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THE SCIENTIFIC BASIS, SOME RESULTS, AND PERSPECTIVES OF MODELING EVOLUTIONARILY CONDITIONED NOOGENESIS OF ARTIFICIAL CREATURES IN VIRTUAL BIOCENOSES

This research aimed to gain a profound understanding of virtual biocenoses intricate digital ecosystems, with the goal of elucidating and replicating the emergence and evolution of intelligence in artificial creatures – referred to as noogenesis. A comprehensive analysis of existing studies within virtual biocenoses was undertaken to glean valuable insights into the complexities of modeling dynamic ecosystems where artificial agents engaged in intricate interactions. The pivotal role of neural networks in shaping the adaptive behaviors of artificial creatures within these environments was underscored. A meticulous investigation into neural networks' evolution methodologies revealed the evolution of their architecture complexity over time, culminating in the facilitation of flexible and intelligent behaviors. However, a lack of study existed in the domain of nurturing evolutionary-based communication and cooperation capabilities within virtual biocenoses. In response to this gap, a model was introduced and substantiated through simulation experiments. The simulation results vividly illustrated the model's remarkable capacity to engender adaptive creatures endowed with the capability to efficiently respond to dynamic environmental changes. These adaptive entities displayed efficient optimization of energy consumption and resource acquisition. Moreover, they manifested both intellectual and physical transformations attributed to the evolution and encoding principles inspired by the NeuroEvolution of Augmented Topologies. Significantly, it became apparent that the evolutionary processes intrinsic to the model were inextricably linked to the environment itself, thus harmonizing seamlessly with the overarching goal of this research. Future research directions in this field were outlined. These pathways provided a foundation for further exploration into the evolution of artificial creatures in virtual biocenoses and the emergence of advanced communication and cooperation capabilities. These advancements hold the potential to move artificial life and artificial intelligence to new levels of understanding and capability.

Keywords: agent-based modeling, artificial life, artificial intelligence, growing neural networks, evolution, noogenesis, evolutionary design.

Introduction. In the dynamic landscape of modern science and technology, the study of biocenoses, complex ecological communities recreated within virtual environments where artificial agents interact, holds profound significance. These virtual ecosystems mirror the intricate interplay observed in natural habitats and serve as the backdrop for the process of noogenesis modeling – the emergence and development of intelligence and knowledge. Understanding and harnessing the mechanisms underlying intelligence within these virtual biocenoses have implications in various domains and applications.

Artificial agents, ranging from autonomous entities to coordinated swarms, have permeated diverse fields, including research, business practices, and creative arts. Within the realm of Artificial Life, notable simulations like PolyWorld [1] and EcoSim [2] employ virtual agents to model the evolution of digital organisms within dynamic 3D environments, emulating aspects of natural ecosystems. These simulations have paved the way for exploring the evolution of intelligent behaviors and complex interactions among artificial entities.

Neural Networks have emerged as a powerful model for controlling agents, enabling them to exhibit advanced and unpredictable behaviors. Crucially, the control of such agents often involves machine learning techniques, with a primary focus on reinforcement learning. This versatility is evident in various applications, from generating nuanced non-verbal facial expressions synchronized with agent speech [3] to orchestrating intricate team dynamics in competitive video games against professional human players [4].

Furthermore, within the realms of artificial intelligence and evolutionary algorithms, the concept of "Evolutionary design" has gained prominence. This approach, rooted in the principle of gradual cost function complication reminiscent of natural evolutionary processes, offers a systematic means to synthesize and optimize intricate systems [5, 6]. The article [6] proposes to use an evolutionary approach to the design of multi-tier filters for a new generation of radio-telecommunication systems for ultra-high-speed and ultra-wideband information transmission. The essence of the method is to replace traditional multi-parameter optimization of a complex structure with evolutionary optimization of previous, more superficial structures. It allows us to find global extrema on a limited number of optimization parameters and use them as initial ones for optimizing subsequent increasingly complex descendant structures with a more significant number of parameters. Methodologically, this is an alternative approach to the design of complex systems, regardless of their nature, based on the principles of evolution from the simplest forms. Our study of virtual biocenoses from these positions will make it possible in the future to formulate general methodological principles of such evolutionary design.

In the context of advancing technology and scientific inquiry, the study of biological evolution through virtual models stands as a critically important endeavor. These studies provide valuable insights that enhance our understanding of intelligence and offer the potential for innovative applications and interdisciplinary solutions. This paper embarks on a rigorous exploration, analysis, and expansion of knowledge within virtual biocenoses. We are going to elucidate the mechanisms underpinning evolutionary-based communication and cooperation capabilities.

Goals of the study. To analyze existing models incorporating biological evolution, the use of neural networks for controlling virtual agents, and the evolution of neural networks influenced by genetic factors. Through comparative analysis, we aim to provide a comprehensive overview of the current state of research, highlighting both achievements and limitations.

Build a basic model of artificial creature evolution in virtual biocenose capable of further complexification. Study its capability to model the evolution process.

To investigate the intricate interplay among evolutionary theory, artificial neural networks, and the design of virtual agents within simulated environments, specifically focusing on the emergence of communication, socialization, and intelligence.

Furthermore, to establish a conceptual framework for an innovative evolutionary design approach applied to developing creatures and their intelligence within virtual biocenoses. Drawing insights from evolutionary biology, neural network control, and artificial life systems, we aim to pave the way for novel methodologies that promote the emergence and growth of intelligence in artificial ecosystems.

Models of biological evolution. Darwin and Wallace's theory is the bedrock of contemporary evolutionary models, elucidating the principles of variation, selection, and heredity [7]. These principles have given rise to various computational paradigms aimed at replicating these processes in simulated virtual reality.

Genetic Algorithms (GAs) Introduced by John H. Holland [8], GAs are optimization and search techniques emulating genetic variation and selection. GAs maintains candidate solution populations, favoring fitter individuals through selection pressure while preserving diversity via recombination and mutation. GAs finds applications in complex optimization problems, machine learning, and evolutionary design.

Genetic Programming (GP), as an extension of GAs, GP evolves computer programs and algorithmic structures [9]. These programs are represented as trees and undergo genetic operations like crossover and mutation. GP is utilized in automated program generation, symbolic regression, and diverse problem-solving domains.

Artificial Life (ALife) is an interdisciplinary field introduced by Langton in the 1990s [10, 11] that focuses on emulating lifelike behaviors, patterns, and systems within computational environments. It employs evolutionary concepts to simulate lifelike behaviors, exploring self-organization, emergence, and adaptation. Typical tools in ALife include cellular automata, agent-based simulations, and virtual ecosystems.

Valentin Turchin's Theory of Metasystem Transitions introduces a modern outlook on complex system evolution [12]. This theory suggests that systems can progress to higher organizational levels through a series of transitions, each marked by the emergence of new control mechanisms at a higher level. It extends the concept of evolution beyond genetics and biology to encompass control hierarchies and metasystems.

Incorporating these computational models and theories, our research will advance the understanding of evolutionary processes in both natural and artificial realms.

Models of biological evolution. In the realm of Artificial Life (ALife), various models have emerged, each with distinct attributes and methodologies. This review offers a comparative analysis of these models, focusing on key features like neural networks, learning, topology evolution, encoding, environment, and communication and cooperation capabilities.

Early ALife models, pioneered by Langton [10, 11], centered on principles of cellular automata to study self-organization and basic lifelike patterns. These models lacked complexity and adaptability.

Tierra by Thomas Ray introduced self-replicating computer programs [13], delving into the evolutionary dynamics of digital code within computational environments. Though devoid of neural networks, it marked progress in illustrating the evolution in digital systems. Inspired by Tierra, Avida [14] featured organisms as code segments in a 2D grid. It exhibited self-replication through mutations and local interactions. Communication was limited to the local neighborhood, fostering diversity. Avida supported genetic encoding, dynamic topology evolution, and Poisson-random mutations but operated in a simplified digital environment.

Larry Yaeger's PolyWorld [15] expanded the horizons of ALife by simulating 3D artificial creatures, each under the control of evolving neural networks. Notably, PolyWorld leverages evolving neural networks as the cognitive substrate for its virtual organisms, fostering dynamic topological changes in network architecture as a result of natural selection. These networks serve as the neural underpinning for various learning methods and behaviors exhibited by artificial organisms. Encoding in PolyWorld is grounded in software-coded genetics, and the environment is structured to accommodate predation, mimicry, sexual reproduction, and communication, rendering it a complex and competitive ecological crucible. The communication and cooperation abilities of the agents within this environment give rise to emergent behaviors, as their actions are shaped by individual survival strategies and group dynamics. In essence, PolyWorld is a noteworthy platform where neural networks, learning methods, topology evolution, encoding, environmental characteristics, and communication abilities intersect to explore the dynamics of evolving digital lifeforms. Since PolyWorld is a simulated 3D environment, it allowed agents to receive a sensory input based on image and color sensors as an input for a neural network agent control center. The communication is limited by signaling via agent color changing. The study focuses on successful survival strategies and has a static genome size, which limits neural network topology complexity. That limits its ability to simulate meta-system transition and observability of evolution.

Framsticks [16, 17] featured artificial creatures constructed from stick-like components, aiming to simulate creature-environment interactions in a highly configurable 3D environment. At the same time, it had limitations in topology evolution and communication.

EcoSim [2] introduced an individual-based predator-prey model employing Fuzzy Cognitive Maps (FCMs) for agent behavior modeling. It allowed agents to assess their environment and evolve unique FCMs. EcoSim incorporated species concepts and provided insights into macroevolutionary processes. However, predefined agent behaviors limited innovation.

Summarizing these studies achieved behavior similar to biological natural objects at some scale focusing on different aspects. Only PolyWorld and Framsticks utilize agent control on neural-based or neural network approaches. Learning strategies vary from clearly evolutionary-based to Hebbian-learning in PolyWorld, which enables behavioral difference even in agents with identical phenotypes. Models utilize different environments, from purely static in Tierra, Avida, and EcoSim, to static but a highly per-session configurable environment with limited resources in PolyWorld and Framsticks. The mentioned studies do not have a highly dynamic environment that evolves with the population, gradually increasing the complexity and driving the population to open-ended evolution. None of the mentioned studies utilize the potentially infinitely growing and adapting neural network separately but in sync with the creature's body to enable the possibility of meta-system transition in the context of the evolutionary progression of artificial creatures.

Core challenges in evolutionary modeling of virtual biocenoses. The endeavor to model virtual biocenoses encompassing artificial life forms unveils a spectrum of intricate challenges that merit meticulous consideration within the scientific discourse. In this section, we explore these core challenges, delving into the complexities underpinning virtual ecosystems' evolutionary modeling.

- Genetic Encoding of Phenotypes and Structural Congruence. Central to the efficacy of evolutionary modeling lies the genetic encoding of phenotypes and the alignment between an organism's physical structure and its neural architecture [18]. This alignment, sometimes involving pruning mechanisms, necessitates meticulous design to ensure that the neural system accurately embodies the intended physical attributes.
- Stability of Evolution and Preservation of Useful Innovation. Sustaining the stability of evolution while safeguarding opportunities for innovation presents a multifaceted challenge. It includes the study of neuro complexification, a process vital in preventing the population from becoming entrenched in local optima or succumbing to collapse within highly intricate environmental settings [19].
- Environmental Complexity and Neural Network Elaboration. The environment in which virtual biocenoses evolve plays a pivotal role in shaping the complications and elaboration of neural networks. Understanding the environmental conditions that give rise to neural complexity is crucial for comprehending the dynamics of artificial life systems.
- Lifelong Learning or Open-Ended Evolution. Enabling virtual organisms to engage in lifelong learning is imperative for facilitating open-ended evolution. This approach prevents populations from stagnating within minimal optima and bolsters adaptability, even in dynamic and intricate environments. Notable contributions from researchers such as Larry Yaeger, Tim Taylor, L. B. Soros, Kenneth O. Stanley, Rui Wang, Joel Lehman, Jeff Clune, and Jonathan C. Brant have illuminated pathways in this regard [20–25].
- Environmental Prerequisites for Communication and Socialization. Formulating artificial agents' communication and socialization behavior hinges on understanding the environmental prerequisites that foster these intricate interactions.

These insights underscore the need for careful consideration of genetic encoding methods, the role of environmental complexity in shaping neural networks, and the importance of lifelong learning mechanisms in evolutionary systems. Addressing these challenges will be essential for advancing the modeling of virtual biocenoses and understanding the emergent behaviors of artificial life forms.

Neural networks that control agents and other virtual objects. In the ever-evolving realm of artificial intelligence and virtual environments, neural networks (NNs) have become pivotal in controlling virtual entities across various applications.

Karl Sims utilized Recurrent Neural Networks (RNNs) to evolve virtual creatures' neural systems [26]. Focused on morphology and sensory input, it excelled in single-agent environments, primarily for applications in gaming.

Non-verbal facial behaviors in virtual agents using Generative Adversarial Networks (GANs) and RNNs with Long Short-Term Memory (LSTM) cells were studied in [3] – the training process involved supervised learning, resulting in realistic facial expressions for gaming and cinematography.

The research emphasized energy-efficient control for mobile agents, employing fully connected spiking neural networks and Spike-Timing-Dependent Plasticity (STDP)-based unsupervised learning [27]. Promising for autonomous mobile agents, it showcased energy-efficient control mechanisms.

Exploring multi-agent scenarios, this study investigated the emergence of tool use behaviors [28]. It employed fully connected RNNs with LSTM cells and Reinforcement Learning (RL), promoting competition and coordination among agents. It is vital for gaming, where tool use behaviors are crucial.

RNNs with LSTM cells facilitated infant agents' learning from parent agents in a virtual 3D environment [29]. RL drove interaction, revealing the potential for virtual agents to exhibit curiosity-driven behaviors and engage in social interactions.

Convolutional Neural Networks (CNNs) and RNNs with LSTM cells to control a robot hand solving a Rubik's Cube studied in [30]. Although single-agent, it hinted at robotics and automated problem-solving applications.

Using Graph Neural Networks (GNNs), the study trained control admissibility models with spatial data [31]. RL methodologies were applied, promising applications in the enterprise, robotics, and complex environments.

Investigated the emergence of maps within 'blind' AI navigation agents' memories [32]. RNNs with LSTM cells utilized GPS, compass, and touch sensor data – valuable insights into spatial cognition development.

Achieved performance enough to beat the team of professional players in the Dota 2 video game through self-play reinforcement learning [4]. RNNs with LSTM cells controlled agents, facilitating multi-agent interactions within the gaming domain.

In summary, NNs are pivotal in controlling virtual entities across diverse applications. From evolutionary algorithms to GANs, these studies contribute to gaming, cinematography, autonomous agents, virtual software agents, robotics, and more. A common theme is the single-agent focus, suggesting opportunities for exploring multi-agent interactions and collaborations. Additionally, when applying to NN, Evolution Strategies could surpass RL in certain aspects, offering avenues for future research [33].

Evolving Neural Networks under the Influence of Genetic Operators. In the dynamic fields of artificial intelligence and evolutionary computation, the evolution of neural networks under the influence of genetic operators has emerged as a captivating and highly promising research frontier, finding applications in various domains, including robotics and gaming.

Carl Sims' pioneering work [26] centers on the evolution of virtual creatures within physical environments. Neural networks govern creature behavior and undergo coevolution with creature morphological structures through genetic algorithms. This approach has implications for embodied AI, particularly in evolving robots with adaptable neural control systems.

The NeuroEvolution of Augmenting Topologies (NEAT) algorithm [34] refines neural network structures iteratively across generations. NEAT preserves population diversity, making it versatile for domains like robotics and gaming. It introduces principled crossover, speciation, and incremental growth, providing expedited learning and insights into the evolution of increasingly intricate solutions. NEAT serves as a cornerstone in the continuum of neural network evolution methodologies, establishing a framework for subsequent advancements in this evolving field, leading to more than 61 extensions [35]. Real-Time NEAT (rtNEAT) [36] empowers neural networks to adapt continuously to changing conditions in real-time environments, ideal for autonomous robotics and adaptive game AI. rtNEAT creates a new genre of video games, enabling evolving and adapting agents during gameplay. HyperNEAT [37] and the following ES-HyperNEAT [38] focus on evolving neural networks with the capacity for dynamic behaviors. It employs generative encoding, connective compositional pattern-producing networks (CPPNs), and hypercube-based NeuroEvolution of Augmenting Topologies (HyperNEAT) to optimize neural networks controlling agents with intricate morphologies and behaviors. The Coevolution of Brain and Morphology in Robotics (NEAT-M) [39] explores the concurrent evolution of robot structures and neural control systems. Genetic algorithms optimize both, leading to adaptive robots, significantly impacting embodied AI within robotics and autonomous systems. CoDeepNEAT extends NEAT's principles to evolve architectures tailored for deep networks, making it vital in domains relying on deep learning.

These studies collectively advance neural network evolution, showcasing their effectiveness in optimizing architectures for various tasks and understanding the interplay between neural networks, morphologies, and behaviors. However, computational complexity and the need for multi-agent exploration remain challenges, leaving room for further research. Furthermore, while the mentioned investigations excel in single-agent scenarios, there is room for further exploration of multi-agent interacttions and collaborations. Many mentioned investigations primarily focus on single-agent environments, leaving untapped potential in domains requiring coordination among multiple agents.

Our Approach. In the realm of artificial intelligence and the emergence of intelligence, a significant research gap exists in the domain of lifelong evolution applied to multi-agent open problems. This void encompasses scenarios where creatures can undergo intellectual and physical transformations through NEAT-inspired evolution and encoding mechanisms. Specifically, these transformations target the facilitation of communication and socialization among creatures. Moreover, this model is unique because it drives evolution and selection processes primarily through interactions with the environment, without external algorithmic control.

To better comprehend the core principles of artificial intelligence and how intelligence evolves, there is a need for a significant shift in focus. Instead of emphasizing complex models, we should start with basic models, gradually evolving them into more sophisticated structures [6]. This approach promises to offer deeper insights into the fundamental principles governing intelligence and its development.

Model Overview. The proposed model logically continues the previous study [40] and operates within a 2D spatial environment possessing finite dimensions. Within this environment reside creatures, each comprising two integral components: a physical body and a control center represented by a neural network. The foundational structure of a creature's physical body takes the form of a circle. Additionally, creatures can be equipped with sensors to perceive environmental information and effectors to enact various actions, including movement and rotation. The neural network of each creature serves as the interface between sensory inputs and motor outputs.

Genetic Encoding. The model encodes creatures' physical attributes and their neural networks within their respective genomes. Inspired by NEAT [34], this encoding encompasses the topology and assignment of weights of the neural network, all meticulously derived from the genetic information contained within the creature's single genotype. The critical update was to add specific types of nodes representing the different physical attributes, such as sensors and effectors. Similar updates were made in [39].

The genetic encoding of creatures is captured as a genome, denoted as G, which consists of genes representing various attributes of the creature. Each gene is represented as a tuple (I, T, V), where I denotes the innovation number, T denotes the gene type, and V represents the value associated with that gene, its role is different for each gene type. The gene type T encompassed within the genome includes:

- food_sensor (FS): Represented as (I, FS, PL), where PL represents the placement of the sensor within the creature's circular body.
- wall_sensor (WS): Represented as (I, WS, PL), with the same attributes as food sensors.
- bot_sensor (BS): Represented as (I, BS, PL), with the same attributes as food sensors.
- energy_sensor (ES): Represented as (I, ES), value is not used for ES.
- neural_node (NN): Represented as (I, NN, AF), where AF signifies the activation function applied within the neural node $AF \in \{\text{sigmoid}, \tanh, \text{relu}\}$. The neural node does not have its own bias.
- movement_effector (ME): Represented as (I, ME, RV), where RV indicates the movement effector's reactivity value.
- rotation_effector (RE): Represented as (I, RE, RV), where RV indicates the rotation effector's reactivity value.
- neural_connection (NC): Represented as $(I, NC, (F, T, W))$, F denotes the source neural node, T represents the target neural node, and W signifies the weight of the connection.
- creatures_body_node (CBN): Represented as (I, CBN, SZ), where SZ indicates the size of the creature's main circular body. This node cannot establish a neural connection.

So $T \in \{FS, WS, BS, ES, NN, ME, RE, NC, CBN\}$. Innovation number I is a global counter that helps track gene history [34] while not playing the role of crossover in this model.

Mutation Mechanisms. Define the mutation process M as a stochastic function that takes as input a creature's genotype G and returns a modified genotype G',

$$M : G \to G'. \quad (1)$$

Mutation could be different $MT \in \{\text{AddNode}, \text{AddConnection}, \text{RemoveGen}, \text{UpdateGen}\}$. It is picked randomly, $X_{mt} \sim \text{Weighted}(MT, W_{mt})$, where X_{mt} is a picked mutation type, W_{mt} is a weighted probability for each possible type, which is a hyperparameter for the current model. When $X_{mt} = \text{AddNode}$, the type of node picked randomly between available types $X_{nt} \sim \text{Weighted}(T, W_{nt})$, where X_{nt} is a picked node type, W_{nt} is a weighted probability for each possible type, which is also a hyperparameter for the current model. The additional NC is also being added: 1 for sensors and effectors and 2 for NN. When two random connectable nodes within the whole genotype are picked, and two connections are created between them with random coefficients to reduce the initial impact of newly connected nodes, the maximum weight of the connection is limited to 0.5. When $X_{mt} = \text{UpdateGen}$, the random gen is picked from the genotype, and its associated value is randomly changed. When $X_{mt} = \text{AddConneciton}$, two random connectable nodes within the creature genotype are being picked, and a connection between them is being created with random weight also upper limited to 0.5 for reduction of initial impact which enhance population stability as previous experiments shown, recurrent connections are allowed. When $X_{mt} = \text{RemoveGen}$ mutation occurs, the random gen is selected and removed. If it is a node with some connections, all related connections are also being removed. Since the current model uses clonal replication, there is no need to preserve disabled nodes for further crossover operation like in the original NEAT approach [34].

Sensory and Motor Capabilities. Creatures are equipped with limited-length ray sensors, the placement and object type reactivity of which are encoded within the creature's genotype. These sensors can detect objects such as obstacles, food sources, and other creatures. They activate on the range $[0, 1]$. The closer the intersection to the source of the ray, the higher the activation, zero, when there is no intersection. The energy sensor is not represented as physical and activates with the amount of the creature's energy. Creature effectors encompass actions for movement (forward propulsion) and rotation. If a creature has several movement and rotation effectors, their effect is summarized.

Simulation Setup. The simulation is initialized with a carefully constructed set of conditions. The initial population of creatures is introduced into the 2D spatial environment, and their placement within this environment is randomized to ensure spatial diversity. Each creature in the initial population possesses a minimal genetic structure, including essential basic functionality components. These components consist of one food sensor, an energy sensor, a neural node, and movement and rotation effectors. The connections between these elements are initialized with random weights, giving the creatures a degree of variability in their initial behaviors. The sample for the initial creature phenotype is shown in fig. 1 *a–b*. Each one is also given the introductory amount of energy to survive for the first time. Additionally, food resources are distributed randomly across the environment. These food sources serve as vital sustenance for the creatures, motivating them to explore and interact with their surroundings. The random placement of food resources introduces an element of uncertainty and competition, driving the creatures to adapt and develop diverse foraging strategies. Wall-like obstacles are strategically positioned at random locations within the environment. These obstacles create physical barriers that creatures must navigate around, adding complexity to their interactions with the environment and fostering the development of obstacle-avoidance behaviors.

Simulation Dynamics. The simulation proceeds in discrete time intervals referred to as ticks. It initiates with a population of creatures, accompanied by randomly distributed obstacles and food sources within the environment. Creatures possess an energy resource that is expended as they perform actions over time. Creatures whose energy reserves deplete below a critical threshold die. During each simulation tick, sensor activations are conveyed through the creature's neural network, subsequently dictating actions based on effector activations. Creatures can restore their energy by colliding with and collecting food sources. When a creature's energy surpasses a predefined threshold, it creates an offspring using clonal reproduction with a mutated parent's genotype using (1), transferring half of its own energy to this offspring. The model incorporates the cyclical introduction of food resources into the environment at specified intervals. These intervals are governed by a food restoration schedule encompassing high and low food influx periods. Additionally, obstacles are strategically repositioned at periodic intervals, and how will be shown in future studies – fostering speciation and innovative adaptations among creatures. This environmental dynamism serves to shuffle ecological niches, engendering competition among creatures for limited resources.

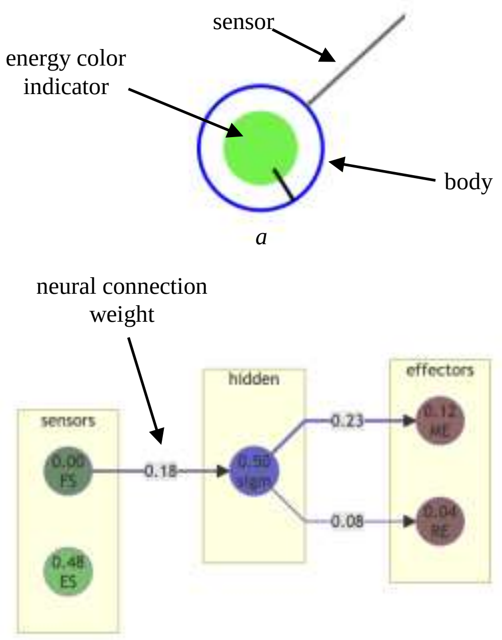


Fig. 1. Sample initial artificial creature phenotype: *a* – in environment, *b* – its neural network

In this model, the creatures' primary objective is the population's survival, achieved through personal survival and the generation of offspring. The population, as a whole, can progress towards this objective through mutations that allow enhanced adaptability to the environment. In addition to the base model [40], this version introduces several enhancements, including support sensors for obstacle and bot detection, recurrent connections in the hidden layer, food seasoning, random wall placement, energy sensing, and an energy penalty associated with genotype size. This model was implemented as simulation software and subjected to a series of experiments for study and analysis.

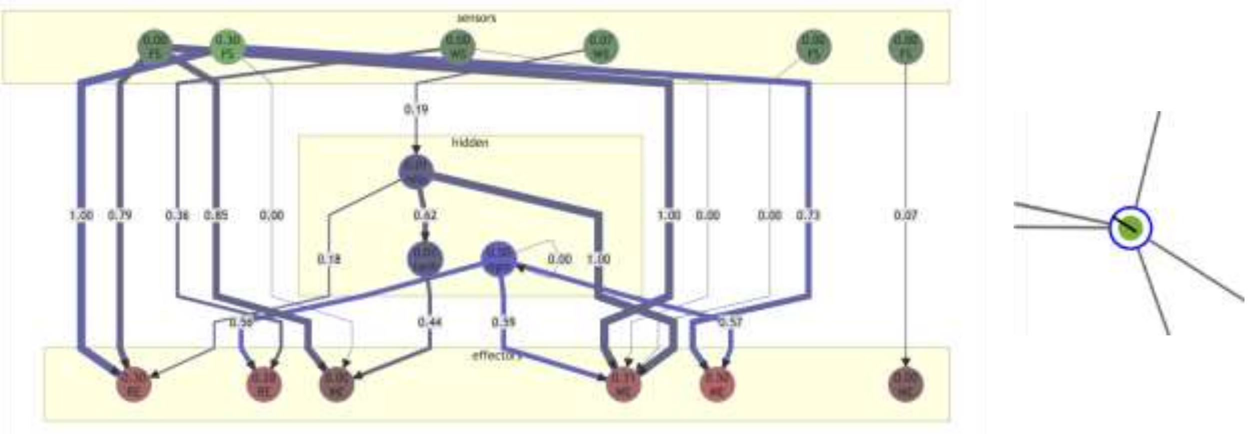
Results. Emergence of Adaptive Agents. The model presented in this study effectively demonstrated the emergence of adaptive agents within virtual biocenoses. These agents displayed the capacity to respond to dynamic changes in their environment over successive simulation intervals. These agents evolved strategies through evolutionary processes that enabled them to proficiently acquire food resources while efficiently managing their energy levels.

Emerged behaviors. For several experiments, artificial creatures have embraced different behaviors, including seeking food by forward or circular movements, reducing movement to save energy and prolong life, detecting obstacles and turnaround from them, detecting bots around, and increasing speed to win in local competition for a food resource. This model enables creatures to develop a variety of strategies. In several experiments, most of the population developed a strategy to rotate in place and wait for food to appear in their field of sensitivity, as soon as they notice it, they move forward as fast as possible. This strategy is similar to the one in saying by Confucius, "If you sit by the river long enough, the bodies of your enemies will float by".

Metasystem Transitions. In several experimental instances, we observed intriguing phenomena characterized by metasystem transitions [40]. These phenomena require an additional investigation into the underlying preconditions that triggered such transitions.

Evolutionary Trends in Neural Network Complexity. Our experimental findings unveiled a captivating trend in the evolutionary dynamics of neural networks within virtual biocenoses. as illustrated in fig. 2, *a*. fig. 2, *b* provides a visual representation of a creature within the simulated environment. Initially, there was a noticeable growth in the size and complexity of these neural networks, possibly driven by the pursuit of heightened cognitive capabilities. However, a remarkable adaptation emerged during the course of our simulations. Artificial agents within the system, when confronted with the increased energy consumption associated with larger genotype sizes, exhibited a strategic shift towards evolving more compact neural networks, fig. 2, *a*. This adaptation appeared to be a deliberate response aimed at conserving energy resources while simultaneously maintaining a degree of variability within the agent population. Since nodes in creatures' neural networks do not have bias, they emerged that the energy sensor is adaptive bias, and the hidden neural node with sigmoid activation function became static bias due to the nature of this function. These results underscore the dynamic and context-sensitive nature of evolution within artificial environments, highlighting the innovative strategies employed by virtual agents to optimize their cognitive resources while preserving population diversity.

Genotype evolution dynamics displayed a trend in controlled genotype growth with dominance of genes represented neural links as shown in fig. 3. Biocenose state over simulation displayed the rapid population size growth. At the same time, initial resources were highly available. The population sought an adaptation to limited food resources per creature and reached near equilibrium plateau for a given environment near tick 10^6 as shown in fig. 4.



a *b*

Fig. 2. Artificial creature phenotype, generation 2888, simulation tick 10^7:
a – its neural network, *b* – its body in the environment

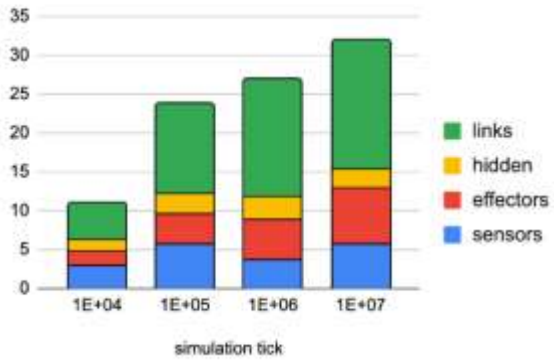


Fig. 3. Distribution of gene types amount, average in population genotypes over simulation time

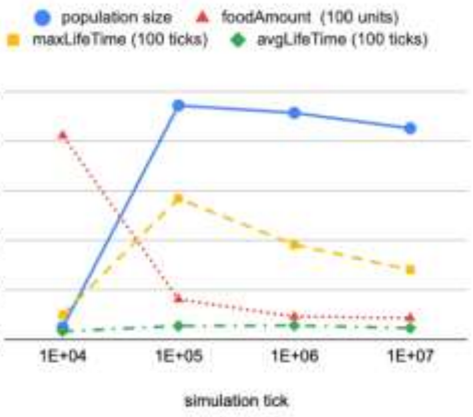


Fig. 4. Simulation dynamics of biocenose

Conclusions. While acknowledging the valuable contributions of previous studies, it is essential to note that some of these endeavors have leaned towards employing complex models within static environments.

Furthermore, some of these investigations have primarily focused on locomotion movement patterns development as a separate issue, which may have diverted their attention from the broader context of communication and socialization processes within artificial environments.

Modeling the evolution of artificial life's simplest form will allow investigation of the emergence and development of intellect, in contrast to complex models primarily constrained to study strategies. Attaining this understanding can be facilitated by gradually increasing model complexity as it is required for evolving neural networks. The complexification could be both in creatures' potential abilities and environment influence them.

The interest in modeling the emergence of communication and socialization is in exploring and studying the ability of evolving agents to form enough physical and neural enhancements to be able for these functions. Model potentially allows us to study social formations in the evolving agents when reflection communication could transform into a social one. It is necessary to study if unconditional, acquired features are sufficient to formulate communicational behavior or if artificial creature needs personal experience.

The proposed model creates the basis for the complexity of a virtual biocenosis, which will stimulate the progressive development of artificial life forms to increase their intellectual component. The conducted studies show that even in the simplest models, the main trends in biological evolution are observed, both metasystem transitions of the neural network and its simplification to occupy a specific ecological niche. In the future, it will be necessary to determine the conditions for strengthening the first trend and eliminating the second.

Future research. Dynamic Environment Complexification: Building upon these results, future enhancements could involve further complexification of the environment. This might include introducing additional environmental factors or challenges to stimulate more intricate agent behaviors.

Complex Effectors and Sensors: The model's capacity to accommodate more complex effectors and sensors opens doors for research into advanced agent capabilities, potentially leading to more sophisticated communication and socialization.

To study the ability to apply evolutionary design in gaming (Video Games), cinematography, and business, as well as research in AI, communication, and socialization. The perspective of applying this approach is based on the fact that it is too hard to create complex virtual objects in perfect form directly. Evolutionary design could offer a reliable possibility to grow perfect artificial creatures from simplest to target environments where they can act for business needs.

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НАУКОВІ ОСНОВИ, ДЕЯКІ РЕЗУЛЬТАТИ ТА ПЕРСПЕКТИВИ МОДЕЛЮВАННЯ ЕВОЛЮЦІЙНО ОБУМОВЛЕНОГО НООГЕНЕЗУ ШТУЧНИХ СТВОРІНЬ У ВІРТУАЛЬНИХ БІОЦЕНОЗАХ

Це дослідження мало на меті отримати глибоке розуміння складних цифрових екосистем віртуальних біоценозів з метою з'ясувати та відтворити появу та еволюцію інтелекту в штучних створінь, що називається ноогенезом. Було проведено комплексний аналіз існуючих досліджень у віртуальних біоценозах, щоб отримати цінну інформацію про складність моделювання динамічних екосистем, де штучні створіння беруть участь у комплексній взаємодії. Було підкреслено ключову роль нейронних мереж у формуванні адаптивної поведінки штучних створінь у цих середовищах. Ретельне дослідження методології еволюції нейронних мереж виявило еволюцію складності їхньої архітектури з часом, кульмінацією якої стало сприяння гнучкій та інтелектуальній поведінці. Однак існував брак досліджень у сфері розвитку еволюційних можливостей спілкування та співпраці у віртуальних біоценозах. У відповідь на цю прогалину була введена модель та обґрунтована шляхом імітаційних експериментів. Результати моделювання яскраво проілюстрували дивовижну здатність моделі породжувати адаптивних істот, наділених здатністю ефективно реагувати на динамічні зміни навколишнього середовища. Ці адаптивні штучні істоти показали ефективну оптимізацію споживання енергії та отримання ресурсів. Крім того, вони продемонстрували як інтелектуальні, так і фізичні трансформації, пов'язані з принципами еволюцієї та кодування, натхненними нейроеволюцією доповнених топологій. Важливо, що стало очевидним, що еволюційні процеси, властиві моделі, були нерозривно пов'язані з самим середовищем, таким чином бездоганно узгоджуючись із головною метою цього дослідження. Були окреслені майбутні напрями досліджень у цій галузі. Ці напрями забезпечили основу для подальшого дослідження еволюції штучних створінь у віртуальних біоценозах і появи передових можливостей спілкування та співпраці. Ці досягнення містять потенціал для підняття штучного життя та штучного інтелекту на новий рівень розуміння та можливостей.

Ключові слова: агентне моделювання, штучне життя, штучний інтелект, зростаючі нейронні мережі, еволюція, ноогенез, еволюційний дизайн.

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