

Coevolutionary Computational and Multiagent Systems

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Preface

One of the remarkable features of modern science and technology is the mutual penetration and promotion between life science and engineering science. The rapid development in the field of computational intelligence, which includes neural networks, fuzzy logic, natural computation, evolutionary computation, and so on, also reflects such a feature. The research in the field of computational intelligence and recognition aims to achieve human intelligence by intelligently handling nonlinear real-world information, including image, video, voice, touch, etc. Due to its importance in information technology, computational intelligence has attracted increasing attention, and is also listed as one of the five key directions by the National Natural Science Foundation Committee of China.

According to fossil records, life has preceded the singled celled organism, and undergone a roadmap of evolution from a low level to a high level, and from the simple to the complex. Human beings, superior living organisms with thought and intelligence, are a spectacular success of evolution. Human beings can not only adapt to their environment, but also improve their adaptability via learning, imitation, and creation. Since the last century, researchers have extended the areas they study to include nature and human beings. Researchers have studied the evolutionary process of human beings itself, and extracted it as an optimization process. The classic example being evolutionary algorithms (EAs).

EAs are a kind of stochastic optimization approach, inspired by theories of biological evolution. Traditionally, EAs have been categorized into four subfields: Genetic Algorithms (GAs), Evolution Strategies (ESs), Evolutionary Programming (EP), and Genetic Programming (GP). Nowadays, the boundaries between these subfields are more fluid and the methods are often grouped together using the term Evolutionary Algorithms. This class of method does not require derivatives of the functions defining the problem and it is relatively robust and flexible for solving nonlinear optimization problems, due to the stochastic search operators involved in the algorithmic definition.

Although simplistic from a biologist's viewpoint, EAs are sufficiently complex to provide robust and powerful adaptive search mechanisms. Today, Evolutionary Computation (EC), the computation model based on EAs, is a thriving field, and EAs have been successfully applied to a broad variety of problems in an extremely diverse array of fields, such as acoustics,

aerospace engineering, astronomy and astrophysics, chemistry, electrical engineering, financial markets, game playing, geophysics, materials engineering, mathematics and algorithmics, molecular biology, pattern recognition and data mining, robotics, routing and scheduling.

Although EAs have many advantages over traditional optimization approaches and have been successfully applied to many fields, they still have weaknesses. Their main disadvantages are the ability to be trapped in local optima and have a high computational cost, thus traditional EAs' ability in solving large-scale problems is weak. It is worth stepping back and exploring how to best learn from nature and how to incorporate our existing knowledge of artificial intelligence into EC.

As a new promising branch of EC, coevolutionary computation has attracted increasing attention recently. The further development of this branch will require further efforts from various researchers. This book studies the background and foundation of coEC in depth, and introduces organizational coevolutionary algorithms and multiagent evolutionary algorithms. We introduce the dynamics of coevolutionary systems, prove the convergence of algorithms, and analyze the computational complexity of algorithms. This book focuses on both the theoretical foundation and practical applications, and not only provides new coevolutionary algorithms, but also provides new ideas and methods for further developing computational intelligence.

The whole book is divided into 10 chapters, which include the introduction on EC, coEC, complex adaptive systems, and multiagent systems (Chapter 1), organizational coevolutionary algorithms and their applications on large-scale classification, satisfiability problems, numerical optimization, and VLSI Floorplan problems (Chapters 2, 3, 4, 5, 6), multiagent evolutionary algorithms and their applications to high-dimensional numerical optimization, combinatorial optimization problems, and constraint satisfaction problems (Chapters 7, 8, 9, 10).

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