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Swarm Intelligence Algorithm Inspired by Route Choice Behavior

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Abstract

Travelers' route choice behavior, a dynamical learning process based on their own experience, traffic information, and influence of others, is a type of cooperation optimization and a constant day-to-day evolutionary process. Travelers adjust their route choices to choose the best route, minimizing travel time and distance, or maximizing expressway use. Because route choice behavior is based on human beings, the most intelligent animals in the world, this swarm behavior is expected to incorporate more intelligence. Unlike existing research in route choice behavior, the influence of other travelers is considered for updating route choices on account of the reality, which makes the route choice behavior from individual to swarm. A new swarm intelligence algorithm inspired by travelers' route choice behavior for solving mathematical optimization problems is introduced in this paper. A comparison of the results of experiments with those of the classical global Particle Swarm Optimization (PSO) algorithm demonstrates the efficacy of the Route Choice Behavior Algorithm (RCBA). The novel algorithm provides a new approach to solving complex problems and new avenues for the study of route choice behavior.

Keywords: swarm intelligence, route choice behavior, particle swarm optimization, mathematical optimization

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1 Introduction

Swarm intelligence algorithms originate from swarm intelligence behavior. Scholars have studied some swarm intelligence phenomena in nature to propose new methods for solving complex optimization problems that are difficult to solve using classical optimization algorithms. Holland[1] proposed Genetic Algorithms (GAs) in 1975 as a simulation of natural selection and the genetic mechanism of Darwin's theory of biological evolution. Other examples include the Ant Colony Optimization (ACO)[2,3], the Particle Swarm Optimization (PSO)[4–8], the Artificial Fish Swarm Algorithm (AFSA)[9], the Quantum Multi-Agent Evolutionary Algorithm (QMAEA)[10], the Firefly Algorithm (FA)[11], and the Bacteria Foraging Optimization (BFO)[12]. Tao *et al*.[13,14] proposed the idea of Configurable Intelligent Optimization Algorithms (CIOA), and a framework for CIOA has been studied and a series of algorithms have been developed based on the idea and framework, which are employed for addressing green material selection[15], dynamic migration of virtual machines[16], energy-aware cloud service scheduling[17], multi-objective service composition and optimal-selection[18–20], and so on. All these swarm intelligence algorithms were inspired by swarm behaviors and formulated by simulating those behaviors and learning the evolutionary mechanisms. However, nearly all those swarm behaviors are those of microorganisms or animals. Very few researchers have utilized human swarm behavior as the basis of a swarm intelligence algorithm[21]. Kaur *et al*.[22] proposed a new optimization algorithm for complex optimization problems based on human opinion formation models. Route choice behavior is one of the most important aspects of transportation systems for traffic prediction and management. As easily

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observed in recent research, route choice behavior is a constant day-to-day evolutionary process[23,24].

Route choice behavior can be divided into two types: single choice situations and repeated choice patterns[25]. Several theories have been applied for single choice situations, such as the Expected Utility Theory (EUT)[26], the Random Utility Theory (RUT)[27], and the Prospect Theory (PT)[28]. A route is chosen in EUT by maximizing the expected utility of potential route choices, and in RUT, a random utility term is added based on EUT to express the uncertainty of travelers. Predictions based on EUT and RUT often disagree with experimental results in real life, but PT, proposed in economics, is applied in route choice decision for its accurate description of decision making in uncertain circumstances. Route choice behavior has been described as a utility maximization or minimization for travelers in single choice behavior. In fact, route choice behavior is not only a utility maximization or minimization, but also an evolutionary process for achieving better route choices[29]. Many other theoretical models have been introduced for describing the repeated choice patterns, such as the Cumulative Prospect Theory (CPT)[30]. In these models, route choice behavior is described as an iterative process based on travelers' perceptions of road networks and traffic information from transportation systems.

Travelers continually adjust route choice based on their own experience and traffic information regarding better routes. The evolutionary mechanism of route choice behavior can inspire its use for optimization. In fact, a traveler's route choice behavior is not only determined by traffic information and his/her perceptions of road networks, but also impacted by other travelers' route choices. What's more, traffic information is based on the aggregated behaviors of travelers. The other travelers' influence and traffic information make the route choice behavior from individual to swarm. In a word, an alternative route set is dependent on travelers' perception of a transportation network, traffic information regarding transportation systems, other travelers' influence, and historical travel information. Travelers cooperate with each other constantly to explore transportation networks and pursue more suitable route choices. Analogous with current swarm intelligence algorithms, such as PSO, these characteristics of route choice behavior encouraged us to propose the RCBA, an evolutionary algorithm for real optimization problems.

2 Route choice behavior algorithm

Routes can be categorized for travelers as guidance, historical, and others. For travelers not familiar with a transportation network, the first need to consider is whether to select guidance routes. From current research, the probability of selecting guidance routes is dependent on market penetration of guidance information systems, guidance information accuracy, and traveler characteristics. When travelers do not choose guidance routes, historical routes are likely to be selected, with a probability based on the gains or losses of selecting the best historical route compared with a reference point. Travelers tend to choose a historical route, when gains or losses are small; otherwise, they select another more satisfying route. When neither guidance nor historical routes are chosen, travelers will consider other routes based on exploration of the transportation network, travelers' preference for unfamiliar routes, or perhaps the influence of other travelers. RCBA is organized into three parts, the solution space, alternative solutions, and update of probabilities for choosing guidance, historical, and new solutions.

The solution space is the constraint condition for solutions. In route choice behavior models, the solution space consists of the routes from an origin to a destination in a transportation network, with each route separate from others. The evolutionary mechanism of route choice behavior is actually a discrete optimization, hence RCBA requires discretization of a continuous solution space when used for continuous optimization problems, and binary coding is applied for this purpose in this paper.

Alternative solutions are the solution sets that particles can choose at each step. Analogous to alternative routes in route choice behavior, alternative solutions are classified into three kinds: guidance, historical, and new. The global best solution at previous time t is used as the guidance solution at time $t + 1$, and the best of the historical solutions at previous times represents the historical solution for each particle. New solutions are those in the solution space that have not been visited, but this cannot express the theory of choosing other routes in route choice behavior. In this paper, other routes in the alternative routes are assumed to come from the influence of other travelers, route alteration based on explo-