global optimal solution before converging, which is proved to be feasible by experiments.

The dynamic path planning problem in RCRSS includes that according to the task requirements assigned by agents, searching an optimal path from the starting point to the target node through the path planning algorithm, which is embodied in short journey, safety and high pass rate.

Traditional path planning algorithm can only solve the problem of optimizing path length and direction only under known global environments. However, RCRSS needs to solve the optimization multi-index problems such as road safety, roadblock size and algorithm complexity under the non-ideal environment of dynamic complexity and incomplete information.

Heuristic algorithm such as A* algorithm, is a mature and widely used algorithm, which has the characteristics of high searching efficiency and monotonicity, being able to achieve good results in a static environment, but lacks dynamism. Relatively, ant-colony algorithm has high real-time performance, but also has inherent disadvantages that the results tend to converge and have the risks of precocity, stagnation and local optimization in the later stage of search.

Based on Dijkstra algorithm, A* algorithm provides global information to lead the selection of next node, and makes the cost estimation of current node to target node \[f(x) = g(x) + h(x)\] which ensures the path of priority search may to be the optimal solution and improves the search efficiency. The general formula of A* algorithm is:

\[f(x) = g(x) + h(x)\]  \hspace{1cm} (1)

Where \(g(x)\) is the cost from the current node to the target node \(x\). This paper uses Manhattan distance to calculate. \(h(x)\) is the heuristic estimated cost of the distance from target point. Adaptive ant colony algorithm is adopted to evaluate the cost \(h(x)\), which not only increases the algorithm's dynamics, but also ensures the high efficiency and reliability of the algorithm.

3. Adaptive Ant-Colony Algorithm (AACA)

3.1 Advanced Ant Colony Algorithm in RCRSS

Ant path finding in ant colony algorithm is very similar to rescue agents' rescue path search and has strong adaptability and robustness to dynamic environment. However, the traditional ant colony algorithm described above is prone to the problems such as local optimum, early maturity and slow convergence rate when searching.

In RCRSS, there may be uncertain factors such as the spread of fire, aftershocks and dynamic changes of road conditions with the progress of rescue work that may be affected by wind force, building materials and other factors. Beyond that, map information is usually noisy, locally unknown. Therefore, how to search for the optimal path and shorten the rescue time in complicated and diversified environments are keys to the rescue work.

3.2 Rules of stating transition probability

When traditional ant colony algorithm plans the path, the heuristic function \([6]\) in formula (1) is generally defined as \(\eta_{ij} = 1/d_{ij}\). Since it only considers the distance between nodes, it is easy to fall into local optimum. To overcome this circumstance, the Target Evaluation Factor (TEF) is introduced to replace the heuristic function \(\eta_{ij}\) above.

In RCRSS, the path planning of agents rescue should not only consider the path length, but also needs to consider the influence of roadblock situation and real-time fire on the health status of agents (HP value) so as to enable agents to obtain a fast and safe path through path planning model. Target evaluation factor was defined as:
$TEF_{ij}^k = \begin{cases} 
  w_1 \cdot (1 - \frac{d_{ij} + \text{shortest}^{\text{target}}_j}{\sum_{t \in allowed_k} d_{it} + \text{shortest}^{\text{target}}_j}) + w_2 \cdot \frac{\text{pass}_{ij}}{T_{\text{pass}_{it}}} & j \in allowed_k \\
  0 & \text{otherwise} 
\end{cases}$

In the formula (2), $d_{ij}$ is the length of path(i,j). $\text{shortest}^{\text{target}}_j$ is the Manhattan distance [7] from the candidate node j to the target node target which is more accurately to represent the distance between places in the city map. $\text{pass}_{ij}$ is the rate that agents get through path(i,j). $w_1, w_2$ are weight factors of distance and pass rate respectively.

Target evaluation factor (TEF) mainly considers about two aspects: the distance between the candidate node and the target and the pass rate of the current node to the candidate node, which reflects the advantages and disadvantages of the candidate node.

However, the above two factors are often incompatible. In this paper, different proportions of distance and pass rate are selected through the categories, division of labor and different behavioral modes of agents. For example, police force agents take charge of obstacle clearance, so they only consider the single factor of distance. When the ambulance team agents can approach to the wounded, they normally prefer the roads with few roadblocks and high pass-rate if they have been predicted the HP values of the wounded are high, and prefer the shorter routes if the wounded has poor health condition. With the heuristic function $\eta_{ij}$ that replaced by the objective evaluation factor (TEF), the final state transition probability of the ant to the next node is:

$p_{ij}^k = \begin{cases} 
  \frac{[\eta_{ij}] [TEF_{ij}]}{\sum_{s \in allowed_k} [\eta_{is}] [TEF_{is}]} & j \in allowed_k \\
  0 & \text{otherwise} 
\end{cases}$

Where $allowed_k = \{0, 1, ..., n-1\}$ is the set of next candidate nodes of ant $k$. $\eta_{ij}$ is the heuristic function of path(i,j), namely the expectation from i to j. $d_{ij}$ is the distance between node i and node j. $\alpha, \beta$ respectively express the effects of pheromone and heuristic function on node selection.

### 3.3 Rules of pheromone update

In the process of path search, ants will trigger the pheromone update, and the better path with short distance and high pass rate will get more pheromones, which reflects the globality of the algorithm’s pheromone update, and shows the advantages and disadvantages of each candidate path within the global search range. The method of pheromone update defined in this paper is shown in formula (4):

$$\tau_{ij}(t + T) = (1 - \rho) \times \tau_{ij}(t) + \Delta \tau_{ij}^{\text{local}} + \Delta \tau_{ij}^{\text{global}} + \Delta \tau_{ij}^{\text{commu}}$$

Where $\tau_{ij}$ is the pheromone concentration on the path(i,j). T is the time required for the ant colony to complete a search,. $\rho$ is the duration of pheromone. According to formula (4), the pheromone update is global and local. And the ant colony will also share the pheromone update.
However, it is noteworthy that when the concentration of road segment pheromone is low, the positive feedback of pheromone is relatively not obvious, the path search reflects strong randomness, and the convergence speed of the algorithm is slow.

On the contrary, when the pheromone concentration is high, the randomness will be weakened, the positive feedback effect will be stronger, and the convergence speed of the algorithm will be accelerated, but it is easy to fall into local optimum[8]. To avoid such problems, the pheromone adaptive updating rules are defined in the paper as follows:

1) Local pheromone update

All ants in the ant colony release a certain amount of pheromone on the path \((i,j)\) passing through according to the local update rule. During the search, the increment of pheromone on the path \((i,j)\) is:

\[
\Delta \tau_{ij} = \sum_{k=1}^{N} \Delta \tau_{ij}^k
\]

Where \(N\) is the total number of ants, \(\Delta \tau_{ij}^k\) is the pheromone released by ant \(k\) on path \((i,j)\) during this search. Its definition is as follows:

\[
\Delta \tau_{ij}^k = \begin{cases} 
q_k/L_k & j \in \text{allowed}_k \\
0 & \text{otherwise}
\end{cases}
\]

Where, \(q_k\) is the local pheromone strength constant, and \(L_k\) is the path length obtained by ant \(k\).

The localization of pheromone update rules reflects the positive feedback characteristics of pheromones, that is, ants release more pheromones on the fast road. Considering that the pheromone local update rule lacks the control of the global environment, it may lead to the short-sighted phenomenon[9]. At the algorithm level, the path reflected in local planning cannot guarantee reaching the target position, obtaining the global ideal solution, avoiding falling into local optimal, dead zone, premature algorithm and other problems. Therefore, the following improvements are made:

\[
\tau_{ij}(t+1) = \begin{cases} 
\tau_{ij}(t) - \frac{s}{d_{ij}} & \text{Situation 1} \\
\tau_{ij}(t) + \frac{s}{d_{ij}} & \text{Situation 2}
\end{cases}
\]

Where \(s\) is a constant with a smaller value. Situation 1 and 2 respectively refer to that when there are more than or less than \(N/s\) ants in the ant colony choosing this path, the pheromone will update adaptively. The rationality of this approach lies in that ants tend to choose the road section with large pheromone at the later stage of search. When multiple ants find the same path, the pheromone concentration of this road section will increase rapidly, leading to the early maturity of the algorithm. Therefore, regular reduction of pheromone concentration of such road sections can increase the possibility of other paths being searched and the diversity of feasible solutions.

2) Global pheromone update

At the end of this search, pheromone update is carried out according to the degree of advantage and disadvantage in the candidate path set obtained from ant colony planning according to the objective function. The global pheromone increment on the path \((i,j)\) is:
\[
\Delta \tau_{ij}^{\text{global}} = \frac{N}{\sum_{k=1}^{N_{\text{global}}} \tau_{ij}^k(t)}
\]  

(8)

Where \( \tau_{ij}^k \) is the pheromone content finally released on the path \((i,j)\) by the \(K\)th ant according to the global pheromone update rule after the search. And it is defined as:

\[
\tau_{ij}^k = \begin{cases} 
q_2 \frac{L^k}{j \text{ allowed}} & j \in \text{allowed}_k \\
0 & \text{otherwise}
\end{cases}
\]  

(9)

Where \( q_2 \) is the constant of the strength of global pheromone, \( L^k \) is the path length searched by ant \( k \). \( \sigma_k \) is introduced to represent the influence of the candidate path obtained by ant \( k \) on the pheromone update of path \((i,j)\):

\[
\sigma_k = (1 - \mu_{ij}) \cdot n_{ij} - \text{rank}[k]
\]  

(10)

\[
\mu_{ij} = \frac{C_t}{C_p}
\]  

(11)

Where \( n_{ij} \) is the total number of ants passing through path \((i,j)\), \( \mu_{ij} \) is the weight of path \((i,j)\), and is proportional to the concentration of road segment pheromone. \( C_t \) is the number of road segment passing through path \((i,j)\) in all candidate paths, and \( C_p \) is the total number of candidate paths searched by ant colony. Rank array is generated by arranging all the candidate paths in descending order according to the value of the objective function. Rank\([k]\) is the rank of the candidate paths obtained by ant \( k \). The smaller the value of rank\([k]\) is, the better the solution is.

From the path of each ant in this search process, if the path searched by the \(K\)th ant is short, rank\([k]\) is small, and the stronger the pheromone enhancement is, the more effective the pheromone enhancement is in this section. From the perspective of the current node \( i \), if it passes through more paths, the difference among paths will be small and the influence on each candidate path will be relatively uniform. On the contrary, when node \( i \) passes through a small number of paths, the paths differ greatly, and the pheromone update intensity on the optimal path will be greater, so that the pheromone concentration on it will be higher. Thus, the over-concentrated global pheromone concentration can be avoided and the pheromone concentration in the pathway can be maintained.

(3) Pheromone sharing and updating among ant colonies

The sense field and ability of single agents are limited, which reflects the advantage of information sharing mechanism.

In order to obtain the global optimal path, it is necessary to make full use of the communication mechanism, share the optimal solution searched by a single ant among ant colonies, expand agent's perception of the global environment, and optimize the candidate solution obtained by dynamic path planning. The formula is as follows:

\[
\Delta \tau_{ij}^{\text{comm}} = \begin{cases} 
q_{\text{comm}} & j \in \text{allowed}_k \\
\frac{L_{\text{comm}}}{j \text{ allowed}} & \text{otherwise}
\end{cases}
\]  

(12)
Where $q_{comm}$ is the pheromone strength constant of paths sharing among ant colonies, and $L_{comm}$ is the globally optimal path length obtained in ant colonies.

4. EXPERIMENT

ACA pheromone concentration has an important influence on path planning. In the simulation experiment, we successively colored each road section as light yellow, yellow, orange, green and grass green according to its pheromone concentration from low to high, and respectively carried out experiments on A* algorithm, traditional ant colony algorithm (ACA) and the adaptive ant colony A* hybrid algorithm (AACA & A*) proposed in this paper. Take $Q = 10$, $\rho = 0.6$, $\alpha = 1$, $\beta = 5$. As the roadblock has been cleared by PF agents basically at cycle 50, the pheromone distribution of the 50th cycle and the simulation results of the final cycle were selected for multidimensional comparison of each algorithm, as shown in figure 1:

| Pheromone distribution | A* | ACA | AACA & A* |
|------------------------|-----------------|-----------------|-----------------|
| simulation result | ![simulation result](image1.png) | ![simulation result](image2.png) | ![simulation result](image3.png) |

Figure 1. Comparison of path planning effects of each algorithm

By analyzing the above figure, it can be seen from the simulation results that the adaptive ant colony A* hybrid algorithm (AACA & A*) proposed in this paper is obviously superior to the traditional A* and ant colony algorithm (ACA).

From the distribution of pheromone, as AT agents need to transport the wounded to refuges, the concentration of pheromone is relatively high AT refuges. In addition, at the intersection and i.e. the place where the path interchanges, the pheromone is also relatively large, which is in line with the actual situation.

Beyond that, it seems that the influence of Blockade on the distribution of pheromone was relatively insignificant, because in the later stage of rescue, the obstacles on the road were basically removed by the PF agent, during which the path length was the dominant factor of path planning.

On the whole, the algorithm designed in this paper can dynamically adjust the pheromone distribution of each road segment, so that the optimal path is not too concentrated or dispersed, and avoid premature convergence at the same time.

5. Conclusions

In conclusion, Hybrid Adaptive Ant Colony and A* Algorithms proposed in this paper, compared with various popular path planning Algorithms nowadays, can achieve good results in A dynamic and unknown environment with the consideration of not only the path length but also the accessibility of the path and the dynamics of the road conditions. In the follow-up work, we should also pay attention to the following issues:
(1) Different pheromone values (including \( q_1 = q_2 = q_{comm} \)) are designed for different simulation scene sizes and fire prediction sizes.

(2) The pheromone updating rules between ant colonies are relatively simple, with a large room for improvement. In addition, in order to strike a balance between the optimal solution and the time complexity of the algorithm, the setting of the number of ant colonies also needs further study.

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