Bioinspired Algorithms and Complex Systems ☆

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Abstract

Complexity is a prevalent feature of numerous natural and artificial systems and as such has attracted much scientific interest in the last decades. The pursuit of computational tools capable of analyzing, modeling or designing systems exhibiting this complex nature –in which the properties of the system are not evident at the bottom level but emerge from its global structure– is a major issue. Metaheuristics can play here an important role due to its intrinsic adaptability and powerful optimization capabilities. In many regards, metaheuristics are also examples of complex systems since their behavior emanates from the orchestrated interplay of simpler algorithmic components. This bidirectional connection between metaheuristics and complex systems offers numerous avenues for fruitful research.

Keywords: complex systems, bioinspired algorithms, metaheuristics

1. Introduction

The term *bioinspired algorithms* [1] refers to metaheuristic methods that draw some inspiration from nature to solve search, optimization or pattern recognition problems; genetic algorithms, for instance, are inspired by Darwin's evolutionary theory [2] whereas ant-colony optimization algorithms are based in the concept of stigmergy [3], introduced to explain self-organization

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in ant colonies via indirect communication through modification of the environment. Indeed, these are two examples of the two main families of bioinspired metaheuristics, namely evolutionary algorithms [4] (based on the metaphor of evolution, either biological or cultural) and swarm intelligence [5] (based on the collective behavior of decentralized collection of agents, i.e., birds, insects, etc.). Overall, these techniques have set an impressive record of success in solving complex optimization problems.

On the other hand, complex systems are composed of many components, whose structure and interaction lead to emergent properties of the system as a whole, that is, the system exhibits properties and behaviors that are not explicit in its isolated components. This kind of systems are prevalent in natural an artificial contexts, i.e., ecosystems, financial markets, social environments, etc. [6, 7, 8]. Complex systems are often at the edge of chaos [9], in the sense that they lie in the middle ground between ordered systems and chaotic ones. This is often the result of the presence of non-linear interactions and feedback loops, often leading to self-organization patterns [10, 11].

Bioinspired algorithms and complex systems are connected in many ways. Firstly, it is possible to model bioinspired algorithms using using complex systems at a certain level; This is particularly true for hybrid or composite approaches, e.g., memetic algorithms [12], in which different algorithmic components are integrated aiming to obtain an improved emergent search behavior via their synergistic interaction. From a socio-biological point standpoint, this ought to be the outcome of competition and collaboration processes among components. In general, the complexity of the interaction structure and the possible presence of uncontrollable changes in the environment underpins the need for using adequate analytical tools. For example, one can follow some well established organization of components/individuals forced by their conditioning and skills or/and by some social tradition. If such structure is observed to be efficient in solving particular group of problems (e.g. surviving) then it might be mapped into the problem area of interest by defining an appropriate complex system of data structures and algorithms.

Recent years have witnessed different attempts to incorporate ideas and/or properties of complex systems into bioinspired algorithms in order to improve their performance or to better understand their behavior. For instance, self-organized criticality [13], self-stabilization [14] or complex topologies [15], just to mention a few. The obverse is also true: complex systems models can also understood, analyzed and studied using bioinspired algorithms, e.g., [16, 17]. As a matter of fact, studying complex systems often requires the use of composite strategies whose components approach the problem (or parts of it) from different perspectives, e.g., [18, 19]).

This thematic special issue revolves precisely around the intersection of bioinspired algorithms and complex systems from the two points of view mentioned, namely the use of bioinspired algorithms to tackle and analyzing complex systems, and the design of complex bioinspired algorithms. We have gathered five papers [20, 21, 22, 23, 24] targeted to cover algorithmic and implementation aspects of such complex meta-heuristics in both discrete and continuous domains, as well as applications to complex systems. Some contributions to this thematic special issue are extended versions of results communicated at the EvoCOMPLEX track of the EvoApplications conference [25], held in Porto, 30 March - 1 April 2016 as a part of the EvoStar event[1].

2. An Overview of this Special Issue

The papers included in the special issue tackle a variety of topics. Three of them [26, 27, 28] deal with multi-objective optimization, underlining the polyhedral nature of many complex problems. Complex networks [29] are prominently featured in one contribution [30] and other different hard complex optimization problems are considered in four contributions [26, 27, 28, 31]. Finally, one of the contributions [32] tackles the use of agent-based metaheuristic computing, a prime example of complex collective system [33] – see also [34]. A more detailed introduction to these papers is provided next.

Li et al. [28] consider an optimization approach termed chemical reaction optimization which draws inspiration from molecules transitioning to lower energy states by collisions. In an analogy to chemical reactions, each molecule carries some energy which changes upon collisions but is globally conserved. The role of energy supporting certain types of reactions bear some resemblance with the homonym concept in multi-agent systems. This approach is extended to multi-objective optimization problems by considering the Tchebycheff aggregation of different single-objective functions. This approach is benchmarked against other multi-objective evolutionary algorithms on the ZDT and DTLZ functions.

Harrison et al. [30] focus on the analysis and modeling of complex networks. Considering the different structural properties that can be measured

[1] http://www.evostar.org

for a given network, they address the question of which ones can be used as good estimators of this structure in the sense of discriminating between networks generated using different network models. This issue is tackled using a meta-analysis of network properties based on Fischer's method, whose outcome is subsequently used as the fitness function of a genetic-programming system aimed to generate networks structurally similar to a certain target network. This approach is validated using both artificial and real-world complex networks.

Hernández et al. [26] also consider a multi-objective problem, in this case in the context of computer vision and more precisely in object classification tasks. They build upon a model known as artificial virtual cortex, which approaches the object recognition problem based on the human visual cortex by combining a psychological model and a neurophysiological model. This model is extended in this work in order to be able to provide both an image descriptor vector for classification and the location of objects within the image. This is done by means of the brain programming paradigm, an approach related to genetic programming but featuring a complex heterogeneous multi-tree representation for individuals. The approach is benchmarked against other state-of-the-art techniques on two standard image databases.

Turek at al. [32] focus on the parallelization of agent-based metaheuristic computing. To this end, they consider a framework in Erlang, the concurrent functional programming language. This framework is deployed in a multicore computing system, aiming to study the scalability of three different implementations when up to 64 cores are used. They study how different algorithmic aspects such as representation or asynchronicity influence performance. After introducing different optimizations in the system, they validate the performance of the approach on a complex real-world problem related to crossroad light management in a simulated traffic system.

Łazarz et al. [27] delivers a study of solving multi-objective optimization problems by using a hierarchy of demes (the so-called Hierarchic Genetic Strategy – HGS). A new invented maturing mechanism is proposed in order to both improve efficiency and reducing the redundancy of computations. The proposed strategy is especially well fitted for ill-conditioned multi-objective problems and can significantly decrease the computational cost in the case for which the cost of single fitness evaluation depends on the solution accuracy. The proposed strategy was exhaustively tested with six various selections preferring individuals closer to the Pareto set. The test results for many benchmarks were compared to the results of single- and multi-deme state-of-the-art MOEA algorithms.

Obuchowicz and Smołka [31] study the idea of improving the exploratory skills of complex multi-deme metaheuristics by introducing mutation based on stable probability distributions with low stability index α. This improvement is used for solving an advanced ill-conditioned inverse parametric problem connected to oil and gas resource exploration. An interesting aspect of this work is the method used for intelligently scaling the hard-computing simulation module that evaluates the fitness function. The experimentation indicates how this improved mutation operator can contribute to finding more solutions in less computational time and in a more predictable way.

3. Perspectives

The research results presented in the special issue show clear directions for future developments in the area of complex systems and nature-inspired algorithms. They decidedly will go towards new algorithmic inventions allowing for handling ill-conditioned problems, featuring multimodality and areas of insensitivity and uncertainty of the search objectives. Another important direction of development will lead to more effective software architectures, that allow solving larger challenging problems. One of the recurring ideas is to couple hard- and soft-computing components resulting in complex systems themselves, e.g. multi-deme genetic searches with the twin-grid, sophisticated *hp*-FEM adaptive solvers. Complex collective systems such as agent-based metaheuristics or chemical reaction optimization algorithms are also ripe for success in solving hard optimization tasks. From an applied point of view, complex systems are plentiful in appealing optimization problems of real-world interest and enormous difficulty. Both the analysis of complex networks and tasks related to human-like vision systems can be successfully tackled with nature-inspired algorithms, as shown here. Needless to say, there are many other complex domains such as cellular automata [35] or social computational systems [36], just to mention a few, in which this kind of techniques can be deployed, thus bringing many interesting avenues for further research.

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