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Guest Editorial

Evolutionary neural networks for practical applications

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Evolutionary neural networks (ENN) combine the evolutionary computation and neural networks to solve many interesting problems [11]. It automatically determines the weights and the topology of neural networks simultaneously and minimizes the intervention of human experts. It is a quite attractive technology for optimization, learning, and control of intelligent systems and there have been a lot of research issues raised. Figure 1 shows the general procedure for evolutionary neural networks. At first, it is necessary to determine the representation of neural networks because there are a lot of different ways to represent neural networks as genetic encodings. In the initialization step, it creates a number of neural networks randomly. It is natural that they are not working well on the problem to be optimized. The next step is to evaluate the goodness of each neural network given problems. Based on the fitness values, it selects some neural networks from the whole population and applies genetic operations to them. It creates new offspring by exchanging genetic codes from two successful neural networks and mutating small portions of the codes. It goes to the evaluation step and repeats the procedure until satisfying stopping criterion.

According to Yao's work [11], the evolutionary neural networks can be classified into the evolution of connection weights, the evolution of architectures, and the evolution of learning rules and others. In the evolution of connection weights, it assumes that the topology of the neural network is fixed and only the weights are trained using evolutionary algorithms. In the evolution of architectures, it evolves network topology, node transfer functions, and both of architectures and connection weights. In the evolution of learning rules, it evolves the learning rules used to adjust connection weights of architectures under investigation. In addition to the three categories, there are some works on the evolution of input features, artificial neural network as fitness estimator, and evolving artificial neural network ensembles.

Evolutionary neural networks have great potential for practical applications and there are a lot of publications in different domains. In evolutionary robotics, it is one of the popular methods to train controllers of robots. Floreano et al. investigated the use of evolutionary neural networks for several robotic tasks such as navigation, cooperation, altruism and communication [3]. As a tool for ecology, biology, and social science, the evolutionary neural networks are promising because they resemble the evolution of human brain [4]. In evolutionary games, the evolutionary neural networks are very successful and show human-competitive performance in chess, checkers, and backgammon [1]. In evolutionary art, the tool has been applied to generate novel dancing behavior, music, and figures [9].

This special issue aims to present the recent successful stories about ENN for practical applications. It is intended to give the researchers and practitioners insight on the use of ENN for several interesting new application areas. Based on the contributed articles, you might be able to find the way to apply the ENN to your problems. It is not straightforward to apply ENN for specific engineering problems because there are several decision points critical to the success of the projects. It is not trivial to choose the representation of ENN and their corresponding genetic operators (selec-

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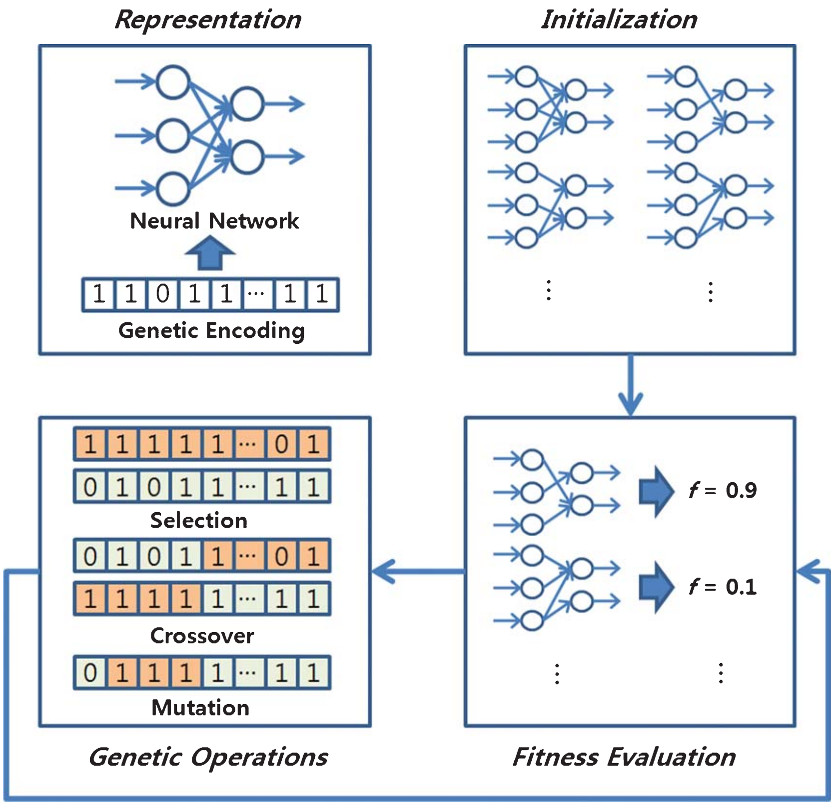

Fig. 1. Overview of the evolutionary neural network algorithm.

tion, crossover and mutation). Ideally, it is possible to evolve all of the weights, topology, learning rules, and transfer functions of neural networks simultaneously, but it fails to find good solutions due to intractable complexity. It is possible to boost the ENN's performance by carefully adopting several sophisticated techniques such as speciation, co-evolution, and ensemble. You need to realize the additional advanced materials on the ENN.

At first, there are three papers dedicated to the development of novel methods for evolutionary neural networks. Tan et al. propose a novel evolutionary neural network algorithm to integrate fuzzy ARTMAP (FAM) and hybrid evolutionary programming (HEP) for pattern classification [10]. They report that the performance of FAM-HEP outperforms FAM-EP and FAM, and shows equivalent performance as compared those from other statistical classification methods. Especially, they apply the model to the promising computerized decision support tool for handling medical diagnosis tasks. Maia et al. propose a novel method of evolutionary neural networks for visual tracking of objects in video sequences [6]. The traditional detection-based algorithm uses a simple geometric template to track an object assuming rigid object, fixed camera and slow movement. In their work, the template is interpreted as the output grid of a topographic map of features and an evolutionary self-organizing algorithm is used to locate the object frame by frame. They report a qualitative assessment of the algorithm subjected to partial occlusion and self-occlusion, and outliers as well as quantitative tests. Kim et al. investigate the effect of different distance measures for the evolutionary neural networks with speciation [5]. Because a simple evolutionary algorithm often suffers from prematured convergence, it is necessary to increase the diversity of population. In this line of research, one of the most difficult problems is to measure distance or similarity between two evolutionary neural networks. In this study, they attempt to compare several distance measures for different ENN representations with UCI benchmark datasets. This paper gives an extensive survey of distance measures for ENN and their experimental comparison for pattern recognition problems.

Remaining three papers are devoted to the development of successful applications using the evolutionary neural networks. Mandziuk et al. apply the ENN to the problem of a short-term stock index prediction for the data from the German, Tokyo, and New York Stock Exchange markets [7]. In their approach, the genetic algorithm is used to find appropriate set of input variables for prediction. They report that it is better to calculate a new set of inputs every five trading days due to the high volatility of mutual relationships between them. They report that their approach works well in cases of both upward and downward trends. Duro et al. evolve ensembles of collaborating neural networks which solve tasks through the interaction of members [2]. This enables to handle lifelong learning of the society adapting to changing situations and demands in dynamic environments. They propose Asynchronous Situated Co-Evolution (ASiCo) which supports any type of neural network structure or even neural network construction mechanisms. Their operation and characteristics are illustrated through some experiments carried out using a well-known benchmark collaboration task. Tortosa et al. describe 2D triangle mesh simplification preserving the shape of the original mesh using adaptive self-organizing algorithms [8]. They verify the effectiveness of their approach through the design and development of some urban network problems. Especially, the algorithm is applied to two real problems: The design of a tramway network in a town, and the design of an information point network within a real bus transport network.

This special issue deals with several novel approaches for the successful applications of evolutionary neural networks. In details, it includes applications for pattern classification, time-series prediction, visual tracking, multi-agent cooperation and mesh simplification. Because ENN hybrids the evolutionary computation and neural networks, they show powerful generalization ability and some interesting properties. For example, it provides with better accuracy, adaptive behavior, and emergent cooperative behavior. However, it is not trivial to use the ENN model successfully for your problem because of the several decision points. As guest editors, we hope that this special issue contributes to the development of intelligent systems using ENN. Finally, we would like to express great thanks to the Editor-In-Chief, Prof. Reza Langari, for his support on this special issue.

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