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Zachepylo Mykhailo

PhD Student, Department of Information Systems named after V. A. Kravets, National Technical University «Kharkiv Polytechnic Institute», 2, Kyrpychova str., 61002, Kharkiv, Ukraine
e-mail: Mykhailo.Zachepylo@cit.khpi.edu.ua
https://orcid.org/0000-0001-6410-5934

Yushchenko Oleksandr

PhD of Physical and Mathematical Sciences, Professor, professor at the Department of Information Systems named after V. A. Kravets, National Technical University «Kharkiv Polytechnic Institute», 2, Kyrpychova str., 61002, Kharkiv, Ukraine
e-mail:agyu@kpi.kharkov.ua;
https://orcid.org/0000-0002-0078-3450

Research on survival strategies of artificial life in dynamic environment

This research seeks to develop evolutionary methods for constructing deep neural networks, offering potential improvements to machine learning techniques by modeling adaptive architectures under selective pressures.

Purpose. The goal of the work is to explore the dynamics of neural complexity in artificial life agents exposed to progressively challenging environments.

Research methods. We conducted a two-dimensional simulation to model populations of agents with evolving neural networks and physical forms. The environment progresses from simple conditions to increasingly complex scenarios, including static walls, moving obstacles, hazardous zones, and lethal poisons. Our approach builds on fundamental artificial life systems such as Tierra, Avida, and PolyWorld. The neural architectures evolve based on principles inspired by the NeuroEvolution of Augmenting Topologies. We apply the Tononi–Sporns–Edelman complexity measure to evaluate neural integration and specialization, helping us understand how agents adapt their networks to achieve a balance between global coherence and localized functionality.

Results. Research indicated that while complex environments can temporarily enhance neural sophistication, harsher conditions often favor simpler, more prolific reproductive r-strategies. Effect, populations may create reflex-driven, stimulus-response behaviors instead of developing complex neural structures.

Conclusions. These findings enhance our understanding of adaptive intelligence and guide approaches for designing scalable, matching learning systems in robotics and deep neural network architecture development, contributing to the broader goal of understanding how artificial intelligence should evolve. We propose utilizing a recursive genetic algorithm to optimize these balance challenges, promoting long-term neural adaptation to dynamic environments.

Keywords: artificial life, neural complexity, evolutionary adaptation, dynamic environments, incremental complexity, open-ended evolution, neuroevolution of augmenting topologies, r-strategy

1. Introduction

Significant progress in deep neural network machine learning has led to revolutionary advancements in technologies such as image recognition, natural language processing, and autonomous systems [1–3]. However, challenges like overfitting, poor generalization, LLM hallucinations, and high computational demands persist, motivating the search for alternative methods of building intelligent multilayered neural networks. The human brain, along with those of higher cetaceans, represents some of the most complex intelligent systems evolved by biological processes, serving as inspiration for simulating the progressive development of artificial neural networks in virtual biocenoses.

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The evolution of artificial life (ALife) models has played a crucial role in understanding adaptive behaviors and the emergence of intelligence (noogenesis). Over the decades, researchers have explored diverse systems simulating ecological and evolutionary dynamics. However, significant challenges persist in modeling open-ended evolution, particularly in environments with increasing complexity.

The evolution of Alife models has been instrumental in advancing our understanding of adaptive behaviors. However, previous studies have largely focused on adaptation and have not directly addressed noogenesis within computational ecologies. Over the decades, pioneering systems like Tierra [4] and Avida [5] have offered glimpses into open-ended evolutionary processes. Recent frameworks have built upon foundational systems by exploring morphology, neural complexity, and multi-agent systems, advancing our understanding of these aspects. However, despite these advancements, the challenge of fostering truly open-ended complexity remains unresolved, particularly in dynamic, non-episodic environments that progressively increase in difficulty over time.

This paper addresses a critical gap in ALife research: how does progressive environmental complexification influence the trajectory of morphological, behavioral, and neural complexity in evolving agents? Understanding these dynamics not only advances theoretical knowledge but also has broader implications for designing adaptive artificial systems and improving our grasp of how intelligence might arise in both natural and synthetic contexts. Our study differs from traditional RL setups that reset tasks each episode and from static ALife environments that fail to provide long-term evolutionary pressure. By exploring non-episodic, incrementally complex ecosystems, we aim to illuminate the factors that promote or hinder the emergence of neural complexity and adaptive intelligence. While some studies set the ambitious goal of achieving human-level intelligence [6], we do not aim to produce such outcomes, recognizing this as an unreachable target for now given the current state of ALife research. Instead, we seek to create conditions conducive to the gradual noogenesis of agent populations, offering insights into why complexity sometimes stalls and what might be done to encourage it.

2. Literature review and problem statement

Foundational systems like Tierra [4] and Avida [5] revolutionized our understanding of digital evolution, yet their static environments limited complexity growth. Subsequent studies, such as Karl Sims' evolving virtual creatures [7] and Framsticks [8] extended the exploration of morphology and control. These works primarily focused on objectives like locomotion and simple foraging, without addressing the complexities of open-ended ecosystem dynamics. PolyWorld [9] introduced evolving neural networks to agents in a competitive environment, revealing adaptive behaviors but not exploring progressive complexity. EcoSim [10], JaxLife [6], and multicellularity models [11] further diversified the multi-agent interaction within However, these models often operated in environments that lacked dynamic complexity, limiting insights into long-term evolutionary processes. Hamon et al. [12] incorporated spatiotemporal dynamics in large multi-agent systems, advancing our understanding of distributed interactions. POET [13] investigated paired adaptation in reinforcement learning, illustrating flexibility in task evolution. However, both approaches depend heavily on episodic resets or predefined objectives, restricting their applicability for studying open-ended noogenesis. Efforts by Auerbach and Bongard [14] on how environmental factors can shape morphological complexity, while Giannakakis et al. [15] extended this by highlighting the role of environmental variability in shaping plasticity mechanisms, emphasizing adaptation over time. Notably, this study was not an ALife simulation but rather focused on genetic algorithm optimization in embodied agents, which is important to differentiate. Similarly, Canino-Koning et al. [16] demonstrated that changing environments promote rapid adaptation in Avida, but these instructions-based grid systems differ from more ecology-driven models.

The neural complexity measurements in artificial life simulations were proposed by Yaeger and Sprons [17] and studied over PolyWorld [18], [19]. However, these measurements were conducted in a competitive yet static environment, limiting insights into dynamics under progressively complex conditions.

Despite these achievements, a fundamental question remains unresolved: How does ongoing, continuous environmental complexification, beyond simple predator-prey dynamics, impact the long-term evolutionary dynamics of neural complexity and adaptive behavior? Does increasing environmental complexity consistently drive the evolution of more sophisticated neural architectures, or do resource-efficient strategies, such as simpler yet prolific adaptations, dominate under harsher conditions?

This paper directly addresses this gap. We investigate the interplay between increasing environmental complexity and evolving neural architectures, raising important questions about whether neural network complexity always increases or if other strategies take precedence under harsher conditions.

3. Methods

This section provides an overview of our computational model, evolutionary procedures, and metrics while highlighting additions to previously published work [20]. Our goal remains the simulation of open-ended evolution of artificial creatures in a two-dimensional, progressively complex environment, focusing on neural complexity and adaptive strategies.

3.1. Overview of the Evolution Model

Our model builds on the framework described in [20], which simulates a population of autonomous, embodied agents (artificial "creatures") in a two-dimensional arena. Each creature's characteristics include a connected Physical Body with Neural Network Control. The physical body is represented as a circular entity occupying continuous space, with physics-like rules for movement and interactions. Neural Network Control is governed by an evolving neural network inspired by the NeuroEvolution of Augmenting Topologies (NEAT) [21], with topology and weights subject to mutations. Reproduction is asexual cloning with mutations. In this study, we introduce key updates to the model. Dynamic Environmental Features: The environment evolves over time, incorporating new hazards, spatial obstacles, and resource variability to provide incremental complexity. Additional Sensors: Beyond the basic food sensor, wall sensor, bot sensor, and energy sensor described in [17], creatures now include hazard zone sensors and poison sensors to better navigate increasingly complex environments. Refined Mutation Mechanisms: Mutation probabilities have been recalibrated to include newly added sensors.

3.2. Neural Network Architecture and Complexity

Each creature's control center is a neural network that processes sensory inputs and produces motor outputs. Initially, creatures start with a minimal configuration, typically one food sensor, one energy sensor, one neural node, and a simple pair of effectors (movement and rotation). Over evolutionary time, mutations can add hidden nodes, extra sensors, and more elaborate connections, potentially increasing behavioral sophistication.

We employ the Tononi–Sporns–Endelman (TSE) [22] complexity measure as described and adapted by Yaeger and colleagues [17], [19]. TSE complexity is designed to quantify the balance between integration and segregation in a neural system. Integration refers to the degree of global information sharing among all parts of the system, while segregation reflects how certain subsets of the system maintain specialized, relatively independent patterns of activity. The TSE complexity measure captures how a system's overall integration changes when considering subsets of different sizes.

Consider a neural network composed of n nodes, represented as variables $\{X_i...X_n\}$. The TSE complexity $C_N(X)$ is defined by comparing the full-system integration against average integrations computed over all subsets of different sizes. Formally (3.1) [22]:

$$C_N(X) = \sum_{k=1}^{n}\left[(k/n)I(X)-\left\langle I(X_k)\right\rangle\right],$$

(3.1)

where: X – the full set of variables (nodes);

$I(X)$ – the integration of the full system;

$I(X_k)$ – the integration computed over a subset X_k of size k ;

$\left\langle I(X_k)\right\rangle$ – denotes averaging over all combinations of subsets of size k.

Integration $I(X)$ can be viewed as a multivariate mutual information measure indicating how much of the system's entropy cannot be explained by treating variables as independent (3.2) [22]:

$$I(X) = \sum_{j=1}^{n} H(X_j) - H(X),$$

(3.2)

where $H(X_j)$ – the Shannon entropy [23] of a single node X_j

$H(X)$ – a joint entropy of the entire system.

By considering subsets of various sizes k, the measure $C_N(X)$ captures how integration scales and is reduced when parts of the system are examined in isolation. If the system behaves uniformly at all scales, integration values scale linearly, and complexity is low.

Direct computation of all subset combinations is often computationally prohibitive, particularly for large networks. To address this, we employ approximation techniques described by Yaeger [19] and utilize the hardware-accelerated implementation [24]. This implementation leverages JAX, a high-performance library for numerical computation, to significantly speed up the estimation of integration and complexity metrics. The corresponding code is publicly available on https://github.com/WorldThirteen/neural_complexity_jax.

Under the assumption of Gaussian processes, the joint entropy of X can be computed via the covariance matrix **COV** (3.3) [19]:

$$H(X) = \frac{1}{2}\ln(2\pi e)^n |\mathbf{COV}|,$$

(3.3)

where $|\mathbf{COV}|$ – the determinant of the covariance matrix of the n nodes' activation patterns.

For our simulations, node activities are recorded during the last 5,000 timesteps of a creature's life. We derive complexity values from these data. By averaging complexity metrics over the population, we gain insights into how environmental pressures influence the evolution of integrated yet specialized neural structures.

This accelerated implementation of TSE complexity enables efficient computation even for large-scale simulations, providing a rigorous framework to examine how creatures' neural architectures balance global coherence with local specialization in response to escalating environmental challenges.

3.3. Environmental Setup and Complexity Increments

The simulation world is a 2D continuous plane with finite dimensions (50,000 x 50,000 units). Initially, this environment is relatively benign, containing only food resources placed at random. Over time, we incrementally introduce complexity to assess how creatures adapt to different survival pressures:

Initial Environment: 500 creatures with minimal neural architecture start in the environment. Food resources are distributed randomly. No hazards, walls, or moving obstacles are present.

Introduction of static walls: we introduce 50 static wall obstacles at random positions. Walls block movement, forcing creatures to navigate around them. The presence of walls tests spatial navigation and obstacle avoidance strategies.

Dynamic obstacles: we add 100 dynamic obstacles that move at a constant velocity (1.5 units/timestep) and bounce off walls. These moving entities require creatures to predict obstacle trajectories and adjust their paths accordingly.

Hazard zones: 100 hazard zones, each a circular area of radius 700 to 2,500 units, are introduced. Entering a hazard zone drains 0.5 energy per simulation tick from a creature, imposing a continuous penalty. Hazard zones test a creature's ability to detect and avoid dangerous regions.

Poison elements: 1,000 poison entities, each with a radius of 90 to 120 units, move at a velocity of 2 units/timestep. Contact with poison is lethal, instantly removing the creature from the population. Poisons represent a severe threat demanding rapid avoidance behaviors.

Environmental elements are updated periodically. For example, walls may randomly change position once every 10,000 timesteps, and hazard zones regenerate every 25,000 timesteps. Visualization of these complexifications can be visible in Fig. 3.1.
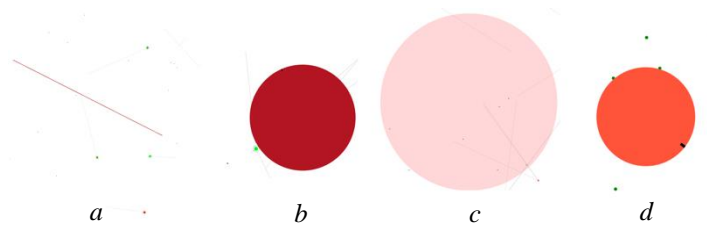

a   *b*   *c*   *d*

Fig. 3.1. Environmental elements: a – static wall; b – dynamic obstacle; c – hazard zone; d – dynamic poison

The experiment concludes when the population size drops to zero or the simulation reaches a predefined timesteps limit, whichever comes first.

3.4. Simulation Dynamics

The simulation operates in discrete timesteps. During each tick, creatures perceive their environment by reading sensor values and processing these through their neural networks. The resulting neural computations translate sensory inputs into effector outputs, which determine actions such as moving forward, rotating, or remaining stationary. Creatures consume energy continuously and through movement, replenishing it by consuming food (50 energy units per food item). When a creature's energy exceeds 200 units, it reproduces asexually, sharing energy with its offspring. Creatures die if their energy falls below zero or if they collide with poisonous entities, at which point they are removed from the simulation. Meanwhile, the environment evolves dynamically, with obstacles moving, hazard zones regenerating periodically, and poison entities navigating the space.

3.5. Data Collection Protocol

We record data throughout the simulation to analyze evolutionary and behavioral outcomes. Population size – we track the number of living creatures at regular intervals. Mean Lifetime – the average lifespan of creatures is recorded over time. Lifetimes offer insights into survival strategies, reflecting how creatures cope with environmental challenges. Neural Complexity Metrics – using the recorded node activities, we compute the entropy-based complexity measures. These computations are performed offline after the simulation to reduce computational overhead during runtime.

Each metric is saved for post-processing analysis. Visualizations such as population trends, complexity graphs, and network structure diagrams are generated from these recorded data sets.

3.6. Analytical Methods

After the simulations conclude, we use Python-based tools for data analysis. Time-series analysis – we plot population size, mean lifetime, and neural complexity as a function of simulation timesteps. Abrupt changes at known complexity increments (walls, obstacles, hazards, poison) highlight correlations between environmental complexity and evolutionary responses. Complexity computation – the information-theoretic complexity of neural networks is calculated by analyzing node activity logs. Shannon entropy and integration measures are computed for each creature's neural data. We average values over selected populations and compare complexity trends between simple and complex environmental conditions. Comparative studies – we run multiple experiments under different parameter settings or seeds. Comparisons across runs reveal consistent trends and confirm robustness. Qualitative behavioral analysis – in addition to quantitative metrics, visual observations of creature behavior are qualitatively analyzed. Behavioral patterns such as movement strategies, resource gathering, avoidance of hazards, and interaction with the environment are closely monitored. These qualitative insights help identify emergent behaviors, strategies, and adaptations that complement the numerical results.

4. Results

4.1. Population Dynamics Under Increasing Complexity

Figure 4.1 shows population size over time across the incrementally complex environment as a blue line and simple static environment as an orange line. Initially, when conditions are simpler (0–200,000 timesteps), populations stabilize from the "primordial soup" phase, reflecting abundant resources and minimal threats. Following the introduction of static walls at 200,000 timestep, the populations in complex environments follow the same stabilization trend as populations in simple environments but fluctuate more as creatures must navigate obstacles.
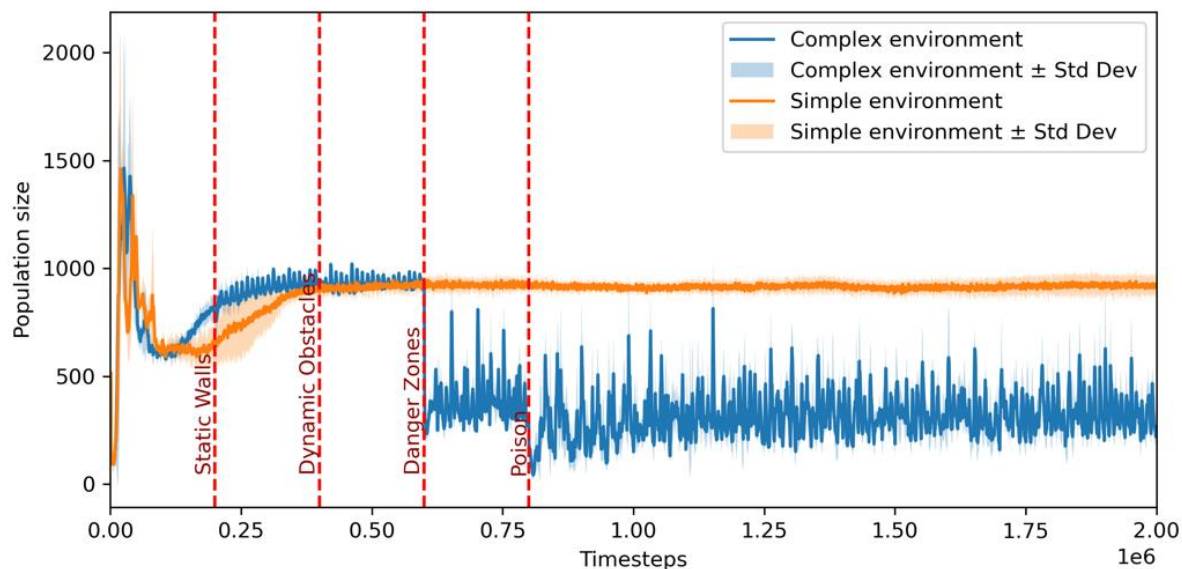
Fig. 4.1. Population size over time

When dynamic obstacles appear at 400,000 timestep, the population size does not indicate a major difference from the previous conditions.

The introduction of hazard zones at 600,000 timestep leads to more significant challenges. As creatures enter these energy-draining regions, their lifespans shorten, reflected by declining population numbers. These zones reward careful navigation and energy management strategies. By this point, the population dynamics show broader oscillations, indicating a struggle between lineages that adapt and those that fail compared to a simple environment that reached a stale state in population size by this time.

Finally, at 800,000 timestep, the environment becomes most lethal with the presence of poison elements. Creatures that encounter poison are instantly removed from the gene pool, drastically increasing selective pressure. The population size (Fig. 2), and the blue line have high fluctuations at a lower threshold or show steep episodic declines as new hazards periodically reshuffle conditions. The result is a population characterized by rapid turnover and intense evolutionary pressure.

4.2. Survival Strategies and Lifespans

To evaluate creature longevity, we tracked mean lifetimes across different environmental complexities (Fig. 4.2, where the blue line indicates an environment with complexities and a simple static environment is depicted as an orange line). In simpler conditions, creatures exhibited extended lifespans, capitalizing on abundant resources and reproducing multiple times. The introduction of static dynamic obstacles at 200,000 and 400,000 timesteps increased lifespans fluctuations.
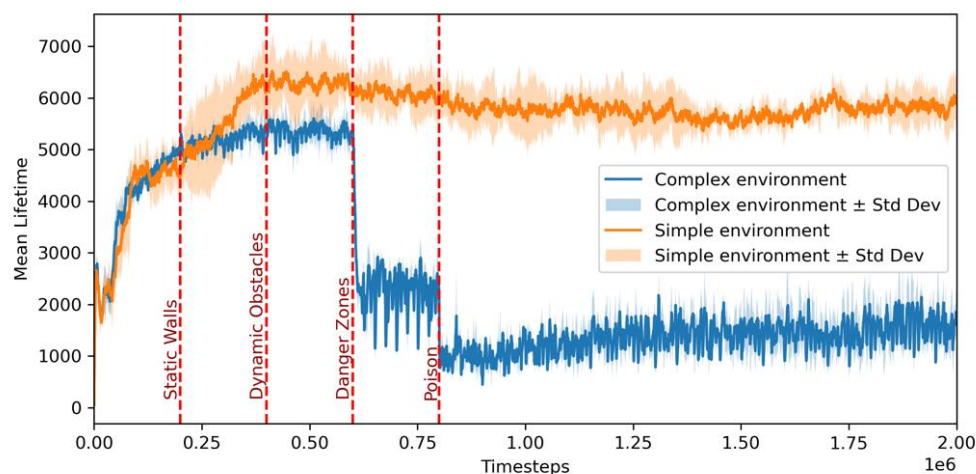

Fig. 4.2. Mean creature lifetime in population over time

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Hazard zones introduced at 600,000 timestep reduced mean lifetimes, with only a few lineages evolving avoidance or energy-conservation behaviors. By 800,000 timestep, the addition of poison elements led to the predominance of short-lived, fast-reproducing strategies, minimizing neural and morphological investments. In contrast, in the simpler control environment devoid of these escalating challenges, mean lifetimes remained consistently higher as creatures invested in stable, energy-efficient behaviors, favoring long-term survival and reproduction.

4.3. Morphological and Neural Adaptations

Fig. 4.3, *a* depicts a representative evolved creature morphology under a complex environment. Over many generations, body size and sensor placements can change, reflecting attempts to cope with walls, obstacles, hazard zones, and poison. These lineages often sacrifice stability and complexity for speed and agility, resulting in more streamlined morphologies optimized for quick bursts of foraging and immediate reproduction before encountering lethal conditions.
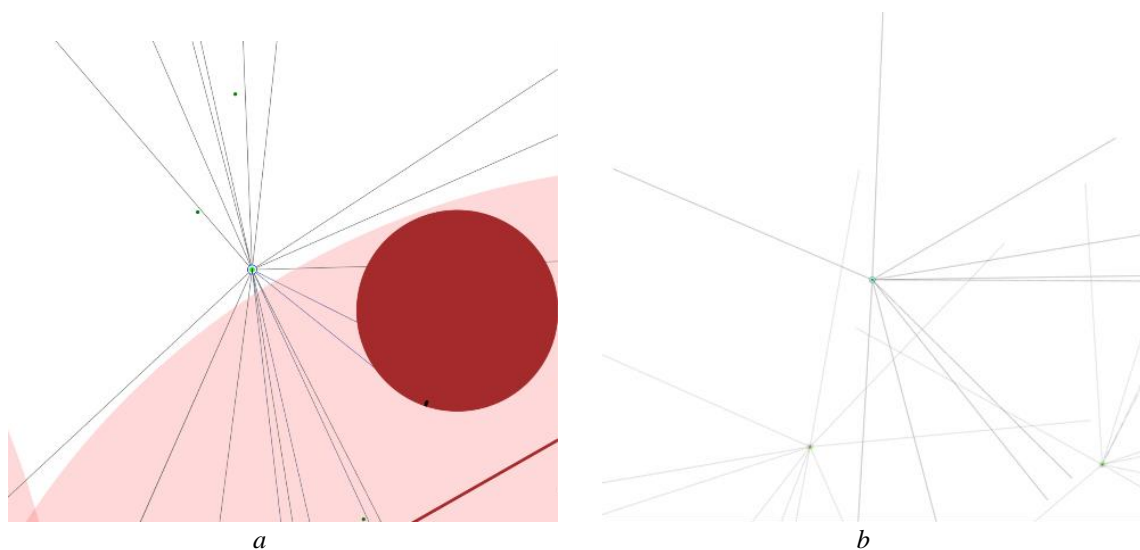

a   *b*

Fig. 4.3. Visual representation of the evolved creature morphology in, circles are bodies, lines are sensors. Where a – in complex environment, b – in simple environment

In contrast, creatures evolved under simpler conditions, illustrated in Fig. 4.3, *b*, often maintain more moderate body sizes and sensor distributions. Without harsh selective pressures, these lineages can afford slower, more energy-efficient foraging strategies. They do not need extreme agility and/or rapid reproduction since they face fewer existential threats. From a neural architecture perspective, Fig. 4.4 compare the neural networks of evolved creatures in complex versus simple environments. Under a complex environment (Fig. 4.4), neural networks may initially expand to incorporate sensors and interneurons for threat detection. However, over time and under extremely lethal conditions, there is a trend toward minimal networks that directly connect critical sensors (e.g., poison or hazard detectors) to effectors for rapid avoidance maneuvers. These networks often remain shallow and specialized, favoring direct stimulus-response paths instead of integrative, deeply hierarchical architectures. This pattern resembles the emergence of direct reflex-like mechanisms, optimized for immediate survival in highly selective environments.
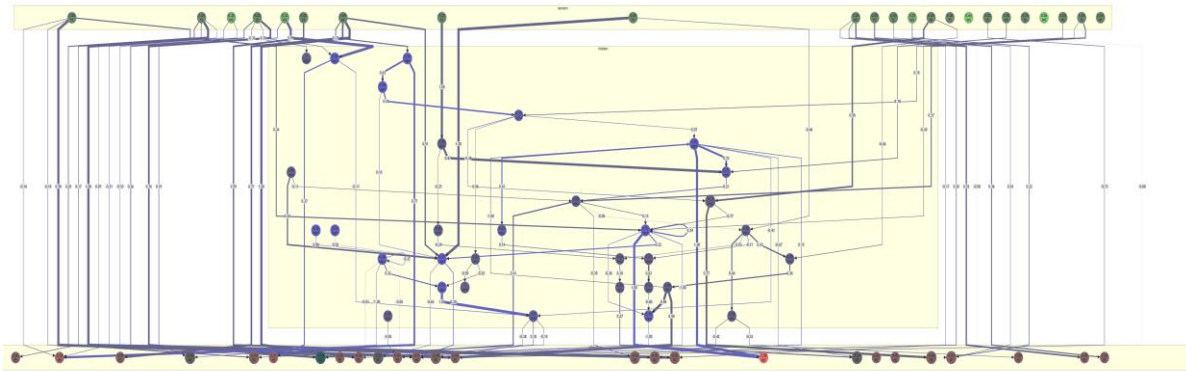
Fig. 4.4. Visual representation of the evolved creature neural network in a complex environment. The top row contains sensor neurons, the bottom row contains effectors, the middle are processing neurons, and the lines are synaptic links.

In simple environments, the neural networks of the creatures often become more elaborate. A sample of such a network is depicted in Fig. 4.5. With less pressure to avoid lethal threats immediately, creatures explore more sophisticated sensor integration, potentially leading to richer behavioral repertoires. These creatures can afford neural complexity that does not yield an immediate survival advantage but may improve long-term foraging efficiency or energy management.
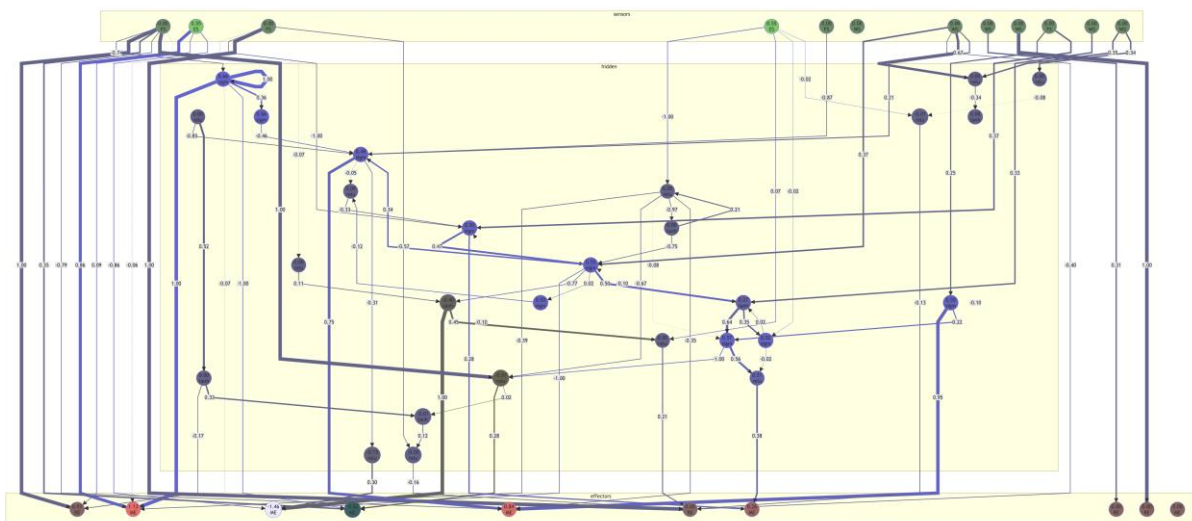

Fig. 4.5. Visual representation of the evolved creature neural network in a simple environment. The top row contains sensor neurons, the bottom row contains effectors, the middle are processing neurons, and the lines are synaptic links.

4.4. Neural Complexity Trends

The mean population neural complexity over time is shown in Fig. 4.6, where orange lines are simulations in a simple environment and blue lines are simulations within environments of grown complexity. Simple environmental complexifications – static walls and dynamic obstacles briefly stimulate neural complexity growth as creatures experiment with more intricate sensorimotor mappings to cope with new obstacles. However, as the environment becomes more hostile (post-600,000 and especially post-800,000 timestep), complexity does not continue to rise. Instead, simpler, more direct strategies dominate, leading to a plateau or even a decline in complexity metrics right after high instability.
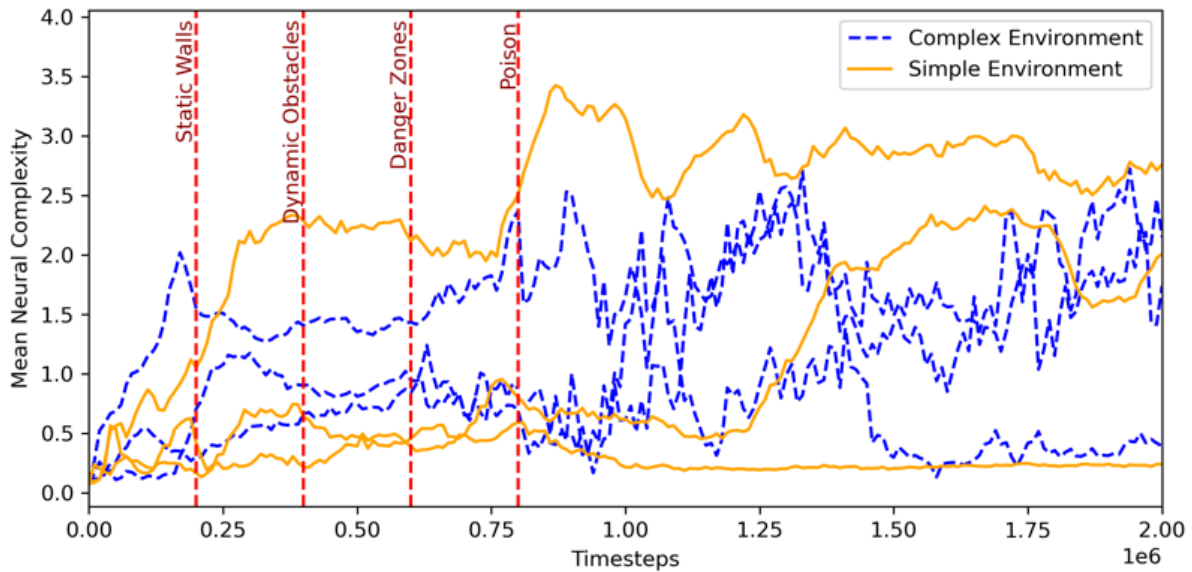
Fig. 4.6. Mean population Neural Complexity over time for simulation runs with complex and simple environments

Figure 4.7, which presents longer simulation runs with matched initial seeds, confirms that complexity is not guaranteed to increase simply by making the environment harder, even if more time is given for the population to adapt. While both complex and simple conditions start similarly, the complex environment lineages eventually diverge, often settling on less complex neural configurations.
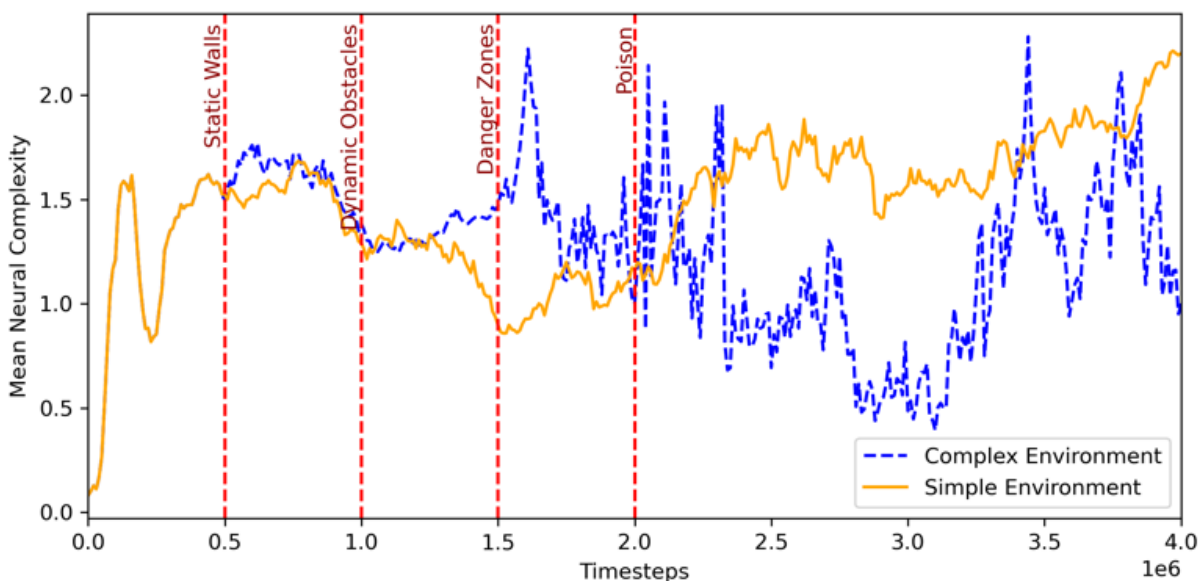

Fig. 4.7. Mean population Neural Complexity over time for simulation runs with complex and simple environments with the same seed

4.5. Generational Turnover and Reproductive Strategies

To understand how lineages maintain themselves under severe selection pressures, we examined the generational patterns of births and deaths over time. Figure 4.8 shows a scatter plot of the generations of newly born creatures per time window. In the complex environment, the high turnover rate is evident. As the environment grows more lethal, lineages adopt rapid reproductive strategies, producing large numbers of offspring in quick succession. This ensures that some descendants survive by sheer volume, even if most die young and fail to evolve more intricate neural control systems.
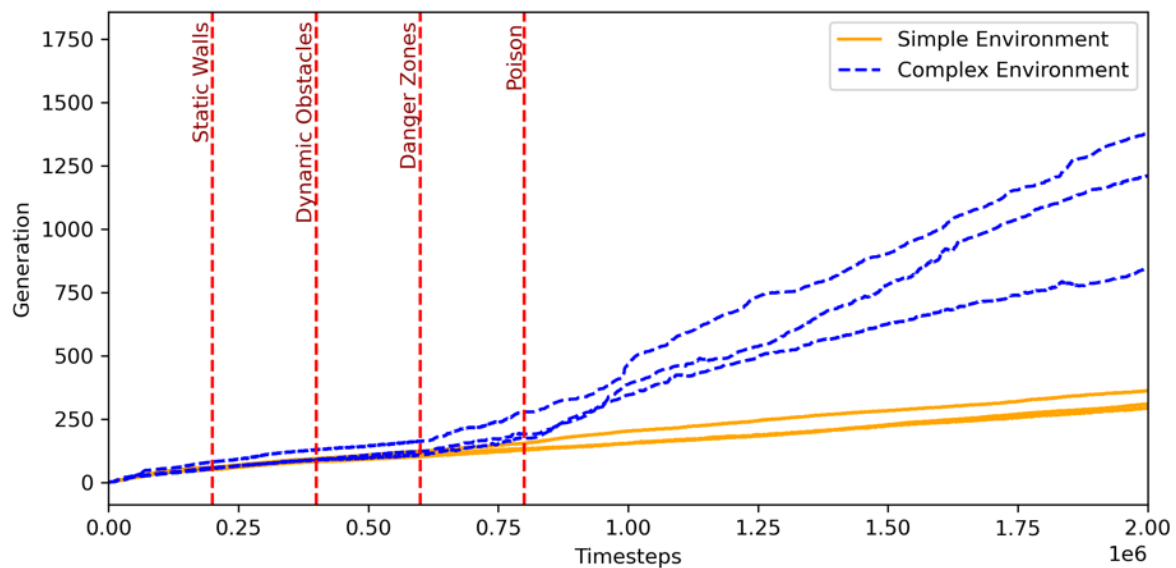
Fig. 4.8. Mean generation of born in its generation per simulation timesteps, complex environment, simple environment

In a simpler environment, generation turnover is more gradual. Creatures reproduce at a moderate pace, often retaining more complex neural networks since their survival is not constantly threatened. This leads to more stable population structures and longer-lived individuals.

4.6. Summary of Findings

Across three repeated experiments under each setting, we found consistent trends. Under escalating complexity (walls at 200,000, dynamic obstacles at 400,000, hazard zones at 600,0000, poisons at 800,000), we observe several trends. Population sizes fluctuate more widely, with pronounced crashes following the introduction of deadly elements (Fig. 4.1). Mean lifetimes decrease significantly, especially once hazard zones and poisons appear (Fig. 4.2). Morphologies shift toward lean, agile forms prioritizing fast reproduction (Fig. 4.3, *a*), whereas simpler environments yield more moderate, stable morphologies (Fig. 4/3, *b*). Neural architectures do not necessarily become more complex; instead, they often remain or even revert to simpler stimulus-response patterns under lethal pressures (Fig. 4.4 vs. Fig. 4.5). Neural complexity measures (Fig. 4.6, Fig. 4.7) show that complexity growth is not guaranteed in more challenging environments. High generational turnover (Fig. 4.8) characterizes populations in harsh conditions, reflecting a strategic pivot away from complexity toward rapid proliferation.

5. Discussion

The results of this study provide a nuanced perspective on the evolutionary trajectories of ALife populations under incrementally increasing environmental complexity. While it is reasonable to hypothesize that adaptation to complex environments would grant individuals with greater cognitive capacity (i.e., higher neural complexity) an adaptive advantage, thereby driving a gradual increase in population-wide neural complexity and fostering noogenesis, the findings suggest that this outcome is not guaranteed.

Initial increases in environmental complexity (e.g., walls, moderate obstacles) occasionally encouraged the emergence of diverse sensorimotor strategies and incremental neural complexity. However, these trends were neither stable nor consistent. As environmental conditions became increasingly lethal, populations often adopted strategies prioritizing survival through quantity rather than quality. Organisms reproduced rapidly, had shorter lifespans, and exhibited simpler stimulus-response neural networks. In essence, rather than evolving toward cognitively complex forms, evolutionary lineages frequently gravitated toward r-strategist solutions characterized by high reproduction rates and rapid generational turnover, as described by r/K selection theory in ecology [25]. This allowed populations to persist despite constant existential threats.

This phenomenon aligns with certain ecological and evolutionary principles observed in nature. Darwin's concept of the "economy of nature" [26] posits that evolution is not a linear progression toward complexity but a process driven by immediate survival and reproductive needs. Many biological systems, particularly in harsh environments, favor strategies that maximize short-term fitness. For instance, r-strategists thrive in unpredictable or lethal conditions by producing numerous offspring quickly, often at the cost of individual longevity or complexity. Analogously, our ALife populations exhibit similar behaviors, demonstrating that increased environmental difficulty does not inherently lead to greater complexity. On the contrary, the presence of critical threats often necessitated reductions in neural complexity, reverting neural architectures to simplified, reflex-driven networks.

Neural complexity metrics derived from the Tononi–Sporns–Edelman (TSE) measure [22] indicate that complexity can rise temporarily but often plateaus or declines under lethal environmental pressures. While Yaeger L. and Griffith V. anticipated that increasing environmental complexity would drive higher neural complexity in agents [18], our findings underscore the necessity of avoiding parasitic r-strategy dynamics. The conditions must provide stable incentives for complexity – selective pressures that consistently reward integrated, adaptive cognitive strategies over short-term exploitative tactics.

These insights suggest that complexity emerges most readily in balanced environments where agents are pressured to adapt and explore richer behavioral niches without facing mortality rates so high that reproductive quantity becomes the most viable strategy.

To promote progressive neural network development through adaptive control of artificial life in dynamic environments, it is advisable to use recursive genetic algorithms [27] with several strategies. Layered Challenges that Reward Complexity – Rather than introducing merely lethal elements, design scenarios where certain high-value resources or safe zones can only be accessed through complex behaviors or problem-solving. Complexity should be not only useful but necessary for stable survival. Social and Cooperative Pressures – introducing tasks that require cooperation, communication, or social learning may incentivize more integrated neural networks. Complexity may flourish if communication or coordination among agents confers a clear survival advantage. Gradualism and Stability – providing stable intermediate niches, where complexity pays off before lethal threats dominate, could help complexity accumulate. Environments that ramp up difficulty more gradually might prevent populations from collapsing into simple r-strategies. Penalizing Simplicity – another approach is to modify fitness landscapes so that purely r-strategic solutions have diminishing returns. For example, increasing energy costs or imposing metabolic trade-offs that only complex networks can efficiently navigate might nudge the evolutionary trajectory toward complexity.

6. Conclusion

Diverse biological organisms have evolved distinct survival strategies, with intelligence being one of them, albeit the most successful. The fact that evolution in terrestrial and aquatic environments has led to the emergence of highly cephalized forms highlights the inherent patterns driving noogenesis. Observations of instances where artificial neural networks exhibit excessive complexity during sustained adaptation further support the arguments against traditional objections to Darwin's theory. These objections often claim that the genetic basis for advanced cognitive abilities, such as mathematical skills, could not have evolved prior to the existence of such cognitive needs.

To replicate simplified noogenesis within neural networks through adaptive control of artificial life, future models must incorporate mechanisms capable of identifying and mitigating parasitic strategies—those that enable populations to thrive without contributing to increased complexity. The use of recursive genetic algorithms offers a promising approach, allowing for the dynamic adjustment of environmental complexity to foster a sustained trend of neural network intellectualization. This iterative, feedback-driven process mirrors the dynamics of natural evolution and holds significant potential for achieving stable noogenesis in artificial life systems.

The practical significance of this study lies in the development of alternative methods for developing and training multilayered neural networks, overcoming existing limitations such as overfitting, poor generalization, high computational demands, and improving approaches to training autonomous robots. These findings have direct applications in various fields, including evolutionary design methods and solving complex practical challenges through adaptive, evolution-inspired learning systems.

REFERENCES

1. Krizhevsky A., Sutskever I., Hinton G. E. ImageNet Classification with Deep Convolutional Neural Networks. *Advances in Neural Information Processing Systems*. 2012. vol. 25, pp. 84–90. DOI: 10.1145/3065386.

2. Vaswani A., Shazeer N., Parmar N., Uszkoreit J., Jones L., Gomez A. N., Kaiser Ł., Polosukhin I. Attention is all you need. *Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17).* Curran Associates Inc., Red Hook, NY, USA, 2017, pp. 6000–6010. https://dl.acm.org/doi/10.5555/3295222.3295349.

3. Silver D., Huang A., Maddison C. J., Guez A., Sifre L., van den Driessche G., Schrittwieser J., Antonoglou I., Panneershelvam V., Lanctot M., Dieleman S., Grewe D., Nham J., Kalchbrenner N., Sutskever I., Lillicrap T., Leach M., Kavukcuoglu K., Graepel T., Hassabis D. Mastering the game of Go with deep neural networks and tree search. *Nature*. 2016, vol. 529, no. 7587, pp. 484–489. DOI: 10.1038/nature16961.

4. Ray T. S. Evolution, Ecology, and Optimization of Digital Organisms. Santa Fe, 1992. 47 p. https://faculty.cc.gatech.edu/~turk/bio_sim/articles/tierra_thomas_ray.pdf

5. Adami C., Brown C. T. Evolutionary Learning in the 2D Artificial Life System "Avida". Artificial Life IV. 2020. pp. 373–377. DOI: 10.7551/MITPRESS/1428.003.0049.

6. Lu C., Beukman M., Matthews M., Foerster J. JaxLife: An Open-Ended Agentic Simulator. *Proceedings of the ALIFE 2024: Proceedings of the 2024 Artificial Life Conference*. Online, July 22–26, 2024. p. 47. DOI: 10.1162/isal_a_00770.

7. Sims K. Evolving virtual creatures. *In Proceedings of the 21st Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH '94)*. New York, 1994, pp. 15–22. DOI: 10.1145/192161.192167.

8. Adamatzky A. Framsticks. Kybernetes. 2000, vol. 29, no. 9/10. DOI: 10.1108/k.2000.06729iad.001.

9. Yaeger L. Computational Genetics, Physiology, Metabolism, Neural Systems, Learning, Vision, and Behavior or PolyWorld: Life in a New Context. *Santa Fe Institute Studies in the Sciences of Complexity - Proceedings Volume*. 1994, vol. 17, p. 263. https://www.researchgate.net/publication/2448680_Computational_Genetics_Physiology_Metabolism_Neural_Systems_Learning_Vision_and_Behavior_or_PolyWorld_Life_in_a_New_Context

10. Gras R., Devaurs D., Wozniak A., Aspinall A. An individual-based evolving predator-prey ecosystem simulation using a fuzzy cognitive map as the behavior model. *Artificial Life*. 2009, vol. 15(4), pp. 423–463. https://pubmed.ncbi.nlm.nih.gov/19463060/

11. Cope D. Real-time Evolution of Multicellularity with Artificial Gene Regulation. *The 2023 Conference on Artificial Life*. MIT Press, May 2023, pp. 77–86. DOI: 10.1162/isal_a_00690.

12. Hamon G., Nisioti E., Moulin-Frier C. Eco-evolutionary Dynamics of Non-episodic Neuroevolution in Large Multi-agent Environments. *Proceedings of the Companion Conference on Genetic and Evolutionary Computation (GECCO '23 Companion)*. Association for Computing Machinery, New York, NY, USA, 2023, pp. 143–146. DOI: 10.1145/3583133.3590703.

13. Wang R., Lehman J., Clune J., Stanley K. O. Paired Open-Ended Trailblazer (POET): Endlessly Generating Increasingly Complex and Diverse Learning Environments and Their Solutions. 2019. Available at: https://arxiv.org/abs/1901.01753 (access date: 29.08.2023)

14. Auerbach J. E., Bongard J. C. Environmental Influence on the Evolution of Morphological Complexity in Machines. *PLOS Computational Biology*. 2014, vol. 10(1). DOI: 10.1371/journal.pcbi.1003399.

15. Giannakakis E., Khajehabdollahi S., Levina A. Environmental variability and network structure determine the optimal plasticity mechanisms in embodied agents. *Proceedings of the ALIFE 2023: Ghost in the Machine*. Online, 2023, p. 22. DOI: 10.1162/isal_a_00606.

16. Canino-Koning R., Wiser M. J., Ofria C. The Evolution of Evolvability: Changing Environments Promote Rapid Adaptation in Digital Organisms. Proceeding*s of the Artificial Life Conference 2016*. 2016, pp. 268–275. DOI: 10.1162/978-0-262-33936-0-CH047.

17. Yaeger L. S., Sporns O. Evolution of Neural Structure and Complexity in a Computational Ecology. *Artificial Life X: Proceedings of the Tenth International Conference on the Simulation and Synthesis of Living Systems*. MIT Press, Cambridge, MA, 2006, pp. 330–336. https://www.researchgate.net/publication/228630335_Evolution_of_neural_structure_and_complexity_in_a_computational_ecology

18. Yaeger L., Griffith V., Sporns O. Passive and Driven Trends in the Evolution of Complexity. Artificial Life XI: Proceedings of the Eleventh *International Conference on the Simulation and Synthesis of Living Systems*. 2008, pp. 725–732. https://arxiv.org/abs/1112.4906

19. Yaeger L. S. Identifying Neural Network Topologies That Foster Dynamical Complexity. *Advances in Complex Systems*. 2013. vol. 16, iss. 02n03, p. 1350032. DOI: 10.1142/S021952591350032X.

20. Zachepylo M., Yushchenko O. The Scientific Basis, Some Results, and Perspectives of Modeling Evolutionarily Conditioned Noogenesis of Artificial Creatures in Virtual Biocenoses. *Bulletin of National Technical University "KhPI". Series: System Analysis, Control and Information Technologies*. 2023, no. 2 (10), pp. 85–94. DOI: 10.20998/2079-0023.2023.02.13.

21. Stanley K. O., Miikkulainen R. Evolving Neural Networks through Augmenting Topologies. *Evolutionary Computation*. 2002, vol. 10(2), pp. 99–127. DOI: 10.1162/106365602320169811.

22. Tononi G., Sporns O., Edelman G. M. A measure for brain complexity: Relating functional segregation and integration in the nervous system. *Proc Natl Acad Sci USA*. 1994, vol. 91, no. 11, pp. 5033–5037. DOI: 10.1073/PNAS.91.11.5033.

23. Shannon C. E. A Mathematical Theory of Communication. *Bell System Technical Journal*. 1948, vol. 27, no. 3, pp. 379–423. DOI: 10.1002/J.1538-7305.1948.TB01338.X.

24. Zachepylo M., Yushchenko O. Assessing Neural Complexity for Noogenesis in ALife Simulations. *XVIII International Scientific and Practical Conference of Master's and Postgraduate Students Theoretical and Practical Research of Young Scientists*. Kharkiv: National Technical University Kharkiv Polytechnic Institute, 2024, p. 10. https://web.kpi.kharkov.ua/masters/wp-content/uploads/sites/135/2024/11/Zbirnyk-tez-TPRYS2024.pdf

25. MacArthur R. H., Wilson E. O. The Theory of Island Biogeography. Princeton, NJ: Princeton University Press, 1967. 224 p. https://www.semanticscholar.org/paper/The-Theory-of-Island-Biogeography-Macarthur-Wilson/25e2b6dbf36bfe4b269e2dd70f6c3d00fb266484

26. Darwin C. On the Origin of Species by Means of Natural Selection, or the Preservation of Favoured Races in the Struggle for Life. Evolutionary Writings. 2010. DOI: 10.1093/OWC/9780199580149.003.0005.

27. Yushchenko A. G. Recursive Genetic Algorithm for Solving the Traveling Salesman Problem. Anniversary Edition of "Information Systems" Department at NTU KhPI. 2014, pp. 154–162. Available at: https://www.researchgate.net/publication/262686057 (access date: 03.12.2024)

Зачепило
Михайло
Олексаднрович

Аспірант кафедри Системи Інформації ім. В. О. Кравця;
Національний технічний університет «Харківський політехнічний інститут», вул. Кирпичева, 2, Харків, *Україна,* 61024
e-mail: Mykhailo.Zachepylo@cit.khpi.edu.ua
https://orcid.org/0000-0001-6410-5934

Ющенко
Олександр
Георгійович

кандидат фізико-математичних наук, професор;
професор кафедри Системи Інформації ім. В. О. Кравця, Національний технічний університет «Харківський політехнічний інститут», вул. Кирпичева, 2, Харків, *Україна,* 61024
e-mail:agyu@kpi.kharkov.ua;
https://orcid.org/0000-0002-0078-3450

Дослідження стратегій виживання штучного життя у динамічному середовищі

Це дослідження спрямоване на розробку еволюційних методів для побудови глибоких нейронних мереж, пропонуючи потенційні вдосконалення методів машинного навчання шляхом моделювання адаптивних архітектур під впливом селективного тиску.

Мета. Метою роботи є дослідження динаміки нейронної складності у агентів штучного життя, які взаємодіють із дедалі складнішими умовами середовища.

Методи дослідження. Ми провели двовимірну симуляцію для моделювання популяцій агентів з нейронними мережами та фізичними формами, що еволюціонують. Середовище змінюється від простих умов до більш складних сценаріїв, включаючи статичні стіни, рухомі перешкоди, небезпечні зони та смертельні отрути. Наш підхід базується на фундаментальних системах штучного життя, таких як Tierra, Avida та PolyWorld. Нейронні архітектури еволюціонують на основі принципів, натхнених NeuroEvolution of Augmenting Topologies. Ми застосовуємо міру складності Тононі–Спорнса–Едельмана для оцінки нейронної інтеграції та спеціалізації, що допомагає зрозуміти, як агенти адаптують свої мережі для досягнення балансу між глобальною когерентністю та локалізованою функціональністю.

Результати. Дослідження показало, що, хоча складні середовища можуть тимчасово підвищувати нейронну складність, жорсткіші умови часто сприяють простішим, але більш продуктивним репродуктивним r-стратегіям. У результаті популяції можуть формувати рефлекторні, стимул-реакційні поведінкові моделі, замість розвитку складних нейронних структур.

Висновки. Ці результати поглиблюють наше розуміння адаптивного інтелекту і допомагають у розробці підходів до створення масштабованих систем машинного навчання у робототехніці та розробці архітектур глибоких нейронних мереж, що сприяє досягненню ширшої мети розуміння еволюції штучного інтелекту. Ми пропонуємо використовувати рекурсивний генетичний алгоритм для оптимізації цих балансів викликів, що сприяє довгостроковій нейронній адаптації до динамічних середовищ.

Ключові слова: штучне життя, нейронна складність, еволюційна адаптація, динамічні середовища, поступова складність, необмежена еволюція, нейроеволюція розширюваних топологій, r-стратегія