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SWARM INTELLIGENCE AND BIO-INSPIRED COMPUTATION

THEORY AND APPLICATIONS

Edited by

XIN-SHE YANG • ZHIHUA CUI • RENBIN XIAO •
AMIR HOSSEIN GANDOMI • MEHMET KARAMANOGLU

Swarm Intelligence and Bio-Inspired Computation Theory and Applications

Edited by

Xin-She Yang

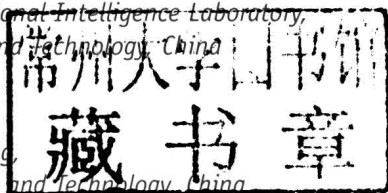
*Department of Design Engineering and Mathematics,
Middlesex University, UK*

Zhihua Cui

*Complex System and Computational Intelligence Laboratory,
Taiyuan University of Science and Technology, China*

Renbin Xiao

*Institute of Systems Engineering,
Huazhong University of Science and Technology, China*



Amir Hossein Gandomi

*Department of Civil Engineering
University of Akron, OH, USA*

Mehmet Karamanoglu

*Department of Design Engineering and Mathematics,
Middlesex University, UK*



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Swarm Intelligence and Bio-Inspired Computation

List of Contributors

János Abonyi Department of Process Engineering, University of Pannonia, Veszprém, Hungary

Rajendra Akerkar Western Norway Research Institute, Sogndal, Norway

Amir Hossein Alavi Department of Civil and Environmental Engineering, Michigan State University, East Lansing, MI, USA

Carlos Arango Ingeniería de Organización, Engineering School of Seville, University of Seville, Camino de los Descubrimientos s/n 41092, Seville, Spain

Ibrahim Aydogdu Civil Engineering Department, Akdeniz University, Antalya, Turkey

Janez Brest Faculty of Electrical Engineering and Computer Science, University of Maribor, Maribor, Slovenia

Xingjuan Cai Complex System and Computational Intelligence Laboratory, Taiyuan University of Science and Technology, Shanxi, China

Jelson Cordeiro Bioinformatics Laboratory, Federal University of Technology Paraná, Curitiba, Brazil

Pablo Cortés Ingeniería de Organización, Engineering School of Seville, University of Seville, Camino de los Descubrimientos s/n 41092, Seville, Spain

Kelton Augusto Pontara Costa Department of Computing, São Paulo State University, Bauru, Brazil

Zhihua Cui Complex System and Computational Intelligence Laboratory, Taiyuan University of Science and Technology, Shanxi, China

E. Doğan Civil Engineering Department, Celal Bayar University, Manisa, Turkey

Alejandro Escudero Ingeniería de Organización, Engineering School of Seville, University of Seville, Camino de los Descubrimientos s/n 41092, Seville, Spain

Iztok Fister Faculty of Electrical Engineering and Computer Science, University of Maribor, Maribor, Slovenia

Iztok Jr. Fister Faculty of Electrical Engineering and Computer Science, University of Maribor, Maribor, Slovenia

Andreas Floros Department of Audio and Visual Arts, Ionian University, Corfu, Greece

Simon Fong Department of Computer and Information Science, University of Macau, Macau SAR, China

Amir Hossein Gandomi Department of Civil Engineering, University of Akron, Akron, OH, USA

Oubay Hassan College of Engineering, Swansea University, Swansea, Wales, UK

Raha Imanirad OMIS Area, Schulich School of Business, York University, Toronto, ON, Canada

Momin Jamil Blekinge Institute of Technology, Karlskrona, Sweden; Harman International, Harman/Becker Automotive Systems GmbH, Karlsbad, Germany

Gilang Kusuma Jati Faculty of Computer Science, Universitas Indonesia, Kampus UI, Depok, Jawa Barat, Indonesia

Maximos A. Kaliakatsos-Papakostas Department of Mathematics, University of Patras, Patras, Greece

Mehmet Karamanoglu Department of Design Engineering and Mathematics, School of Science and Technology, Middlesex University, The Burroughs, London, UK

András Király Department of Process Engineering, University of Pannonia, Veszprém, Hungary

Jonas Krause Bioinformatics Laboratory, Federal University of Technology Paraná, Curitiba, Brazil

Hongbo Liu Department of Computer, Dalian University of Technology, Dalian, China; School of Information Science and Technology, Dalian Maritime University, Dalian, China

Heitor Silvério Lopes Bioinformatics Laboratory, Federal University of Technology Paraná, Curitiba, Brazil

Ruli Manurung Faculty of Informatics, Telkom School of Technology, Jl. Telekomunikasi No. 1, Terusan Buah Batu, Bandung, Jawa Barat, Indonesia

Kenneth Morgan College of Engineering, Swansea University, Swansea, Wales, UK

Rodrigo Yuji Mizobe Nakamura Department of Computing, São Paulo State University, Bauru, Brazil

Luis Onieva Ingeniería de Organización, Engineering School of Seville, University of Seville, Camino de los Descubrimientos s/n 41092, Seville, Spain

Rafael Stubs Parpinelli Applied Cognitive Computing Group, Santa Catarina State University, Joinville, Brazil; Bioinformatics Laboratory, Federal University of Technology Paraná, Curitiba, Brazil

João Paulo Papa Department of Computing, São Paulo State University, Bauru, Brazil

Luís Augusto Martins Pereira Department of Computing, São Paulo State University, Bauru, Brazil

Douglas Rodrigues Department of Computing, São Paulo State University, Bauru, Brazil

M. Rowan Brown College of Engineering, Swansea University, Swansea, Wales, UK

Priti Srinivas Sajja Department of Computer Science, Sardar Patel University, India

M.P. Saka Department of Civil Engineering, University of Bahrain, Isa Town, Bahrain

Shichang Sun Department of Computer, Dalian University of Technology, Dalian, China; School of Computer Science and Engineering, Dalian Nationalities University, Dalian, China

Suyanto Faculty of Informatics, Telkom School of Technology, Jl. Telekomunikasi No. 1, Terusan Buah Batu, Bandung, Jawa Barat, Indonesia

Siamak Talatahari Marand Faculty of Engineering, University of Tabriz, Tabriz, Iran

Tamás Varga Department of Process Engineering, University of Pannonia, Veszprém, Hungary

Michael N. Vrahatis Department of Mathematics, University of Patras, Patras, Greece

Sean Walton College of Engineering, Swansea University, Swansea, Wales, UK

Renbin Xiao Institute of Systems Engineering, Huazhong University of Science and Technology, Wuhan, China

Xin-She Yang Department of Design Engineering and Mathematics, School of Science and Technology, Middlesex University, The Burroughs, London, UK

Julian Scott Yeomans OMIS Area, Schulich School of Business, York University, Toronto, ON, Canada

Hans-Jürgen Zepernick Blekinge Institute of Technology, Karlskrona, Sweden

Preface

Swarm intelligence and bio-inspired computation have become increasingly popular in the last two decades. Bio-inspired algorithms such as ant colony algorithm, bat algorithm (BA), cuckoo search (CS), firefly algorithm (FA), and particle swarm optimization have been applied in almost every area of science and engineering with a dramatic increase in the number of relevant publications. Metaheuristic algorithms form an important part of contemporary global optimization algorithms, computational intelligence, and soft computing.

New researchers often ask “why metaheuristics?”, and this indeed is a profound question, which can be linked to many aspects of algorithms and optimization, including what algorithms to choose and why certain algorithms perform better than others for a given problem. It was believed that the word “metaheuristic” was coined by Fred Glover in 1986. Generally, “heuristic” means “to find or to discover by trial and error.” Here, “meta-” means “beyond or higher level.” Therefore, metaheuristic can be considered as a higher-level strategy that guides and modifies other heuristic procedures to produce solutions or innovations beyond those that are normally achievable in a quest for local optimality. In reality, we are often puzzled and may be even surprised by the excellent efficiency of bio-inspired metaheuristic algorithms because these seemingly simple algorithms can sometime work like a “magic,” even for highly nonlinear, challenging problems. For example, for multimodal optimization problems, many traditional algorithms usually do not work well, while new algorithms such as differential evolution (DE) and FA can work extremely well in practice, even though we may not fully understand the underlying mechanisms of these algorithms.

The increasing popularity of bio-inspired metaheuristics and swarm intelligence (SI) has attracted a great deal of attention in engineering and industry. There are many reasons for such popularity, and here we discuss three factors: simplicity, flexibility, and ergodicity. Firstly, most bio-inspired algorithms are simple in the sense that they are easy to implement and their algorithm complexity is relatively low. In most programming languages, the core algorithm can be coded within a hundred lines. Second, these algorithms, though simple, are flexible enough to deal with a wide range of optimization problems, including those that are not solvable by conventional algorithms. Third, bio-inspired algorithms such as FA and CS can often have high degrees of ergodicity in the sense that they can search multimodal landscape with sufficient diversity and ability to escape any local optimum. The ergodicity is often due to some exotic randomization techniques, derived from natural systems in terms of crossover and mutation, or based on statistical models such as random walks and Lévy flights.

As most real-world problems are nonlinear and multimodal with uncertainty, such complexity and multimodality may imply that it may not be possible to find the true global optimality with a 100% certainty for a given problem. We often have to balance the solution accuracy and computational cost, leading to a (possibly aggressive) local search method. Consequently, we may have to sacrifice the possibility of finding the true global optimality in exchange of some suboptimal, robust solutions. However, in practice, for the vast majority of cases, many bio-inspired algorithms can achieve the true global optimality in a practically acceptable fixed number of iterations, though there is no guarantee for this to be the case all the time.

The history of bio-inspired computation and SI has spanned over half a century, though the developments have been sped up in the last 20 years. Since the emergence of evolutionary strategies in the 1960s and the development of genetic algorithms (GA) in the 1970s, a golden age with major progress in modern bio-inspired computing is the 1990s. First, in 1992, Marco Dorigo described his innovative work on ant colony optimization (ACO) in his PhD thesis, and in the same year, J.R. Koza published a treatise on genetic programming. Then, in 1995, J. Kennedy and R. Eberhart developed particle swarm optimization (PSO), which essentially opened up a new field, now loosely named as SI. Following this in 1996 and 1997, R. Storn and K. Price published their DE. At the turn of the twenty-first century, Zong Woo Geem et al. developed the harmony search in 2001. Around 2004 to 2005, bee algorithms emerged. S. Nakrani and C. Tovey proposed the honey bee algorithm in 2004, and Xin-She Yang proposed the virtual bee algorithm in 2005. D.T. Pham et al. developed their bee algorithms and D. Karaboga formulated the artificial bee colony all in 2005. In 2008, Xin-She Yang developed the FA for multimodal optimization, and in 2009, Xin-She Yang and Suash Deb developed CS. In 2010, Xin-She Yang first developed the BA, and then Xin-She Yang and S. Deb developed the eagle strategy. More bio-inspired algorithms started to appear in 2012, including krill herd algorithm (KHA) by A.H. Gandomi and A.H. Alavi, flower pollination algorithm by Xin-She Yang, and wolf search algorithm by Rui et al. As we can see, the literature has expanded dramatically in the last decade.

Accompanying the rapid developments in bio-inspired computing, another important question comes naturally: Can an algorithm be intelligent? The answers may depend on the definition of “intelligence” itself, and this is also a debating issue. Unless a true Turing test can be passed without any doubt, truly intelligent algorithms may be still a long way to go. However, if we lower our expectation to define the intelligence as “the ability to mimic some aspects of human intelligence” such as memory, automation, and sharing information, then many algorithms can have low-level intelligence to a certain degree. First, many bio-inspired algorithms use elitism and memory to select the best solution or “survival of the fittest,” and then share this information with other agents in a multiple agent system. Algorithms such as artificial neural networks use connectionism, interactions, memory, and learning. Most SI-based algorithms use rule-based updates, and they can adjust their behavior according to the landscape (such as the best values, gradients) in the search space during iterations. To some extent, they can be called

“smart” algorithms. Obviously, truly intelligent algorithms are yet to appear in the future. Whatever the forms such intelligent algorithms may take, it would be the holy grail of artificial intelligence and bio-inspired computation.

Despite the above recent advances, there are many challenging issues that remain unresolved. First, there are some significant gaps between theory and practice, concerning bio-inspired computing and optimization. From numerical experiments and applications, we know bio-inspired algorithms often work surprisingly well; however, we do not quite understand why they are so efficient. In fact, it lacks solid theoretical proof of convergence for many bio-inspired algorithms, though the good news is that limited results do start to appear in the literature.

In addition, for most algorithms, we do not know how parameters can exactly control or influence the performance of an algorithm. Consequently, a major challenge is the tuning of algorithm-dependent parameters so as to produce the optimal performance of an algorithm. In essence, parameter tuning itself is an optimization problem. At present, this is mainly carried out by trial and error, and thus very time consuming. In fact, parameter tuning is a very active research area which requires more research emphasis on both theory and extensive simulations.

On the other hand, even though we have seen a vast range of successful applications, however, in most applications, these are still limited to small-scale problems with the number of design variables less than a few dozens or a few hundreds. It is very rare to see larger-scale applications. In reality, many optimization problems may be very large scale, but we are not sure how bio-inspired algorithms can deal with such large-scale problems. As most problems are often nonlinear, scalability may also be a problem, and computational time can be a huge barrier for large-scale problems.

Obviously, there are other challenging issues such as performance measures, uncertainty, and comparison statistics. These challenges also provide golden opportunities for researchers to pursue further research in these exciting areas in the years to come.

This book strives to provide a timely snapshot of the state-of-the-art developments in bio-inspired computation and SI, capturing the fundamentals and applications of algorithms based on SI and other biological systems. In addition to review and document the recent advances, this book analyze and discuss the latest and future trends in research directions so that it can help new researchers to carry out timely research and inspire readers to develop new algorithms.

As the literature is vast and the research area is very broad, it is not possible to include even a good fraction of the current research. However, the contributions by leading experts still contain latest developments in many active areas and applications. Topics include overview and analysis of SI and bio-inspired algorithms, PSO, FA, memetic FA, discrete FA, BA, binary BA, GA, CS and modified CS, KHA, artificial plant optimization, review of commonly used test functions and labor division in ACO. Application topics include traveling salesman problems, feature selection, graph coloring, combinatorial optimization, music composition, mesh generation, semantic web services, optimization alternatives generation, protein folding, berth allocation, data mining, structural optimization, inventory management, and others.

It can be expected that this edited book can serve as a source of inspiration for novel research and new applications. Maybe, in the not very far future, some truly, intelligent, self-evolving algorithm may appear to solve a wide range of tough optimization more efficiently and more accurately.

Last but not the least, we would like to thank our Editors, Dr Erin Hill-Parks, Sarah E. Lay, and Tracey Miller, and the staff at Elsevier for their help and professionalism.

Xin-She Yang, Zhihua Cui, Renbin Xiao,
Amir Hossein Gandomi and Mehmet Karamanoglu
February 2013

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