Workshop on Self-Organization in Representations for Evolutionary Algorithms: Building complexity from simplicity.

Ivan I. Garibay[1 2], Greg Holifield[1], and Annie S. Wu[1]

[1] University of Central Florida, School of Computer Science,
P.O. Box 162362, Orlando, FL 32816-2362, USA,
{igaribay,ozlem,aswu}@cs.ucf.edu,
WWW home page: http://ivan.research.ucf.edu
[2] University of Central Florida, Office of Research
Orlando Tech Center/ Research Park
12443 Research Parkway Orlando, FL 32826, USA.

1 Motivation

The success of evolutionary algorithms in a wide range of otherwise intractable problems has promoted its use. As evolutionary algorithms are applied to increasingly difficult problems that require increasingly complex solutions, they face a number of problems: premature convergence to suboptimal solutions, stagnation of search in large search spaces, negative epistatic effects, disruption of large building blocks, among others. On the other hand, natural evolution seems to not have any problem evolving strikingly complex self-organized solutions. Self-organization is present in almost every level of natural evolution: gene regulation networks, proteins interaction networks, metabolic pathways, cellular organization, etc; but it is not usually present in evolutionary algorithms. Nature evolves instructions that produce organisms by a process of self-organization. Perhaps, it is the self-organization of genotypic instructions into phenotypes one of the key missing ingredients to unleash evolution of complex and scalable solutions with desirable emergent phenomena such: scale-free, adaptability, innovativeness, evolvability, and robustness. The objective of this workshop is to explore domain-independent methods to represent complex solutions with relatively simple self-organizable building blocks.

2 Self-organization in Representations

There is recent interest in approaches that increase the complexity of solutions without increasing the complexity of genomes in order to better scale evolutionary search. These approaches all share some degree of implicit self-organization. For instance the concepts of developmental mappings [1–3], implicit embryogenies [4, 5], generative representations [6–8], molecular computing [9], self-replicating sequences [10, 11], and constrained generating procedures [12], all share, to some degree, this perspective in which some sort of self-organizing principle drives the representation of the problems.

3 Contributing Papers

The issue of evolution, self-organization and development is analyzed by Kumar in the first paper of the workshop. Using a multicellular test-bed, the author shows the emergence of differentiation as a product of the developmental process. The "central dogma" of molecular biology states the fundamental relationship between DNA, RNA and proteins. Tim Otter contribution challenges the simplicity of the central dogma in favor of a more complex framework focused on the relationships and constrains of a multi-level hierarchically organized system of interactions. Self-organization is pervasive throughout the world of molecular interactions. Tominaga proposes a new artificial chemistry model based on pattern matching and recombination. This model is designed to capture properties of complex systems such self-organizing behavior using a succinct language. Lawson and Lewis present the "Starcat" architecture, where components swim in a virtual sea that allows interaction among themselves and with their environment. The authors discuss the role of knowledge representation on this architecture and conclude that emergent behavior drives emergent representation. Garibay and Wu contribution address the issue of representations that are free to self-organize. The authors present evidence using spectral density analysis that location independent representations organize (or dis-organize) into white noise.

Self-organization in multi-agent systems is exploited by Agogino and Miillulainen to solve the problem of allele fitness assignment. A GA representation typically decomposes problems into components or genes. After that the GA search in parallel for a suitable set of genes or chromosomes. The authors propose instead a system on which each agent have the simpler task of finding a single suitable allele. After this, agents simply self-organize into highly performing chromosomes. Whiterson, Stanley and Miikkulainen present a novel method for feature selection based on neuro-evolution of augmented topologies (NEAT). The authors augmented NEAT to learn simultaneously not only the network topology and weights but also the network's inputs. Iorio and Li show that the self-adaptive technique of Differential Evolution can be use to solve epistatic multi-objective optimization problems. Finally, Majee and Sahoo present a two-population GA approach to DNA sequencing using the oligonucleotide hybridization technique. The authors report good results for short sequences.

4 Workshop Material On-Line

The materials presented during the workshop as well as other related information is available on-line at: http://ivan.research.ucf.edu/SOEA.htm

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