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Research of biogeography particle swarm optimization for robot path planning

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ABSTRACT

Global path planning of mobile robot in a static environment is one of the most important problems in the field of mobile robot. Biogeography-based Optimization (BBO) is a relative new algorithm inspired by biogeography. It mainly uses the biogeography-based migration operator to share the information among solutions. Particle swarm optimization (PSO) is a classical heuristic search method whose mechanics are inspired by the swarming or collaborative behavior of biological populations. This paper presents a new method of global path planning by combining BBO, PSO and approximate voronoi boundary network (AVBN) in a static environment. The idea of this paper is to apply position updating strategy of PSO to increase the diversity of population in BBO and then use the obtained biogeography particle swarm optimization algorithm (BPSO) to optimize the paths in path network obtained by AVBN modeling. Experimental results in simulation show that the proposed method is feasible and effective.

1. Introduction

Robot path planning (RPP) is a key issue in autonomous robot technology. The basic RPP problem deals with static environments, that is, workspaces solely containing stationary obstacles. RPP is also an important problem in navigation of autonomous mobile robots, which is to find an optimal collision-free path from a starting point to a goal in a given environment [1].

There have been various methods proposed by researchers to solve RPP problems. Methods in RPP can be divided into the following two methods. The first method is based on environment information directly. Though such a method has a good adaptability to the changes of environment, it is difficult to find an ideal path under complex environment. So it is generally adopted in the local path planning. The second method is based on a structured model. The structured model embodies the typical character of the environment and can help to decrease the calculation of path planning.

Many conventional path planning methods, such as cell decomposition [2], roadmaps [3] have difficulty in solving RPP with complex environments due to their high cost of computation. Approximate voronoi boundary network (AVBN) is a structured method that obtains the non-smooth path network from the sensors in formation [4]. It needs not decompose the complex obstacles, so the model of the environment is simplified. Such a method embodies the network structure of the free area of environment with less nodes, so the complexity of path planning problem is reduced largely.

In recent years, we have seen that many intelligent optimization approaches inspired by natural phenomenon or mechanisms had been used for RPP due to their robust and abilities of parallel computing. Genetic algorithm and neural networks, both of which are well known intelligent optimization approaches, had been used for solving RPP many years ago. Sugihara et al. had adopted a genetic algorithm to solve the problem based on cell representation of the environment [5]. In [6], Gemeinder et al. presented a genetic algorithm (GA)-based path planning software for mobile robot systems focusing on energy consumption. AL-Taharwa et al. presented genetic algorithm to help a controllable mobile robot to find an optimal path between starting and ending point in a grid environment [7]. In [8], Mohanta et al. used petri-GA for path planning strategy of autonomous mobile robot navigation.Yang et al. applied a neural network to program the collision-free path of a mobile robot in a dynamic environment [9,10]. Xiong et al. proposed a RPP method based on recurrent neural network [11].

Besides the classical intelligent approaches mentioned above, Bell and McMullen had used ant colony algorithm, a well known swarming intelligence approach, to solve RPP [12]. A novel method for the real-time globally optimal path planning of mobile robots is proposed based on the ant colony system (ACS) algorithm in [13]. Another well known swarm intelligence method-particle swarm optimization (ACO) had also been utilized to solve RPP problem. Saska et al. used PSO to optimized the parameters of splines, which was a path description approach proposed by the authors

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[14]. Chen et al.proposed an improved PSO to optimize the path of a mobile robot through an environment containing static obstacles [15]. It can get smooth path. Lu et al. used particle swarm optimization, another well known swarm intelligence method to solve RPP in unknown environment [16]. The other intelligent algorithms used in RPP include artificial immunes systems, which are the intelligent approaches inspired by immunology theories and mechanisms of human immune system also applied in RPP [17–19]. Culture algorithms [20], memetic algorithm [21] and simulation annealing algorithm [22] had also been used for RPP.

Each method has its own advantage over others in certain aspects. So, a hybrid technique based on ACO and fuzzy system was proposed in [23]. In [24], the problem of finding the optimal collision free path in complex environments for a mobile robot is solved using a hybrid neural network, GA and a local search method.

Generally speaking, the main difficulties for RPP problems are computational complexity, local optimum and adaptability, so researchers have always been seeking alternative and more efficient ways to solve the problem.

PSO was invented by Kennedy and Eberhart in the mid 1990s while attempting to simulate the choreographed, graceful motion of swarms of birds as part of a sociocognitive study investigating the notion of 'collective intelligence' in biological populations [25]. In PSO, a set of randomly generated solutions (initial swarm) propagates in the design space towards the optimal solution over a number of iterations (moves) based on a large amount of information about the design space that is assimilated and shared by all members of the swarm. It seems to be an attractive one to study since it has a simple but efficient nature added to being novel. It can even be a substitution for other basic and important evolutionary algorithms.

Recently, the science of biogeography had been paid attention by researchers from computer science. BBO is a bio-inspired optimization technique inspired by biogeography [26]. Over the past three years, many improvement to BBO had been finished by Simon and some other researchers [27–33]. Bhattacharya et al. used BBO to solve the problem of economic load dispatch problem [34]. We have used BBO to successfully solve the problem of traveling salesman problem [35]. BBO is a new intelligent algorithm which shows good performance in many respects.

In the following sections, we design a new RPP method by combining BBO and PSO. In order to calculate the trajectory in the global map, this paper presents a new RPP method based on the combination of BPSO and AVBN method. The biogeography based particle swarm optimization algorithm is adopted to search the possible paths and the best one is obtained.

The remainder of this paper is organized as follows. In Section 2, the basic BBO and PSO algorithm are introduced and then BPSO is proposed. In Section 3, we combine BPSO and AVBN to solve the RPP. Simulation results and analysis are shown in Section 4. Finally, conclusions are drawn in Section 5.

2. Biogeography particle swarm optimization

2.1. Biogeopraphy-based optimization

In BBO, each possible solution is an island and their features that characterize habitability are called suitability index variables (SIV). The goodness of each solution is called its habitat suitability index (HSI) [27]. A habitat is a vector of SIVs initialized randomly and then follows migration and mutation step to reach global minima. For solving an engineering problem, a good solution is analogous to an island with a high HSI, and a poor solution represents an island with a low HSI. High HSI solutions resist change more than low HSI solutions. By the same token, high HSI solutions tend to share their features with low HSI solutions. Poor solutions accept a lot of new features from good solutions. In BBO, a population of candidate solutions is represented as vectors of integers. Each integer in the solution vector is considered to be an SIV.

The main feature of BBO differs from the other evolutionary computation lies in its migration strategy or migration operation. In BBO, each individual has its own emigration rate λ_s and immigration rate μ_s, which are functions of the number of species $s,(s=1,2...i,...P)$ in the habitat and can be expressed by Eqs. (1) and (2) [27].

$$\lambda_s=\frac{E_s}{P} \tag{1}$$

$$\mu_s=I\left(1-\frac{s}{P}\right) \tag{2}$$

where $E=\max\lambda_s$, $I=\max\mu_s$, and $P=$ population size. Generally, E and I are unit matrix.

Let us consider the probability P_s that the habitat contains exactly s species. The probabilities of each species count can be calculated using the differential Eq. (3).

$$\dot{P}_s=\begin{cases}-(\lambda_s+\mu_s)P_s+\mu_{s+1}P_{s+1}, s=0\\ -(\lambda_s+\mu_s)P_s+\lambda_{s-1}P_{s-1}+\mu_{s+1}P_{s+1}, 1\le s<s_{\max}-1\\ -(\lambda_s+\mu_s)P_s+\lambda_{s-1}P_{s-1}, s=s_{\max}\end{cases} \tag{3}$$

where $s_{\max}$is the maximal number of species count.

In migration process, the information shared among habitats is depended on λ_s and μ_s of each solution. Migration strategy is described as follows [27]:

Step 1: For $i=1$ to P
Step 2: Select H_i with λ_i
Step 3: If H_i is selected
Step 4: For $j=1$ to P
Step 5: Select H_j with probability $\propto\mu_i$
Step 6: If H_j is selected
Step 7: Randomly select an SIV σ from H_j
Step 8: Replace a random SIV in H_i with σ
Step 9: End if
Step 10: End for
Step 11: End if
Step 12: End for

In the migration procedure, each habitat (candidate solution) is modified based on other habitats. If a given habitat is selected to be modified, then its immigration rate λ_i is used to probabilistically decide whether or not to modify each suitability index variable (SIV) in that habitat. If a given SIV in a given habitat $H_i$is selected to be modified, then the emigration rates μ_i of the other habitats are used to probabilistically decide which of the habitats should migrate a randomly selected SIV to solution.

Based on the process of migration, the adaptive ability of habitat is improved by regulating immigration rate and emigration rate, migration topology, and migration strategy. Thus, it can get optimal solution of problem. The main characteristic of BBO is that the original population does not disappear in each generation, but improve the fitness by migration, and it can decide migration rate by fitness.

After migration process, the mutation is used to increase the diversity of the population to get better solutions. Mutation operator changes a habitat's SIV randomly based on mutation rate