The Application of the Switching Strategy based on Cloud Model PSO and GA for Robot Path Planning

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***Abstract*—Switching strategy based on cloud model particle swarm optimization (CMPSO) and genetic algorithm (GA) was presented by combining their advantages. In the switching strategy, CMPSO is applied in the former steps and GA is executed in the later steps. The best switching conditions that under three switching indices of iteration steps, population standard deviation, and optimal individual fitness values were determined by large amounts of simulation experiments. In comparison with single GA and single CPSO, the proposed switching strategy CMPSO-GA has a better performance when path length, smoothness, and running time are taken into consideration.**

***Index Terms*—Mobile robots, Path planning, Particle swarm optimization, Genetic algorithms, Switching**

I. INTRODUCTION

Mobile robot path planning is a key technique for robots working in environment with obstacles. Running time by the robot planning path time and path length, its smooth and energy consumption and other performance indicators provide the robot with a path from the starting point to the ending point of the best or second-best collision-free path. In recent years, ant colony algorithm [1] and so on, to the methods of robot path planning, and have obtained an outstanding achievement. As a novel biomimetic intelligence optimization strategy [2], particle swarm optimization (PSO) algorithm has been explored into solving path planning problem. The algorithm has advantages, such as fast searching, implementation simplicity, etc. However, PSO evolves to the optimal solution based on particle self and group cognitions, so it has to face the problems of prematurity, low convergence efficiency, weak global convergence, etc. It is one of the most important ways to appropriately use the two kinds of cognitions for improving PSO. Recent studies in self and group cognitions of particles focus on choice of the acceleration factor and experience information of particles, and attempt to find a way to keep balance between the flow speed of particles shared information and population diversity. As indicated by the authors that the acceleration factor of particle self cognition would decrease over iterations [3]. On the other hand, the authors of [4, 5] proposed a way that the speed of superior particles should vary with a low probability while that of inferior ones should be assigned randomly. The approaches mentioned above have improved the quality of PSO on different levels, while they also have their own disadvantages.

Aiming at the local optimum problem of PSO, we use expectation Ex to represent the average population fitness of the current population, and determine entropy En based on the rule “3En” of the cloud model. In addition, we forcibly varied the position of some dimensions of particles to where there is unconstrained optimization or varied the position information of dimensions near to particles according to cloud model adjusting the probability of mutation operator adaptively. After choice, the obtained particles with the same size and better fitness then evolve to the next generation. The switching optimization strategy uses cloud model particle swarm optimization (CMPSO) in earlier stage and uses GA in late stage. In order to take full advantage of their respective strengths to compensate for insufficient mutual, the application of optimal path planning for a mobile robot verify the effectiveness of the proposed handover strategy in the paper.

II. CMPSO-SWITCH-GA STRATEGIES

CMPSO algorithms used in this paper [6] with global search capability and original high quality solutions, but each dimension also need to update each particle, so the operation is large and the search is slow.

In contrast with [7], the crossover and mutation of genetic algorithm and delete operations only manipulate specific genes. The computation compared with the cloud model particle swarm algorithm is much smaller. This advantage in path planning for such high dimensions and constraints for complex problems is particularly evident, but the quality of its search results relies heavily on initial solution. In order to develop cloud model of particle swarm optimization algorithm and genetic algorithm with special advantages, this paper proposes a combination of switching optimization strategy.

This paper produced different inertia weights according to the adaptive strategy of algorithm of cloud model for different subgroups. The specific production rules of inertial weights are as follows.

(1) $i \in N_1$ is the optimal particle of the group, which adapts a less inertia weight to speed up global convergence.

$$\omega_i(t) = \frac{(\omega_1 - t)\times(\omega_1 - \omega_2)}{MaxT} \quad (1)$$

where ω_1 is provided originally as a larger inertia weight, ω_2 is a last and less one, t is the recent iterations and Max T is the max iteration.

(2) $i \in N_2$, the worst particle of the group(the point in obstacles), which turns describing obstacle polygon (a group of linear inequality to represent), into the limited range of y_i, add a step to check out if y_i falls in the limited scope of obstacles and then enable y_i jump out of that limitation and go back to particle N_3.

(3) $i \in N_3$ is an ordinary particle of the group, which adjusts the inertia weight of i according to the adaptive parameter strategy of cloud mapping algorithm of condition X. The adaptive inertia weight $\omega_i(t)$ of particle is computed by the following equations:

$$Ex = f_{gb} \quad (2)$$

$$En = (f - f^*)/3 \quad (3)$$

$$He = En/(\frac{1}{n}\sum_{i=1}^{n_1} f_i - f^*) \quad (4)$$

$$En' = Randn(En, He) \quad (5)$$

$$p_i(t) = \begin{cases} k_1 \exp(-(Ex - f(y_i))^2 / 2(Ex')^2 \\ k_2 \qquad f(y_i) \geq f^* \end{cases} \quad (6)$$

$$\omega_i(t+1) = \omega_i(t) \times p_i(t) \quad (7)$$

where f^* is the individual fitness of $f(y_i)$, and k_1 and k_2 are adaptive constant integer factors.

The early strategy of implementation cloud model particles group algorithm is considered to make particles group algorithm to initial solutions quality requirements, not high of features for global search. Lately by using dedicated genetic algorithm, cloud model particles group algorithm can get to some convergent level. The solution groups with high quality (shorter path length and better smoothness) as initial solutions of the dedicated genetic algorithm can be gotten. Then using the advantages of simple operations and fast search, we can make further local search.

Switch indicator is the primary parameter in switched strategies. It has a critical effect on the result. According to the actual situation of this article, Switch designs respectively three indicators, namely iterative algebraic, poor population standard deviation and the best individual fitness.

Iterative. When cloud model of particle swarm optimization algorithm iterated to the stipulated algebraic, switch to dedicated genetic algorithms.

Standard deviation of the population. Standard deviation measures the disperse extent of an individual. When it is small, indicating the difference is relatively small between individuals and the search space is relatively limited. You should switch to a dedicated genetic algorithm to continue searching. Standard deviation formula is as follows:

$$\delta = \sqrt{\sum_{i=1}^{N} \frac{(x_i - \overline{x})^2}{N}} \quad (8)$$

where δ is standard deviation and N is the population size, x_i is fitness of the ith particle, $\overline{x}$ is the average fitness of the ith particle.

The best individual fitness difference fitness. When the best individual fitness difference error of several generations in a row is less than the set limit that stocks have difficult to evolve again, cloud model of particle swarm optimization algorithm premature convergence is reached. The next step is to switch to a dedicated genetic algorithm for further searches.

III. SIMULATION RESEARCH

The two algorithms used in Switch policy are cloud model of particle swarm algorithm and special genetic algorithm as mentioned in [8]. The inertia weight w of Particle Swarm Optimization algorithm of cloud models take 0.5, acceleration coefficients C1 and C2 were set to 2and the maximum velocity Vmax equal to 2. A Chebyshev series model was used as private cloud mode. Here the population size n in Switch policy was set as 16. The initial path can be gotten by [8]. Fitness function value was decided by path length L, angle change s, and planning time T. The end condition was either the special genetic algorithm by best individual invariability in 20 consecutive generations, or the whole Switch policy reached to maximum iterative number 1300.

A. *Iterative Number*

In order to overcome the randomness of the switch policy, the Iterative number was running 10 times. The average value of optimal path, smoothness and planning time under the different iterative number were shown in table 1. It can be seen from table 1, as the increasing of switching iterative algebra, there are little change in path length and smoothness. However the planning time has increased continually. The best switching number of this paper was decided as 700.

B. *Standard Deviation of the Population*

The average value of optimal path, smoothness and planning time were got by preceding the simulated program 10 times under the switch indicators of making the standard deviation of the population of 20–50 consecutive generations less than a certain bound on error were shown in table 2. It can be seen from table 2, as the bound on error shrink and the continuous algebraic of the bound on error of standard deviation of the population increase, there are little change in path length. However the smoothness has greatly enhanced and the planning time has the trend of increasing. Because of the above process is not monotony, after overall considering of the three evaluation indicators, the best switching conditions of this paper was decided as standard deviation of the population difference of 40 consecutive generations is less than 0.01.

C. The Best Individual Fitness Difference

The average value of optimal path, smoothness and planning time were got by preceding the simulated program 10 times under the switch indicators of making the optimal individual fitness difference of 20–50 consecutive generations less than a certain bound on error were shown in table 3.It can be seen from table 3, as the bound on error shrink and the continuous algebraic of the best individual fitness differential and the bound on error increase, there are little change in path length and smoothness. However the planning time has the trend of overall upward. After overall considering of the three evaluation indicators, the best switching conditions of this paper was decided as the optimal individual fitness difference of 30 consecutive generations is less than 0.005.

By considering the indicators in table 4, the best switching conditions of the simulation environment was decided as he optimal individual fitness difference of 30 consecutive generations is less than 0.005. The optimal path got by switching 10 times under the optimal conditions in three indicators of the switch strategies were shown in Figure 1.

TABLE I.
SIMULATION RESULTS WHEN THE ITERATION STEP IS SELECTED AS THE SWITCHING INDEX

Iterations	Length of path, L	Sum of angular variation, S/rad	Planning time, T/s
200	60.051	6.301	0.204
300	59.818	4.461	0.366
400	59.465	3.844	0.394
500	59.312	2.178	0.470
600	59.577	2.374	0.615
700	59.284	2.300	0.640
800	59.475	1.955	0.815
900	59.509	2.110	0.908
1000	59.149	3.006	1.051
1100	59.312	2.476	1.145
1200	59.279	2.257	1.261

TABLE II. SIMULATION RESULTS OF THE SWITCHING INDEX USING THE STANDARD DEVIATION OF POPULATION

Margin error	20 generations			30 generations			40 generations			50 generations		
	L	S/rad	T/s	L	S/rad	T/s	L	S/rad	T/s	L	S/rad	T/s
0.01	59.513	3.222	0.626	59.316	2.635	0.137	59.044	2.567	0.527	59.021	1.300	0.638
0.02	59.572	2.996	0.576	59.890	6.762	0.152	60.259	7.731	0.316	59.746	3.770	0.210
0.03	60.871	7.788	0.210	60.885	10.481	0.077	59.848	3.367	0.387	60.349	4.678	0.240
0.04	60.545	6.259	0.128	60.861	8.493	0.105	61.017	14.463	0.222	59.874	4.761	0.332

TABLE III. SIMULATION RESULTS WHEN THE DIFFERENCE OF OPTIMAL INDIVIDUAL FITNESS VALUES IS SELECTED AS THE SWITCHING INDEX

error value	20 generations			30 generations			40 generations			50 generations		
	L	S/rad	T/s	L	S/rad	T/s	L	S/rad	T/s	L	S/rad	T/s
0.001	60.953	4.731	0.347	58.938	1.498	0.898	59.353	3.008	1.147	59.536	2.836	0.932
0.002	59.592	2.393	1.144	59.438	2.008	0.756	59.259	2.359	1.295	58.547	3.980	0.828
0.003	60.348	2.645	0.630	61.300	5.673	0.618	59.227	3.832	0.876	59.814	3.113	0.738
0.004	59.832	3.183	0.360	61.132	6.020	0.602	59.502	4.824	0.865	59.807	3.154	0.795
0.005	59.305	2.208	0.737	58.735	1.295	0.782	60.274	2.969	0.604	59.943	4.165	0.669
0.006	58.951	2.322	0.932	59.099	2.921	0.390	60.604	5.800	0.597	59.489	4.297	0.754
0.007	59.204	4.207	0.342	58.715	3.178	0.882	60.229	6.697	0.418	60.976	6.982	0.634
0.008	59.649	3.672	0.262	59.645	6.686	0.593	59.721	2.980	0.639	59.721	6.184	0.693
0.009	59.328	4.985	0.326	60.227	5.468	0.618	59.677	3.702	0.635	60.034	7.836	0.435

TABLE IV.
SIMULATION RESULTS UNDER THREE SWITCHING CONDITIONS

Switching indexes	Switching conditions	Length of path, L	Sum of angular variation, S/rad	Planning time, T/s
iteration	700	59.284	2.300	0.640
Standard deviation of population	Margin of error 0.001; continuous generations for 40	59.044	2.567	0.527
the fitness error of optimal individual	Margin of error 0.005;continuous generations for 30	58.735	1.295	0.782

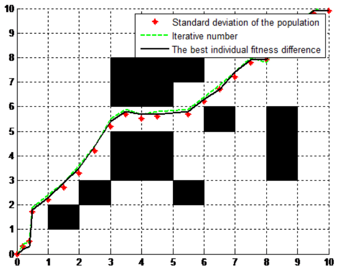

Figure 1. Optimal paths under the best switching conditions

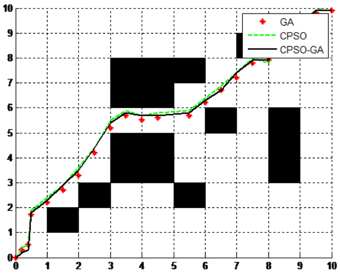

Figure 2. Optimal paths of GA CPSO and CMPSO-GA of three switching indices.

IV. CMEPSO AND GA SWITCH STRATEGY WITH A SINGLE ALGORITHM COMPARISON

Simulation comparative study between switch policies referred to single genetic algorithm mentioned as reference [8], and cloud model particle group algorithm have been proceeded proposed. The switch conditions of Switch policy referred to in this article is the optimal individual fitness difference of 30 consecutive generations is less than 0.005 and by preceding the simulated program 10 times the average results are gotten as shown in table 5.

TABLE V. AVERAGE RESULTS FOR DIFFERENT ALGORITHMS

algorithm	Length of path	Sum of angular variation	Planning time
GA	60.73	1.580	0.096
CPSO	59.207	1.447	1.122
CPSO-GA	58.73	1.29	0.792

We know in table 5 that two species single algorithm and this by mention switch optimization policy in path smooth difference not more; single dedicated GA while in planning time has absolute advantage, but its path more other two species planning method relative more long; single cloud model particle group algorithm while in path length and smooth more this by mention switch optimization policy difference is unlikely to, but its time consumption is switch policy of 1.5 times. By mention switch policy in integrated can more single algorithm has must of superiority. GA and the CPSO and CMPSO-GA are running 10 times the optimal path, as shown in Figure 2.

V. CONCLUSION

An optimizing strategy which switches from cloud model of particle swarm to genetic algorithm for robot path planning has been proposed. The three kinds of different switching targets have also been discussed. Handover optimization strategies and raised by a single private genetic algorithm and Particle Swarm Optimization algorithm for a simple single cloud models comparative study of static barrier environment of simulation, simulation results show that the switching optimization in path length, smoothness and planning time in three areas of overall performance is better than two single optimization algorithms.

Simulations have been made for cases of switch optimization strategy mentioned in this paper, single genetic algorithm, and single cloud model particle group algorithm in simple a static barrier environment. The simulation results show the switch optimization strategy mentioned has a better combination property than the single two algorithms in path length, smoothness, and planning time.

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