早稲田大学大学院情報生産システム研究科

博　士　論　文　概　要

論　文　題　目

Study on Probabilistic Model Building Genetic Network Programming

申　　請　　者
Xianneng LI

情報生産システム工学専攻
ニューロコンピューティング研究

2012 年　11 月

Inspired by Darwin's theory of natural evolution, Evolutionary Algorithms (EAs) use iterative progress to evolve a population of candidate solutions for solving optimization problems. The population is evolved towards more promising region of the search space by natural selection and random genetic operators, such as crossover and mutation. EAs have shown the advantages of simplicity of implementation and flexibility of different problems, comparing with the classical methods of operational research or mathematics which requires much prior knowledge to build the mathematical models of problems. As a result, EAs have attracted much attention by researchers to propose numerous algorithms in the past several years, such as Genetic Algorithm (GA), Evolution Strategy (ES), Evolutionary Programming (EP) and Genetic Programming (GP), etc.

The main difference among these algorithms relies on the representation of individual structures. GA encodes its individual by a sequence of bit-strings, ES individuals are coded as vectors of real numbers, EP represents its individuals by finite state machines and GP uses tree structure to represent its individuals. In the last decade, a new EA named Genetic Network Programming (GNP) was proposed. GNP extends the classical EAs to the graph individual representation, where a directed graph structure is developed. Comparing with the classical bit-string and tree structures EAs, the distinguished directed graph structure allows GNP to ensure higher expression ability for modeling complex problems.

The fundamental basis that makes EAs succeed in solving optimization problems is that evolution is capable of reproducing and combining the high-quality partial solutions (generally called Building Blocks, BBs) to form new solutions with higher quality. However, in classical EAs, this process is achieved implicitly through the problem-independent, stochastic and fixed crossover and mutation. The evolution of crossover and mutation are actually the variants of stochastic search, which have risks for breaking down the BBs which causes the low evolution efficiency or even make the problem unsolvable.

To overcome the above problems, researchers developed a new research branch of EAs called Estimation of Distribution Algorithm (EDA). Different from conventional EAs which implicitly recombine the BBs by stochastic genetic operators, EDA builds a probabilistic model by estimating the probability distribution from the promising solutions and sample the model for generating the new population. The fundamental basis of EDA is that the BBs can be explicitly represented in the probabilistic model and recombined by sampling the model. The process of estimating the probability distribution is carried out by the advanced techniques of statistic and machine learning. Many previous studies have shown that the breakage of the BBs in conventional EAs can be reduced by EDA, which causes the improvement of evolution performances.

A large number of studies have been conducted on EDA to propose numerous algorithms. However, most of the current EDAs were proposed in bit-string structure based GA and tree structure based GP. Due to the restriction of these structures in terms of expression ability, most of the current EDAs are applied to solve the benchmark problems of GA and GP, which produces one of the essential challenges in exploring EDA to solve many other problems. On the other hand, in most of the advanced EDAs, the complex machine learning techniques, such as Bayesian network, are very time consuming for constructing the probabilistic model. The construction of the probabilistic model itself is an optimization problem.

The objective of this thesis is to propose a novel paradigm of EDA named Probabilistic Model Building Genetic Network Programming (PMBGNP). It extends EDA to the graph individual representation, where GNP's directed graph is used. PMBGNP ensures higher expression ability than the existing EDAs, where a number of problems can be explored and solved efficiently and effectively, such as data mining problems and the problems of controlling the agents' behavior. Moreover, the enhancement of PMBGNP is studied by integrating Reinforcement Learning (RL) techniques, which does not require additional large number of time cost for the probabilistic modeling comparing with conventional EDAs.

Chapter 2 proposes standard PMBGNP, where two Maximum Likelihood Estimation (MLE)-based methods are developed for the probabilistic modeling of PMBGNP. The probabilistic model estimates the distribution of node connections for finding the optimal solutions. To verify its performance, PMBGNP is applied to solve the data mining problems, including the time series traffic dataset and the UCI benchmark datasets, by comparing with the conventional EAs and data mining methods.

In chapter 3, the issue of the population diversity loss in PMBGNP is addressed by the theoretical comparison with classical EDAs. A hybrid PMBGNP is therefore proposed to improve its exploration ability for the maintenance of diversity. The effectiveness of the hybrid PMBGNP and its theoretical ability to maintain the population diversity is testified through the problem of controlling the agents' behavior, i.e., robot control.

In chapter 4, an extended PMBGNP is proposed to accelerate the evolution by using both of the good and bad individuals. Most of the existing EDAs focus on estimating the distribution of the good individuals, while the bad ones are ignored. This chapter proposes a RL-based method to extract the good sub-structures from the bad individuals. The proposed method learns the experiences of individuals to formulate the Q values, which can measure the quality of sub-structures. By incorporating the learnt Q values, the good sub-structures from the bad individuals can be extracted and combined into the probabilistic modeling of PMBGNP to boost the evolution. The simulation results on robot control problems show its superiority over conventional methods.

In chapter 5, the algorithm of integrating RL is used from another sight of EDA. That is, the learnt Q values are directly used in the probabilistic modeling of PMBGNP, rather than extracting sub-structures from the bad individuals. The proposed algorithm in this chapter is called Reinforced PMBGNP. Comparing with the existing advanced EDAs based on Bayesian network which requires much time cost, Reinforced PMBGNP only requires linear additional time for the learning of Q values to construct an accurate model. The proposed algorithm is systematically studied in both benchmark problem, i.e., Tileworld system, and robot control problems by the comparison with the state-of-the-art algorithms in EAs, EDA and RL.

Chapter 6 extends PMBGNP from discrete optimization problems to continuous domains, where an algorithm named PMBGNP with Actor-Critic (PMBGNP-AC) is proposed. In PMBGNP-AC, the continuous variables of nodes are formulated by Gaussian distribution, which is updated by the analog of AC through evolution. The superiority of the proposed algorithm is verified in robot control problem by comparing with the classical algorithms.

Finally, chapter 7 concludes the thesis by drawing the unique features of PMBGNP and its contributions.