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Natural neural network as evolutionary trained foundation of unsupervised artificial neural networks

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ABSTRACT

The architecture of artificial neural networks is modeled after the human brain. However, simple biological organisms above a certain complexity are also capable of data classification and analysis. This capability is embedded in them through evolution, rather than training. In this study, we demonstrate how basic functional assumptions, derived from physical and environmental constraints, can lead to the construction of a self-consistent model that explains these capabilities. Furthermore, this model can serve as a foundation for advanced models, as its principles are easily scalable. Naturally, these capabilities develop over time, and we trace their origin until the point where such a network can solve NP-hard problems in polynomial time. The efficient problem-solving demonstrated in this study calls for further quantitative examination of more complex models built on the same principles.

Introduction

In the field of artificial intelligence, artificial neural networks (ANNs) have traditionally been derived from brain dynamics, modeling neurons, synapses and their biological traits [1]. Biologically inspired computing is an integral part of natural computation, utilizing biology or biological processes as models to develop new computing technologies [2]. ANNs have been developed as generalizations of mathematical models of biological nervous systems and have achieved considerable success in applied science [3].

However, recent discoveries have revealed natural computational capabilities in seemingly primitive life forms, such as the unicellular plasmodium of Physarum polycephalum. This organism has garnered significant attention due to its intriguing decentralized computing capabilities [4]. Through morphing its amorphous body, the plasmodium actively searches for optimal routes among food sources, forms regular graphs, and anticipates periodic events. Remarkably, under certain conditions, it solves the traveling salesman problem (TSP), an NP-hard problem, by altering its shape to minimize exposure to aversive light stimuli. Surprisingly, it is capable of finding reasonably high-quality TSP solutions within a time period that grows linearly with increasing problem size. Another important aspect of natural computational capabilities is associative learning, which refers to the process through which organisms learn the relationship between two distinct events. While this phenomenon has been extensively studied in animals, recent discoveries of associative learning in cnidarians [5], such as sea anemones and jellyfish, which possess decentralized neural networks, suggest that the ability to classify data and analyze temporal event dependencies may be an inherent feature of all biological beings. Further research is required to develop and investigate models that explain these behaviors in their simplest forms, thus enabling a better understanding of the origin and evolution of cognition in general. Additionally, it would be valuable to retrospectively apply these newly discovered principles to existing ANN models to assess their compatibility in terms of topology and workflow.

The key question driving our research is whether there is a common denominator among all biological systems capable of performing natural computations. This common denominator should fulfill two criteria: (a) it must be minimal, unable to be further reduced, and (b) it must be viable, enabling successful survival under specific environmental conditions. We hypothesize that there exist organisms, possibly less advanced than unicellular plasmodium or cnidarians, yet capable of performing natural computations in the manner we have described. Furthermore, we believe that their inherent behavioral properties can be explained by our model.
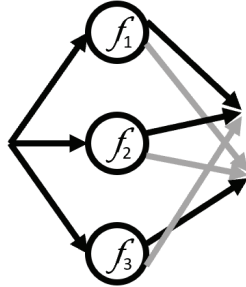
Methods

If we attempt to apply existing artificial neural networks to such simple life forms, we encounter various challenges. While biologically plausible spiking neural networks (SNNs) demonstrate strong performance with supervised learning methods [6,7], training SNNs using unsupervised learning proves difficult due to the lack of clear objectives or metrics for optimization. Furthermore, we can question the applicability of SNNs to the simplest biological systems, as there is no evidence indicating that the functionality of neurons in such systems is not significantly reduced or altered. Rather than focusing on constructing a specific neural network for this scenario, our goal is to understand how they should behave in order to gain an evolutionary advantage.

In this section, we introduce several families of continuous-time rigid-body kinematic models in a virtual environment, ordered by complexity (Table 1):

Table 1. Overview of continuous-time rigid-body kinematic models in a virtual environment.

	Name	Topology	Model
1	Stochastic motion, 1x1		$f_o = \begin{cases} C_1, rand(f_i) < \dfrac{R_{max}}{2} \\ C_2, rand(f_i) \geq \dfrac{R_{max}}{2} \end{cases}$ f_i, f_o – input and output signal frequencies C_N - constant
2	Inverse motion, 1x1		$f_o = \begin{cases} C_1, f_i < C_1 \\ C_2, f_i \geq C_1 \end{cases}$ and $C_1 > C_2$
3	Inverse motion, 1x2		$f_{o1} = \begin{cases} C_1, f_i < C_1 \\ C_2, f_i \geq C_1 \end{cases}$ $f_{o2} = \begin{cases} C_3, f_i < C_1 \\ C_4, f_i \geq C_1 \end{cases}$ and $C_1 > C_2, C_3 > C_4, C_3 > C_1, C_2 > C_4$
4	Inverse motion, 2x2		$f_{o1} = \begin{cases} C_1, f_{i1}^t < C_1 \text{ and } f_{i2}^{t+\Delta} < C_1 \\ C_2, f_{i1}^t \geq C_1 \text{ and } f_{i2}^{t+\Delta} \geq C_1 \end{cases}$ $f_{o2} = \begin{cases} C_3, f_{i1}^t < C_1 \text{ and } f_{i2}^{t+\Delta} < C_1 \\ C_4, f_{i1}^t \geq C_1 \text{ and } f_{i2}^{t+\Delta} \geq C_1 \end{cases}$ and $C_1 > C_2, C_3 > C_4, C_3 > C_1, C_2 > C_4$
5	Composite motion, counter phase, 3x1x2		$f_{o1} = f_{o1}^1 + f_{o1}^2 + f_{o2}^3$ $f_{o2} = f_{o2}^1 + f_{o2}^2 + f_{o1}^3$ and $C_1^3 > C_1^2 > C_1^1$

The virtual environment is defined as a 2D plane populated with actors, which are kinematic models, as well as surroundings that can be consumed by the actors. The surroundings possess a single characteristic, which is density, $0 < p < 1$. This density inversely impacts the terminal velocity of the actors as $v = \sqrt{C * \dfrac{f_o}{p}}$, assuming a constant virtual drag coefficient and area [8]. Correspondingly $f_i = C * p * v$. In this context, the model efficiency (later referred to as "effectiveness") can be naturally defined within a given time interval as $r_{\Delta t} = f_i * \Delta t$, provided that the incoming signal frequency remains constant. This effectiveness value can be integrated over any period $r = \int_{t_1}^{t_2} f(t)\, dt$

We have excluded both Model №1 and №2 from further considerations due to their trivial nature. However, it is worth noting that Model №2 exhibits a significant evolutionary advantage compared to Model №1. For a more realistic representation of these two models, an additional trait of the surroundings is required, namely a small random deviating flow vector that is added to the actor's movement vector.

Furthermore, Model №4 stands out from the group as it introduces the concept of associative learning. Although both functional inputs in this model are of the same type, they are bound to temporally symmetrical signals. Considering that associative learning has been observed in the simplest organisms we will further investigate this model as is [5]. We will demonstrate that the behavioral pattern of this model is very similar to that of Model №3 but its effectiveness is significantly higher. Exploring this model with different functional inputs, combining neutral and aversive stimuli to emulate a classical conditioning scenario, would be an engaging but optional task.

Lastly, we examine how all these models respond to changes in the main characteristic, "resonant frequency" $C1$ and attempt to identify any correlation, if present, between this frequency and the density p with the optimization task of maximizing the model's effectiveness.

All test environments are categorized into these groups (Table 2):

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Table 2. Categorization of test environments in the virtual models.

	Name	Sample
1	Random, Circles of various density and size	
2	Symmetrical or continuous, 1st degree Line or curve or scribble of various density and size	
3	Symmetrical or continuous, 2nd degree Group of lines, curves and scribbles of various density and size	
4	Mixed	№1 and №2 or №1 and №3

For each combination of model and environment, we calculate $r^{model}_{environment}$ based on a series of 1000 runs, with a 95% confidence level. Each run is time-limited. To assess the model's scalability quantitatively, we extend the initial size of the virtual environment linearly using multipliers of x2, x4, x8. The complete virtual environment is implemented as an event-driven state machine, incorporating data collection, statistical analysis, and graphical representation powered by OpenGL. For more detailed information, please refer to the Data Availability section.

Results

In this section, we present the preliminary analysis of the kinematic models within the defined virtual environments. The results focus on identifying correlations between various factors, such as the number of runs, model configurations, and environmental characteristics. The analysis is intended to provide insights into the models' performance, scalability, and effectiveness in different scenarios. The following table outlines the types of correlations we aim to explore (Table 3).

Table 3. Correlation analysis types for kinematic models in virtual environments.

	Name
1	Correlation graph of $r^{model}_{environment}$ based on the number of runs. Calculate the number of runs required to reach a 95% confidence level
2	Correlation graph of $r^{model}_{environment}$ based on the model number (both averaged and not across all environments).
3	Correlation graph of $r^{model}_{environment}$ based on the environment/objects linear size (for all models). Determine the type of correlation, such as polynomial, exponential, etc.
4	Correlation graph of C from density p. Determine the type of correlation, such as polynomial, exponential, etc.

The following figures provide visual representations of the patterns and behaviors observed in the kinematic models as they interact with various virtual environments. Each figure highlights a specific pattern or combination of patterns, showcasing how the models adapt their search and tracking strategies in response to different environmental conditions. These illustrative graphs are essential for understanding the underlying mechanisms of the models and their potential applications in simulating natural computational behaviors:

Discussion

We observed two distinct tactics of exploratory behavior: "tracking" (Figure 1), exhibited by all models, and "outward spiral" (Figure 2), discovered in the composite model, 3x1x2.

The combination of these tactics, when translated into the foraging strategy of primitive organisms, should encompass the following scenarios of resource availability:

- Normal resource availability level;
- Below-average level of resources;
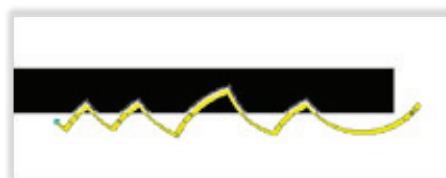- Above average, abundance of resources;

Figure 1. Tracking pattern around different surroundings, pure tracking pattern.

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Figure 2. Outward spiral/search pattern for the composite model, 3x1x2.

Under normal circumstances, when the average amount of resources is gathered in symmetrical or linear structures, we observe a simple "tracking" pattern. However, when resource availability drops below a certain level, the system transitions into an "outward spiral" or "search" pattern, which is considered an efficient search technique [9,10]. Additionally, there is a correlation between the amplitude excursion of the "tracking" pattern and resource density, often directly proportional (Figure 3). This enhances the system's efficiency in environments with 2nd-degree structures, such as symmetrical or continuous groups of lines, curves, and scribbles of various densities and sizes.
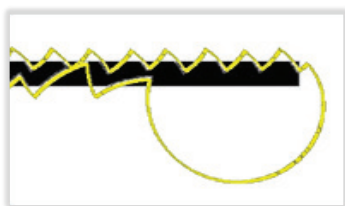

Figure 3. Tracking pattern around different surroundings, tracking/search pattern combined.

It is important to note that the "tracking" tactic works more effectively in a more structured environment, allowing for finding an optimal solution in polynomial time as the linear size of the environment increases. At the same time, the efficiency of the model increases with its internal complexity, reaching a plateau in the configuration Nx1x2, when N>5. When comparing the performance of models with a single input (1x2) and models with spatially divided inputs (2x2), we observe a significant improvement in the latter, (Figures 4 vs 5). This improvement is attributed to the model's ability to distinguish between the left and right sides when approaching linearly congregated resources, resulting in fewer mistakes in determining directions.
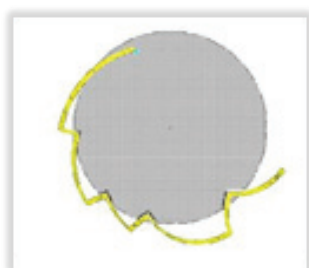

Figure 4. Tracking pattern turning into a shrinking spiral around large objects, tracking pattern around object.

Thus, by applying phylogenetic principles to minimalistic kinematic models, we can explore a possible progression in systems that lack the ability to learn from experience. These systems can be described as "evolutionary trained" and may serve as precursors to more evolved organisms, such as C. Elegans, whose foraging strategy exhibits similarities to what we observe in our model [11]. While recent advances in integrative biological simulation of C. Elegans allow for modeling the strategy to some extent, the model does not provide an explanation for the origin of the behavior or the opportunity to observe it in less complex organisms [12]. We hypothesize that this behavior is ingrained into the control circuits at the lowest level, as it offers evolutionary advantages by facilitating cost-effective foraging.

Figure 5. Tracking pattern turning into a shrinking spiral around large objects. The yellow trace, which highlights the traversed path, has been disabled for clarity.

Foraging, as a distinct subgroup of classic AI search problems, has been extensively studied [13,14]. However, we want to emphasize that even with the underlying logic reduced to a few basic rules, we can still achieve the same goals while maintaining the neuromorphic structure of the network. This network can be seen as a trivial case of spiking neural networks, lacking learning ability yet capable of discovering patterns. In this context, the transition to a Lévy type search strategy can be viewed as a switch between the "tracking" and "search" patterns explained earlier and illustrated in Figure 3 [15,16].

Naturally, the model has certain limitations due to self-imposed restrictions on dimensionality and concurrency, which could take into account the role of competition for scarce resources among peers. However, the main factor that is excluded from consideration is the ability to save state to learn from experience. The model cannot be trained in the conventional sense by repeatedly running it in the same environment. Nevertheless, it demonstrates structural development over longer evolutionary timeframes, suggesting a progression on an evolutionary scale. It would be an intriguing task to further investigate the evolution of such systems by adding more inputs (potentially responsive to aversive stimuli) and outputs, and applying formal natural selection rules, to create a higher-level "evolutionary trained" model [17].

However, before delving into further development, it is important to understand how this "purely behavioral" model could be translated into a neural network model, considering certain restrictions that need to be enforced. The suggested variant of the translation, as depicted in Figure 6, incorporates two distinct properties:

- A wide range of working frequencies is covered by the same topology, as the summarizing neuron will only spike when its input signals of varying frequencies coincide;

- By applying the Hebbian Rule [18] to certain inputs, it becomes possible to generate the required outputs for either part of the behavioral model's piecewise function $fi < C1$ or $fi \geq C1$. The shared input signal would trigger repeated generation through the feedback circuit. In the first case, this circuit takes priority, and subsequent shared input signals would not affect the frequency of the output signal, which is the multiplication of all circuit frequencies. In the other case, the shared input signal is prioritized, and every signal would start the generation process anew, resulting in an indefinite delay in the output for a certain period;
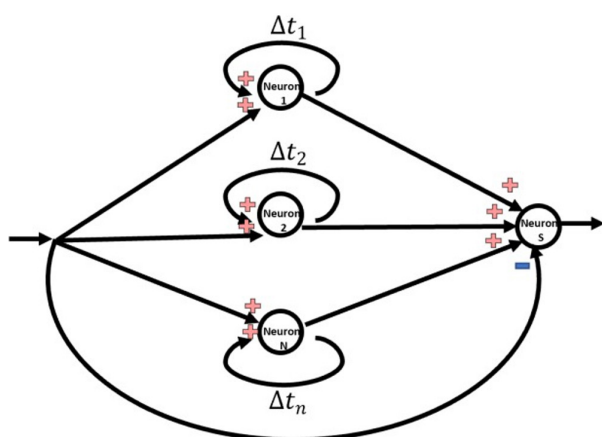

Figure 6. Proposed behavioral model translation into a neural network model.

Thus, this network fragment can fulfill the requirements of both the 1x2 and composite 3x2x1 models serving as a basis for constructing a topologically uniform spiking neural network that describes the behavior of organisms trained by evolution to possess natural computational capabilities.

We hypothesize that these simple functional principles could also be applicable to more advanced species, such as ants, worms, ichnospecies, honeybees, and others, and we encourage further research into this type of natural neural network [19,20,21].

Conclusions

In conclusion, integrating simple spiking networks, each tuned to different frequencies, into a composite model capable of replicating the complex track-and-search behavior observed in nature could offer valuable insights into the foundational principles of intelligence. We hypothesize that the performance of these small-scale networks (We refer to them as "tuning forks" or *camertones*), when they all "play in tune and in harmony", may surpass that of traditional artificial neural networks (ANNs) due to their evolutionary refinement and minimal training requirements. The learning mechanisms of such networks are likely to differ significantly from those of traditional ANNs, warranting further investigation to fully understand their unique learning processes.

Data availability

All code and data are publicly accessible at: https://github.com/FoundAItion-ai/Its

Disclosure Statement

No potential conflict of interest was reported by the author.

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