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Comment

What can AI learn from bionic algorithms? Comment on "Does being multi-headed make you better at solving problems? A survey of Physarum-based models and computations" by Chao Gao et al.

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Physarum polycephalum (literally, multi-headed slime mould) is a multinucleated, unicellular organism that belongs to the protoplast mucus of amoebina. Physarum is increasingly popular in diverse fields including biophysics, evolutionary computation, bioengineering, intelligent algorithms [1–8], because of its striking high-level of biologically intelligent behavior which was first reported in 2010 [9]. For example, inoculated in a maze of corridors on the agar surface with food resources placed at the two terminals of the maze, Physarum polycephalum is able to automatically detect the shortest path along which a protoplasmic pipeline will be formed to connect the food at the terminals [10]. Surprisingly, this is a self-organized process without centralized control.

Gao et al. [11] reviewed the latest progress of Physarum-based models and computations. Through a systematic review of publications in the Web of Science, they constructed a network of scientific citations to overview the hot research areas. Their major interests lie in the computational models inspired by the two fundamental features of Physarum's foraging behavior, i.e., *extension* and *retraction*, which are applied as the *morphology*, *taxis* and *positive feedback dynamics* in the top-down and bottom-up modeling techniques. They also surveyed some real-world applications based on the core features of Physarum for solving difficult computational problems. Furthermore, they outlined recent advancements in bionic algorithms that are grounded in the bio-intelligence of Physarum polycephalum.

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This comprehensive review inspires a thought-provoking question: *What can artificial intelligence* (*AI*) *learn from bionic algorithms?* One of the mainstream directions in AI-based research and development is to guide machines to think like people[19,20]. Recent decades, AI has accumulated substantial achievements in supervised learning via synthesis with neuroscience, psychology and cognitive science [21]. However, unsupervised learning, as the main direction towards the "real" AI, is still a hard problem. Bionic algorithms may inspire useful tools to solving such problems.

For example, social insects such as ants and bees are typical organisms with distributed intelligence [12]. Their population survival relies on the collective predation, the observation of which leads to the establishment of Ant Colony Algorithms (ACA) that was first proposed by Marco Dorigo [13]. For path optimization problems such as "finding a shortest path between two points on a polyhedron", the strategy of ACA is to continuously release "ants" from one of these two points and let them do random walks on the polyhedron. Similar to the real ants that excrete pheromones for triggering social response, the simulated "ants" record their positions to guide others in subsequent simulation iterations. In fact, the development of swarm-intelligence algorithms such as the ACA echoes the progress in modern statistical and machine learning (e.g. Markov chain Monte Carlo and Hamiltonian Monte Carlo [14–17]).

Let us revisit Physarum polycephalum reviewed by Gao et al. [11]. An interesting case study [2] has shown the potential of such unicellular organism in designing planar transportation networks. For example, if food sources are placed according to the spatial location of multiple cities on the map of a country, Physarum can connect the food resources by reshaping its body as a network of growth routes, which resembles the real-world roads and railways networks of that country. This is because of the strong deformability of Physarum, i.e. the dramatic local deformation of cell membrane in response to the chemical source concentration gradient of food resources. Physarum keeps on growing along the directions at which it perceives a higher food chemical concentration after deforming, while its body remains the same or retracts along the other directions with lower perceived concentration. This bio-intelligent strategy is conceptually similar to many other likelihood-based searching algorithms.

Although AI-based research and development have been highly successful in supervised learning, unsupervised learning is still running on a bumpy and winding road [18]. Organisms such as Physarum polycephalum and social insects have shown the advantages in self-organization, adaptive learning, distributed and dynamical optimization and control, etc. Bionic algorithms built by deciphering the mechanisms underlying biological intelligence will provide cues for designing unsupervised learning algorithms.

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