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Distributed learning with biogeography-based optimization: Markov modeling and robot control

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ABSTRACT

Biogeography-based optimization (BBO) is an evolutionary algorithm that is motivated by biogeography, which is the science that describes how biological species are geographically distributed. We extend the standard BBO algorithm to distributed learning, which does not require centralized coordination of the population. We call this new algorithm distributed BBO (DBBO). We derive a Markov model for DBBO, which provides an exact mathematical model of the DBBO population in the limit as the generation number approaches infinity. We use standard benchmark functions to compare BBO and DBBO with several other evolutionary optimization algorithms, and we show that BBO and DBBO give competitive results, especially for multimodal problems. Benchmark results show that DBBO performance is almost identical to BBO. We also demonstrate DBBO on a real-world application, which is the optimization of robot control algorithms, using both simulated and experimental mobile robots.

1. Introduction

Biogeography is the science and study of the geographical distribution of plant and animal life. Alfred Wallace and Charles Darwin were some of the first to observe patterns of biogeography, and they introduced the subject to the scientific world in the 1800s [27]. Biogeography evolved into a quantitative science with the work of Robert MacArthur and Edward Wilson in the early 1960s [19]. Other scientists also contributed to the quantitative study of biogeography, the earliest being Eugene Munroe in 1948 [21].

Biogeography motivated the development of an evolutionary algorithm called biogeography-based optimization (BBO). Since its introduction in [35], BBO has been theoretically analyzed and modeled using Markov theory [14,36,37] and dynamic system models [38]. BBO has also been applied to several real-world problems, including robot controller tuning [13,34], aircraft engine health sensor selection [35], power system optimization [31], groundwater detection [24], mechanical gear train design [33], satellite image classification [23], antenna design [40], and biomedical signal processing [22,28].

In this paper, we introduce a distributed version of BBO, which we call distributed BBO (DBBO). The primary difference between BBO and DBBO is that BBO is coordinated by a central computer. However, DBBO does not depend on a central computer. Instead, each of the DBBO individuals evaluates its own cost function and communicates directly with other individuals for the purpose of information sharing and mutual improvement.

The over-arching goal of this paper is to introduce DBBO and motivate further research in its theory and application. We achieve this goal through four individual objectives.

1) First, we introduce the DBBO algorithm.
2) Second, we develop a Markov model of DBBO, and confirm the model's validity with simulation results.
3) Third, we use standard benchmark functions to show that BBO and DBBO are competitive with other evolutionary algorithms.
4) Fourth, we implement DBBO on an experimental robot system to demonstrate its practicality in real-world systems.

The development of DBBO is motivated by two observations. First, we see that EAs are powerful optimizers, and can find optimal solutions to many important, real-world problems. Second, we see that EAs typically use a central processor that coordinates selection, recombination, mutation, and any other operations that are involved in the evolutionary process. Although parallel EAs are common [6], most EAs are still implemented sequentially for the sake of convenience. The parallelization of EAs requires additional computational resources and design efforts beyond what is required for sequential EAs. However, in the real world, we may want to solve optimization problems by generating candidate solutions that are relatively independent of each other, and that cannot always communicate with a central processor or with the entire population. This is the case, for example, in peer-to-peer networking strategy optimization, and in many mobile robot applications. Distributed EAs may also be

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important in any application where reliability and robustness are important, and where a single-point failure in the optimization process cannot be tolerated.

The DBBO algorithm that we propose is a form of cooperative intelligence. Each individual has the same goal, intentionally communicates with others, and shares information with others to help one another in the attainment of the goal. Our application is robot controller tuning. Each robot has the same goal, which is maintaining a fixed distance from a wall while traveling at a constant velocity. The robots share each other's control parameters among themselves in an attempt to improve their performance.

Researchers have classified distributed intelligence into several different types. The DBBO algorithm that we propose is a form of cooperative intelligence [43]. That is, each individual has the same goal, intentionally communicates with other individuals, and the individuals mutually share information with each other to help one another attain the goal. Our application is robot controller tuning. Each robot has the same goal, which is maintaining a fixed distance from a wall while traveling at a constant velocity. The robots share each other's control parameters among themselves in an attempt to improve their performance.

Each robot has its own control strategy. Some robots perform well, and others perform poorly. The robots interact with each other through wireless radios, but their interaction is sporadic due to the limitations of radio communication, and due to their physical movements from one location to another. We want the robots to evolve controller solutions as they intermittently communicate with each other. This means that each robot needs to implement an EA in its microprocessor. The EA that is implemented by each robot is not aware of the entire EA population, but is aware only of those robots with which it can communicate. This EA, which is implemented in each robot and which involves a dynamically changing subset of the entire EA population, is called DBBO.

This paper is organized as follows. Section 2 gives an overview of centralized BBO [35], which is the standard BBO algorithm, and extends it to our proposed DBBO algorithm. Section 3 derives a Markov model for DBBO, which is an exact mathematical model in the limit as the generation count approaches infinity. Section 4 investigates the performance of BBO and DBBO on benchmark optimization problems, and also provides a comparison to other EAs. Section 5 provides simulated and experimental results of DBBO performance on mobile robot controller tuning. Section 6 summarizes the results of this paper and suggests directions for future work.

2. Biogeography-based optimization

BBO is an evolutionary algorithm that was introduced in [35], and is modeled on the science of biogeography. Biogeography describes how species migrate between habitats based on environmental factors [12,19]. These environmental factors can be represented quantitatively and are called suitability index variables (SIVs). Examples of SIVs include the amount of rainfall, the amount of available fresh water, the diversity of vegetation, and the temperature range. An area that is highly suitable for the habitation of biological species is considered to have a high habitat suitability index (HSI). Biologists have developed mathematical models of migration, speciation, and extinction.

A high-HSI habitat is likely to have a large number of species. Therefore, because of the accumulation of probabilistic effects on its large population, it has a high probability of emigrating species to other habitats. Because of its dense population, and because it may be saturated with so many species that it is unable to support additional life forms, it has a low probability of immigrating species from other habitats. The opposite situation occurs in low-HSI habitats because of its sparse population. A habitat's emigration and immigration probabilities are therefore proportional to the number of species that live in the habitat.

BBO is modeled on the above description of migration probabilities. BBO includes a population of individuals, each of which is a candidate solution to some optimization problem. A BBO individual with high fitness is analogous to an island with a high HSI. That individual has a high probability of emigrating its features (that is, its decision variables) to other individuals. The individuals that receive those features tend to increase their own fitness. Similarly, a BBO individual with low fitness is analogous to an island with a low HSI. That individual has a high probability of immigrating features from other individuals.

The standard BBO algorithm is called centralized BBO here, to distinguish it from the distributed BBO algorithm. Section 2.1 reviews centralized BBO, and Section 2.2 introduces distributed BBO.

2.1. Centralized BBO

BBO individuals with high fitness have high emigration probability μ, and low immigration probability λ. Migration probabilities are normalized to [0, 1].

If we denote the entire population as $\{P_i\}$, with P_i being the ith individual in the population, then the migration probabilities of P_i are given as

$$\mu_i = \frac{f(P_i) - \min_k f(P_k)}{\max_k f(P_k) - \min_k f(P_k)}$$
$$\lambda_i = 1 - \mu_i \tag{1}$$

where $f(P_i)$ is the fitness of P_i. Nonlinear relationships can also be used in BBO [14], but for the purposes of this paper, linear models are sufficient. We see the following from Eq. (1):

$$\text{Most fit individual in population}: \ \mu_i = 1, \quad \lambda_i = 0$$
$$\text{Least fit individual in population}: \ \mu_i = 0, \quad \lambda_i = 1.$$

If all individuals in the population have the same fitness, then the denominator in Eq. (1) is equal to 0. In this case we set the emigration and immigration probabilities to 1/2 for all of the individuals in the population.

As in other EAs, we also implement mutation in BBO to increase the exploration of the search space. Algorithm 1 describes the centralized BBO algorithm. In the "For each individual P_i" loop in Algorithm 1, the immigration decision for each individual and the selection of the emigrating individual are made independently of all previous decisions.

Algorithm 1. The centralized BBO algorithm.

```
Generate a population of individuals (that is, candidate
  solutions) P={P_i}
While not (termination criterion)
  Calculate the fitness f(P_i) of each individual in P
  Use Eq. (1) to calculate the migration probabilities of each
   individual in P
  For each individual P_i
      For each decision variable v in P_i
          Use the immigration probability λ_i to decide
           whether to immigrate to P_i
          If immigrating to P_i then
                  Use {μ_j} to probabilistically select the
                  emigrating individual P_k
                  Migrate from P_k to P_i: P_i(v)←P_k(v)
              End immigration
          Next decision variable
          Probabilistically mutate P_i
      Next individual: i←i+1
Next generation
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