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Special Issue on Evolutionary Learning and Optimisation

Xiaodong Li; Wenjian Luo; Xin Yao

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Nature has been the source of inspiration for many machine learning algorithms. In particular, learning algorithms based on natural evolution have attracted much attention. Evolutionary computation, which concerns methods of simulated evolution, has been widely used as an effective technique to handle difficult learning problems. In the past decades evolutionary algorithms have been successfully applied to a wide variety of real-world problems.

This special issue brings together some recent works from a wide range of topics concerning evolutionary learning and optimisation, including Evolvable Hardware, Bayesian Classifiers, Learning Classifier System Ensemble, Genetic Programming for Classification, and Benchmarking Evolutionary Algorithms. The five papers included in this special issue originated initially from SEAL'06 but are substantially extended and revised from the conference version. These further extended papers were again rigorously reviewed in two rounds by at least two anonymous reviewers.

The paper by He *et al.* deals with the issue of adaptive lossless image compression in the area of evolvable hardware (EHW). The paper proposes an intrinsic EHW model, as opposed to the existing extrinsic EHW models, for predictive lossless image compression. The proposed model allows reformulation of a problem into a task of evolving a set of switches. As a result it can be implemented and executed on a chip directly. The proposed method can reduce the computation time substantially, making it more suitable for real-time applications.

The paper by Miquélez *et al.* describes a new evolutionary algorithm which incorporates Bayesian classifiers into an EA. Rather than using Bayesian or Gaussian networks as in a typical Estimation of Distribution Algorithm (EDA), the proposed model, Evolutionary Bayesian Classifier-based Optimization Algorithm (EBCOA), employs Bayesian Classifiers to evolve individual solutions to a fitter population. The experimental results show that the EBCOAs have comparable performance to existing EAs such as EDAs and ES.

The paper by Gao *et al.* presents a two-level Learning Classifier System Ensemble (LCSE) that combines the traditional learning classifier systems with ensemble learning in order to produce a more generalized model. The first level contains a set of LCSs which are trained with different data sets re-sampled from a training data set, where a genetic algorithm module is used to facilitate rule discovery and a reinforcement learning module is used to adjust the strength of the rules. The second level uses a plurality-vote module to combine the results of the LCSs and generate the final classification results. To improve rule readability, a revised Wilson's compact rule set algorithm is also proposed. Their results suggest that LCSE has an improved generalization ability, and its online performance is better than or comparable to other supervised learning methods such as decision trees and neural networks.

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The paper by Zhang *et al.* presents an approach to solving the multi-calls object recognition problems using the Linear-structured Genetic Programming (LGP). Rather than using the standard tree structures as in the conventional GP to represent evolved classifier programs, this approach uses a linear structure to represent evolved programs. The results on three object classification problems with increasing difficulty suggest that the LGP approach can outperform the traditional tree-based GP in terms of classification accuracy and training time.

The paper by MacNish addresses a very important and challenging issue of benchmarking evolutionary algorithms or other similar optimisation algorithms. MacNish first describes some of the major biases that can be identified in traditional benchmarking functions, and then provides a compelling argument on how an alternative series of benchmarking functions or "fractal landscapes" can be used to avoid these biases in traditional benchmark functions. The algorithm for generating the landscapes (so called the Crater Algorithm) and its main design decisions are also provided. Furthermore, a practical algorithm for evaluating points on the landscapes, and an architecture for accessing the system that overcomes the issues of languages and environmental incompatibility are also presented. It is the hope of the author that this landscape generator will provide a valuable resource for benchmarking evolutionary algorithms.

We would like to thank the authors for submitting their research papers to this special issue, and the reviewers who, in spite of their busy schedules, took the time to provide in-depth comments and constructive criticisms. We would like to express our gratitude to the following reviewers (in alphabetical order): Ying-ping Chen, Shu-heng Chen, Hisashi Handa, Hitoshi Iba, Masaya Iwata, Jiri Jaros, Bob McKay, Lukas Pichl, Ke Tang, Hidenori Sakanashi, Jianyong Sun, Peter Whigham, Bo Yuan, Zhenya Zhang, and Qiangfu Zhao. Last but not least, we thank Editor-In-Chief Professor Noel Sharkey and Dr. Amanda Sharkey for their constant support and assistance during the editing process of this special issue.

Xiaodong Li
Wenjian Luo
Xin Yao

Guest editors, October 2007