Research of Global Localization for Humanoid Robot Based on Vision

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Abstract— **Vision perception plays a key role in the research on humanoid robot. A new version of particle filters called coevolution based adaptive particle filters (CEAPF) is proposed for robot localization. Using vision and odometer, a robust perception model extracting from environmental features, which are unscented by Kalman filter, is established by effective fixed scale feature-transformation method. Dimensional feature points matching algorithms are used to match the feature points based on KD-Tree to merge a species of cooperative coevolution competition mechanisms into particle filters. Coevolution adaptive particle filters are proposed to track the different assumptions and the samples in inter-species evolution can be moved towards the larger desired regions by using the crossover and mutation operators in evolutionary computation. Finally, results of success and precision localization are shown by experiment.**

Keywords— *vision; evolutionary computation; humanoid robot; global localization*

I. INTRODUCTION

In global localization, the robot is required to estimate its pose by local and incomplete observed information under the condition of uncertain initial pose. Recently, several approaches based on probabilistic theory are proposed for global localization [1-3]. Among them approaches based on particle filters [4], which are also called Monte Carlo localization (MCL), have attracted wide attention.

But traditional MCL has some shortcomings. Since samples are actually drawn from a proposal density, if the observation density moves into one of the tails of the proposal density, most of the samples' non-normalized importance factors will be small. So a large sample size is needed to represent the true posterior density to ensure stable and precise localization. Another problem is that samples often converge too quickly to a single high likelihood pose. This might be undesirable in the case of localization in symmetric environments, where multiple distinct hypotheses have to be tracked for extended periods of time. To make the samples represent the posterior density better, Thrun et al. proposed mixture-MCL [5], but it needs much additional computation in the sampling process. To improve the efficiency of MCL, a method adjusting sample size adaptively over time has been proposed [6], but it increases the probability of premature convergence.

In CEAPF samples are clustered into groups which are also called species. A coevolutionary model derived from competition of ecological species is introduced to make the species evolve cooperatively, so the premature convergence in highly symmetric environment can be prevented. The population growth model of species enables the sample size to be adjusted according to the total environment resources which represent uncertainty of the pose of the robot. And genetic operators are used for intra-species evolution to search for optimal samples in each species. So the samples can represent the desired posterior density better, and precise localization can be realized with a small sample size.

II. COEVOLUTION BASED ADAPTIVE PARTICLE FILTERS

The concept of coevolution is derived from ecologic science [7]. In ecology, much of the early theoretical work on the interaction between species started with the Lotka-Volterra model of competition [8]. The model itself is a modification of the logistic model of the growth of a single population and represents the result of competition between species by the change of the population size of each species.

A. Inter-Species Competition

Inspired by ecology, the population growth of a species can be modeled using the Lotka-Volterra competition model when competing with other species. Assuming there are two species, the Lotka-Volterra competition model includes two equations of population growth, one for each of two competing species.

$$\frac{dN_t^{(1)}}{dt} = r^{(1)} N_t^{(1)} (1 - \frac{N_t^{(1)} + \alpha_t^{(12)} N_t^{(2)}}{K_t^{(1)}}), \quad (1)$$

$$\frac{dN_t^{(2)}}{dt} = r^{(2)} N_t^{(2)} (1 - \frac{N_t^{(2)} + \alpha_t^{(21)} N_t^{(1)}}{K_t^{(2)}}). \quad (2)$$

Where $r^{(i)}$ is the maximum possible rate of population growth, $N_t^{(i)}$ is the population size and $K_t^{(i)}$ is the upper limit of population size of species i that the environment resource can support at time step t respectively, and $\alpha_t^{(ij)}$ refers to the impact of an

individual of species j on population growth of species i; here $i, j \in \{1,2\}$.

These equations can be used to predict the outcome of competition over time. To do this, we should determine equilibrium, i.e. the condition that population growth of both species will be zero. Let $dN_t^{(1)}/dt = 0$ and $dN_t^{(2)}/dt = 0$. If $r^{(1)}N_t^{(1)}$ and $r^{(2)}N_t^{(2)}$ do not equal 0, we get four kinds of competition results determined by the relationship between $K_t^{(1)}$, $K_t^{(2)}$, $\alpha_t^{(12)}$ and $\alpha_t^{(21)}$.

For an environment that includes Ω_t species, the competition equation can be modified as:

$$\frac{dN_t^{(i)}}{dt} = r^{(i)}N_t^{(i)}(1 - \frac{N_t^{(i)} + \sum_{j=1,j\neq i}^{\Omega_t}\alpha_t^{(ij)}N_t^{(j)}}{K_t^{(i)}}) . \quad (3)$$

B. Intra-Species Evolution

Since genetic algorithm and sequential Monte Carlo importance sampling have many common aspects, Higuchi has merged them together [9]. In CEAPF the genetic operators, crossover and mutation, are applied to search for optimal samples in each species independently.

In CEAPF, the crossover operator will perform with probability p_c and mutation operator will perform with probability p_m. Because the genetic operator can search for optimal samples, the sampling process is more efficient and the number of samples required to represent the posterior density can be reduced considerably.

III. ENVIRONMENT RESOURCE MODEL

Each species will occupy a part of the state space, which is called living domain of that species. Let matrix $Q_t^{(i)}$ represent the covariance matrix calculated using the individuals in a species i. $Q_t^{(i)}$ is a symmetric matrix of $n \times n$, here n is the dimension of the state. Matrix $Q_t^{(i)}$ can be decomposed using singular value decomposition:

$$Q_t^{(i)} = UDU^T, U = (e_1, \cdots, e_n) \in R^{n \times n} \quad (4)$$
$$D = diag(d_1, \cdots, d_n) .$$

Where $e_j \in R^n$ is a unit vector, and d_j is the variance of species i in direction e_j. We define the

living domain of the species i at time t to be an ellipsoid with radius of $2\sqrt{d_j}$ in direction e_j, and it is centered at $\bar{x}_t^{(i)}$ which is the weighted average of the individuals in species i. The size of the living domain is decided by:

$$A_t^{(i)} = 2^n C_n \prod_{j=1}^{n} d_j . \quad (5)$$

Where C_n is a constant, depending on n, for example $C_2 = \pi$, $C_3 = 4\pi/3$. Environment resources are proportional to the size of the living domain. The environment resources occupied by a species are defined as:

$$R_t^{(i)} = \begin{cases} \delta \cdot A_t^{(i)} & A_t^{(i)} > \varepsilon \\ \delta \cdot \varepsilon & A_t^{(i)} \leq \varepsilon \end{cases} . \quad (6)$$

Where δ is the number of resources in a unit living domain, and ε is the minimum living domain a species should maintain. Assuming a species can plunder the resources of other species through competition. The upper limit of population size that the environment resources can support of a species is determined by:

$$K_t^{(i)} = \exp(1 - \bar{w}_t^{(i)}) \cdot R_t . \quad (7)$$

Where parameter $R_t = \sum_{i=1}^{\Omega_t} R_t^{(i)}$ is the total resources of the system and $\bar{w}_t^{(i)}$ is the average importance factor of species i. It is obvious that the environment resources represent the uncertainty of the robot's pose. And the upper limit of population of species will change according to the environment resources, but the change of the resources will not affect the competition results of the species.

IV. EXPERIMENT RESULTS

We have evaluated CEAPF in the context of indoor humanoid robot localization using data collected with a Pioneer3 robot. The data consist of a sequence of laser range-finder scans along with odometry measurements annotated with time-stamps to allow systematic real-time evaluations. The experimental field is a large hall in our laboratory building whose size is of 15*15m^2, and the hall is partitioned into small rooms using boards to form a highly symmetric map as shown in Figure1 (a).
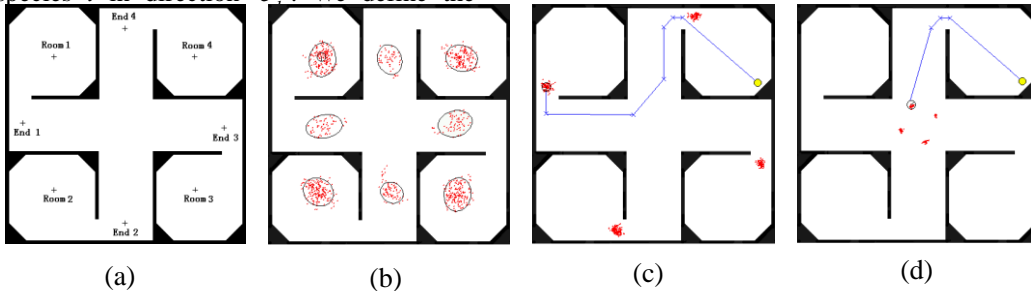

(a)   (b)   (c)   (d)

Figure 1 Localization based on CEAPF

(a) Map of the environment (b) Initial samples (c) Samples at the 7th second (d) Samples at the 16th second

In the localization experiments, the robot was placed at the center of one of the four rooms. And 1000 initial samples that have largest initial importance factor are selected from a lage test sample size of 1000000. Then the samples are clustered into species as shown in Figure1 (b). The robot was commanded to go to the corner of another room. 5 times of experiments were conducted for each initial place. The three filters PF, GPF (genetic particle filters) and CEAPF were applied to localize the robot using the collected data in the experiments. Here genetic particle filters merge genetic operators into PF but without coevolution mechanism. The parameter $\alpha_t^{(ij)} = \overline{w}_t^{(j)} / \overline{w}_t^{(i)}$, where $\overline{w}_t^{(i)}$ is the average importance factor of species i; parameter $r^{(i)}$, the maximum possible rate of population growth of species, equals 0.2; and parameter ε, the minimum living domain of species, equals 0.5m^2; parameter δ, the number of resources in a unit living domain which is m^2 in this paper, equals 80; the crossover probability p_c is 0.85; and the mutation probability p_m is 0.15. Figure1 (c) and (d) show two inter moments when the robot ran from the center of room 1 to the goal using CEAPF for localization.

To compare the localization precision of the three algorithms, we use the robot position tracked by using PF with 5000 samples and the known initial position to be the reference robot position. The average estimation errors along the running time are shown in Figure 2. Since the summary in CEAPF is based on the most likely species and the genetic operator in intra-species evolution can drive the samples to the regions with large importance factors, so localization error of CEAPF is much lower.

The computational time needed for each iteration with 1000 initial samples on a computer with a CPU of PENTUM 800 is shown in Figure 3. From Figure 2 and Figure 3 we can see that the CEAPF can make precise localization with a small sample size. The change of the total environment resources and that of the total number of samples are shown in Figure 4. From the Figureure we can see that the resources will be reduced when the position becomes certain, the total sample size needed for robot localization will also be reduced. The parameter δ which represents the number of resources in a unit living domain is important in CEAPF, because it will affect the competition between species. Large δ will reduce the competition between the species, since there is enough resource for them. The curve of total sample size with different δ is shown in Figure 5.
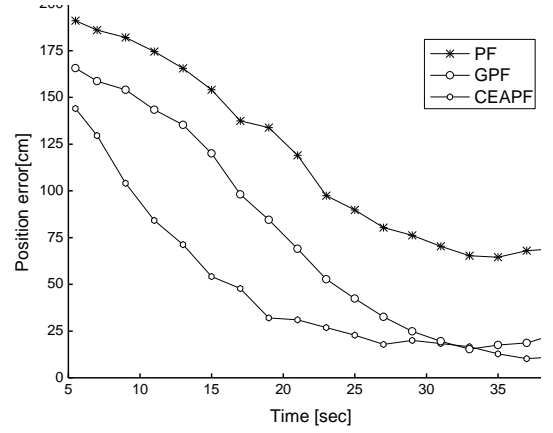

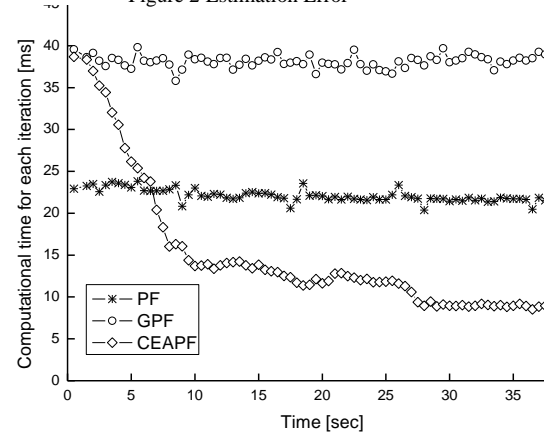Figure 2 Estimation Error

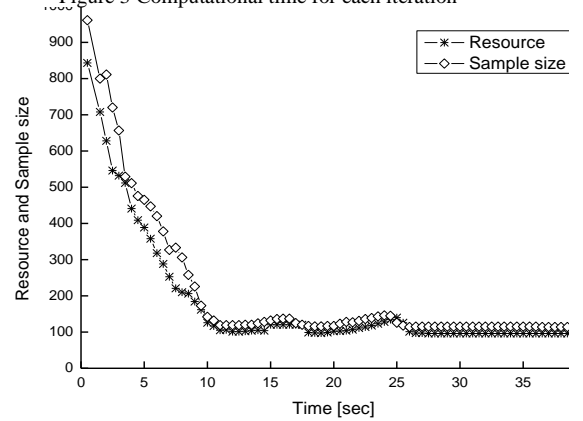Figure 3 Computational time for each iteration

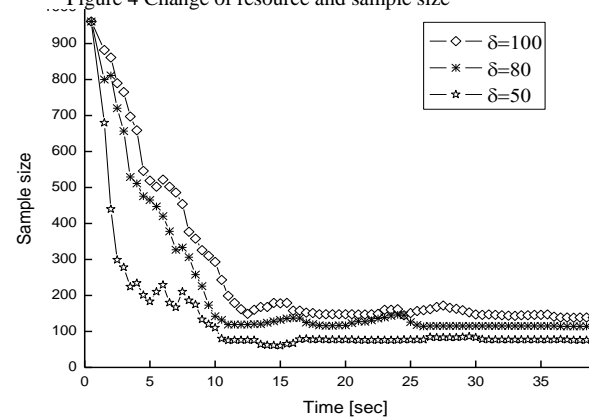Figure 4 Change of resource and sample size

Figure 5 Effect of δ on sample size

V.CONCLUSION

This paper proposes the coevolution based adaptive particle filters (CEAPF) and applies evolution strategy to particle filter, and combines with the scheme of adaptive sampling again to realize localization and map-creating simultaneously for indoor humanoid robot. CEAPF can adaptively adjust the sample size according to the total environment resources by using an ecological competition model. Coevolution between species ensures that the problem of premature convergence when using PF for localization in highly symmetric environments can be solved. Optimal samples in each species can be searched for by genetic operators in intra-species evolution, so CEAPF can realize precise localization with a small sample size. The efficiency of CEAPF in robot global localization have been proved by the experimental results.

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