Global Localization of Monte Carlo Localization Based on Multi-Objective Particle Swarm Optimization

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***Abstract*—Premature convergence often happens when a Monte Carlo localization (MCL) algorithm tries to localize a robot under highly symmetrical environments. In this paper, we propose a novel method of solving such problem for global localization by incorporating a multi-objective evolutionary approach to resample particles with two objectives, including particle weights and population distribution. By employing a multi-objective particle swarm optimization (MOPSO), our approach is capable of enhancing the exploration ability to improve population diversity while maintaining convergence quality to successfully localize the global optima. Simulation results have confirmed that localization performance using the proposed approach is significantly improved.**

Keywords—Premature Convergence, Monte Carlo localization, Multi-Objective Particle Swarm Optimization, Global Localization.

I. INTRODUCTION

According to noisy sensor readings, providing a dynamic state estimation of a robot under an already-known map is a significant matter for an autonomous robot navigation system. Global localization, one of the challenging issues in robot localization, is basically a problem of localizing a robot under unknown initial pose and unstable observations. Several contributions had proposed trying to tackle this problem; however, Monte Carlo localization (MCL) [1], or particle filter localization, outperforms others due to its ability of carrying multiple hypotheses and incomplete Gaussian assumptions. Nevertheless, as soon as highly symmetrical environment is considered, MCL falls into premature convergence very easily because of high similarities of weights of particles. This result in localization failure, and the robot accordingly could not escape from a local optimum. To deal with such difficulty, Clustered-MCL [2], CEAMCL [3], and Local Selection Based MCL [4] are proposed. However, although these substantial improvements have been made to prevent premature convergence, they are not realistic enough to be applied to any real-time localization system.

As an attempt to solve the aforementioned issues, this paper proposes a method, entitled "global localization of Monte Carlo localization based on a multi-objective particle swarm optimization [5] approach" to increase the probability of particles converging to global optima successfully by using the Pareto front to resample particles with better weights and satisfying distribution, allowing particles to explore the whole map while managing its convergence ability. As a result, successful estimation leads to a favorable global localization. To show its qualification of being used in a real-time localization system, experimental results show that the proposed approach improves the performance of MCL in terms of success rate and computational time.

II. GLOBAL LOCALIZATION BASED ON MOPSO

Premature convergence occurs mainly due to extremely similar sensory measurements received by particles and the real robot. Hence, to detect whether premature convergence occurs, there are two rules necessary to be concerned. One is that particles do not converge to a single optimum for a long period of time, and the other is that the weights of particles are getting worse and worse as the iteration goes. Either one of the conditions is satisfied, then premature convergence is triggered. As soon as localization is failed, we consider that all particles are distributed randomly on the map again. After weight assignment is accomplished, the population is divided into several groups based on their weights w by constructing histograms using Doane's formula [6]. Therefore, similar weights will be assigned to the same category, or group. Mean inter-particle distance r [7] is also obtained for each group, implying the diversity of the group members. The best and the average of normalized w as well as r, denoted as w^{best}, w^{avg}, r^{best}, and r^{avg} are determined to obtain two objective functions for MOPSO as shown in (1) and (2),

$$f_1(c) = \exp\left[-\pi \cdot \left(c \cdot w^{avg} - w^{best}\right)^2\right] - \left(1 - w^{best}\right) \tag{1}$$

$$f_2(c) = \exp\left[-\pi \cdot \left((1-c) \cdot r^{avg} + r^{best}\right)^2\right] - \left(1 - r^{best}\right). \tag{2}$$

The decision variable c lise in [0,1] is the candidate of MOPSO, indicating the "convergence pressure" of the evaluation. The objective functions imply that MOPSO has to evaluate a proper value of c so that w^{avg} approaches to w^{best} and r^{avg} approaches to r^{best}. If f_1 is larger, then the convergence pressure is higher, suggesting that MOPSO put more attention on weights. Otherwise, if f_2 is larger, population diversity is highly considered, where convergence pressure is lower. Hence, a Pareto front composed by optimal candidates characterizing favorable weights and acceptable diversity is ontained by maximizing (1) and (2) using MOPSO. Note that (1) and (2) has to gauranteed to be positive, and there's no constraint for the decision variable. Also, the number of

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optimal candidates is equivalent to the number of particles MCL would like to resample in the next step.

As the Pareto front is determined, suppose there are g groups donoted as $b^1, b^2,\ldots,b^g$, and their corresponding w and r are denoted as $w^1, w^2,\ldots,w^g$ and $r^1, r^2,\ldots,r^g$, respectively, where $w^1< w^2<\ldots< w^g$. According to the Pareto front from MOPSO, the resampling technique of MCL then can be considered into two possible cases: One is that if f_1 corresponds to w^h, where h is one specific group, and if $r^h > f_2$, then it implies that a group providing fair weights and acceptable distribution is discovered. MCL then accordingly chooses one particle randomly from that particular group into next generation. The other case is that if f_1 corresponds to w^h, and $r^h < f_2$, then we consider which interval of f_2 lies in, described as $[r^L , r^U]$, and investigate the relationship between w^U and w^h. If $w^U > w^h$, then it means that the group b^U is found in which the weight and the distribution of particles are better than both f_1 and f_2. Therefore, one particle randomly from b^U is chosen to the next iteration. On the other hand, if $w^U < w^h$, then it suggests that although the distribution of particles of b^U is better than f_2, its corresponding weight is worse than f_1. Hence, MCL selects one particle from both b^U and b^h to the next generation. The above mentioned procedure continues until all candidates of Pareto front obtained by MOPSO are used for resampling.

By using MOPSO to obtain a Pareto front chracterizing satisfactory weights and distribution, MCL can balance the convergence and diversity of population to allow particles exploring the whole map without being detected as premature convergence. As a result, particles have higher probabilities to successfully localize the real pose of the robot.

III. EXPERIMENTAL RESULTS

To verify the robustness and the reliability of the proposed approach, a robot is set to move under a highly symmetrical grid map. A laser range finder (LRF) is used as the sensor. Particle numbers include 300, 500, 1000, 1500, 2000, and 2500, and [3], [4], [5] are involved into comparisons in terms of success rate and computational time. To arrive at a reliable statistical conclusion, experiments are conducted 50 times for each number of particles, and the average result is shown in this paper. Table I presents the success rate of global localization after the premature convergence is triggered, and Table II shows the computational result of a successful localization. It is absolutely clear that the proposed approach takes the lead to prevent premature convergence, no matter what number of particles is used. Furthermore, from the computational time of view, we can firmly state that the proposed algorithm is reliable and qualified to be applied to a real-time robot localization system. Note that the unit of Table II is in seconds.

Table I. Comparisons of success rate of global localization in highly symmetrical environment

	Number of particles					
	300	500	1000	1500	2000	2500
MCL	10%	28%	40%	41%	45%	46%
C-MCL	40%	45%	52%	59%	63%	70%
CEAMCL	45%	49%	59%	66%	74%	80%
LS-MCL	10%	30%	46%	55%	64%	72%
Proposed	72%	82%	95%	99%	99%	99%

Table II. Comparisons of computational time for a successful global localization

	Number of particles					
	300	500	1000	1500	2000	2500
MCL	0.135	0.318	0.724	0.968	1.505	2.040
C-MCL	122.8	138.7	158.5	180.3	214.8	269.1
CEAMCL	63.5	81.78	84.39	109.2	131	154.4
LS-MCL	11.64	17.78	25.95	35.53	48.60	64.86
Proposed	4.595	5.177	5.887	6.500	7.284	8.263

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