Socio-cognitive Flock-based Optimization

Aleksandra Urbańczyk[0000−0002−6040−554X], **Krzysztof Czech, Aleksander Byrski**[0000−0001−6317−7012]

Institute of Computer Science
AGH University of Science and Technology
Al. Adama Mickiewicza 30, 30-059 Kraków, Poland
{aurbanczyk, olekb}@agh.edu.pl, kczech@student.agh.edu.pl

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Abstract. *A novel optimization algorithm inspired by socio-cognitive phenomena and based on flock architecture is presented along with promising preliminary experimental results.*
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1. Introduction

Tackling difficult optimization problems requires the use of metaheuristics [1]. Based on the famous No Free Lunch Theorem [2] there is always the possibility that a new algorithm will be better suited to find an optimal solution to hard computational problems. Talbi contends that hybridization and modification of current algorithms can be helpful in this regard [3]. Because metaheuristics are frequently inspired by nature, their hybridization frequently brings together different phenomena observed in the real world. Many metaheuristics that process a large number of individuals, particularly when individuals are perceived to be somewhat autonomous, use socio-cognitive inspirations, e.g. EMAS [4]. Among them there is a group of algorithms with dedicated mechanisms rooted in Social-Cognitive Theory by Albert Bandura [5], e.g. s-c PSO [6], s-c ACO [7] and s-c evolution strategies. We came to realize that by harnessing the power of metaphorical thinking[8], we can create novel, inventive mechanisms and operators that improve the functionality of traditional metaheuristics, not just for the sake of creation, but also to advance the field of computational intelligence. In our current work we decided to explore possibilities of using metaphor based on the theory of different, prominent social psychologist – Elliot Aronson [9]. His reward theory of attraction states that attraction is a form of social learning. According to Aronson, we can generally understand why people are attracted to each other by looking at the social costs and benefits. In summary, reward theory states that we prefer those who provide maximum rewards at the lowest possible cost. Social psychologists have discovered four particularly powerful predictors of interpersonal attraction: proximity, similarity, self-disclosure, and physical attractiveness [10]. We use this inspiration to design a novel socio-cognitive algorithm described below and to perform pilot experiments in order to preliminarily verify its usefulness.

2. Socio-cognitive Flock-based algorithm

The algorithm is based on the concept of the Evolutionary Multi-Agent System with addition of socio-cognitive elements. A flock-based architecture extends the traditional sequential model into the parallel EA, providing an additional level of system organization [11]. The population of individuals is divided into flocks that are managed by agents. Several agents are created at the start of the algorithm. Each of the agents starts with a unique set of individuals in its initial population. Every cycle of the algorithm includes the evolutionary part and the socio-cognitive part. During the evolutionary part, every agent performs an evolutionary algorithm on his flock. The socio-cognitive part consists of a series of communication between two agents. During every communication, one of the agents is gaining information about part of the flock belonging to the other agent, and after a quality check of the acquired data, the agent assimilates part of its own flock to the individuals included in acquired information. The amount of information transferred between agents is determined by the trust between them. The concept of trust is implemented as a global token market where each of the agents starts with a certain amount of trust tokens, which can be passed by the agents during every event of single communication based on the outcome of this event. The more trust agents have, the more information they will acquire from other agents, and the better it will be. The assimilation of flocks is based on the use of simple and fast operators to reduce the distance between two individuals. The algorithm continues until it performs a given number of cycles, the best solution found by the agents is assumed as the solution found by the algorithm.

2.1. Experimental results

The preliminary results of the algorithm running on three standard 100- dimentional benchmark functions: Rastrigin, Ackley and Griewank are shown in Figures 1, 2 and 3, respectively. Each experiment was repeated 10 times and the results were averaged. Each benchmark was tested in 5-agent and 10-agent versions, with single-agent run as a reference. In both experimental settings, in each cycle of the algorithm, every agent does 50 iterations of the evolutionary algorithm, and then every agent attempts to communicate with others 2 times. The evaluation of the fitness function is performed after each such cycle. In the referential system, one agent is making the same amount of evolutionary algorithm iterations as in other experiments.

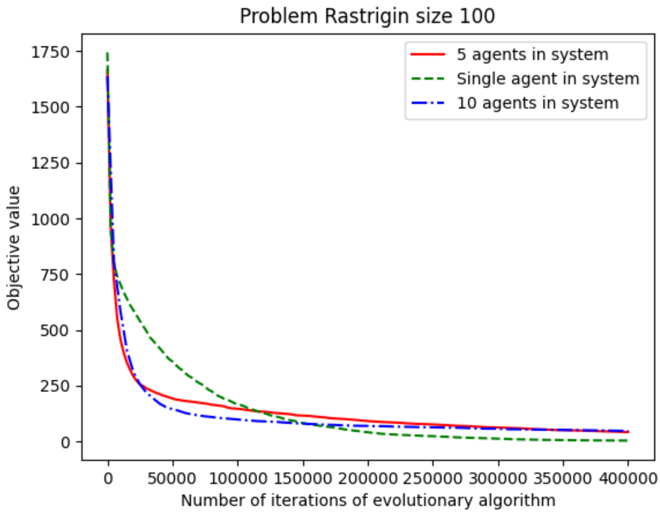

Figure 1. Preliminary results for Rastrigin benchmark. Source: own work.

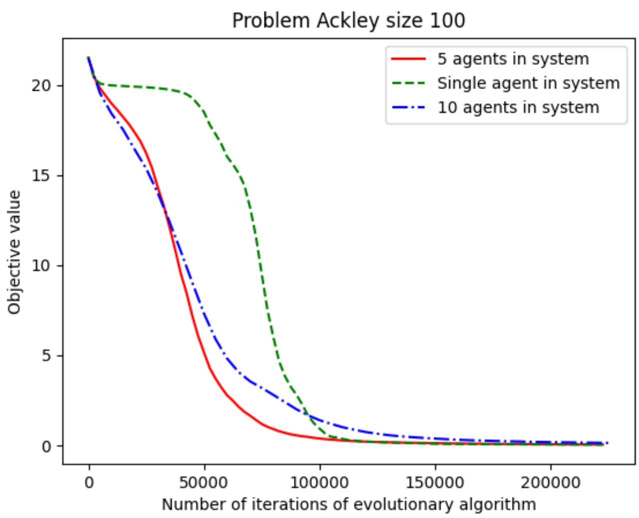

Figure 2. Preliminary results for Ackley benchmark. Source: own work.

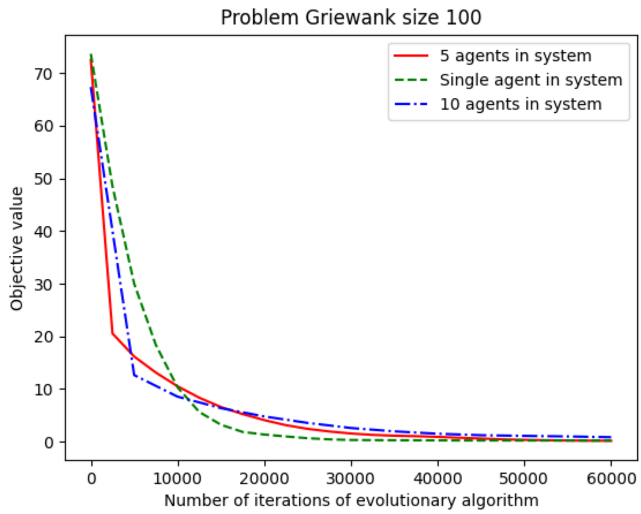

Figure 3. Preliminary results for Griewank benchmark. Source: own work.

3. Conclusions

In the pilot experimental run of the algorithm, promising results were obtained. Both 5-agent and 10-agent versions have found better solutions faster than a single-agent version; however, they were slightly outperformed in the final phase of the Restrigin benchmark. To conclude, communication between agents, based on socio-cognitive mechanisms, facilitates faster convergence in tested benchmark algorithms, but further experiments are needed. In addition to testing the algorithm against various, modern benchmarks, we intend to modify the flock architecture more extensively, by differentiating variation operators' settings among the agents, and compare our idea with an island version of evolutionary algorithm, which seems to be more appropriate.

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