ARTIFICIAL INTELLIGENT LIFE: A NEW PERSPECTIVE ON ARTIFICIAL GENERAL INTELLIGENCE

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ABSTRACT

We propose artificial intelligent life (AILife) as a new perspective to approach artificial general intelligence, inspired by human intelligence. Unlike the data-driven deep learning-based approaches, AILife aims at learning from the interaction with the virtual/real world, following pre-defined activities (similar to human instincts). To achieve that, AILife is composed of a neuron system to learn from interactions, a sensory system to feel the world, and actuators to perform activities. We show a toy example to explain the learning process of AILife.

1 INTRODUCTION

Artificial General Intelligence (AGI) Goertzel & Wang (2007) refers to intelligent systems that can reason, learn, and adapt to new scenarios in a way comparable to human intelligence. In the last decade, deep learning is widely regarded as one of the most promising techniques to approach AGI, because it has been successful on various tasks. AlphaGo Silver et al. (2016) beats the best human Go players, and ResNet Szegedy et al. (2017) achieves more accurate image recognition than human. Although deep learning performs impressively on single tasks, it is constantly struggling with multi-task scenarios Ruder (2017) (e.g., by experiencing catastrophic forgetting De Lange et al. (2021)). Moreover, deep learning models lack satisfactory generalization ability for rare or unseen scenarios Ribeiro et al. (2016). Thus, many researchers start to doubt if data-driven deep learning-based approaches can finally achieve AGI.

To date, human intelligence is the only general intelligence. It is built during interaction with the real world. In fact, infants instinctively explore the world by watching, touching, and crawling to perceive space and time Casasanto et al. (2010). On this basis, they gradually develop more complicated activities. Such interaction is so important that even for adults with well-developed intelligence, without interaction (by depriving sensory) for several days or even a few hours causes severe cognition disorders (e.g., disorientation, auditory/visual hallucination, and deteriorated problem-solving abilities) Sireteanu et al. (2008). This is because the interaction triggers complex communications among biological neurons, which is the basis of cognitive abilities Shine et al. (2019). Thanks to the advances in neuroscience, the basic mechanism of neuron communication has been decently revealed Hawk et al. (2018). This enables the use of the same principles to approach AGI.

Inspired by that, we propose a new perspective to approach AGI, artificial intelligent life (AILife) that develops intelligence in a way similar to human intelligence. Like the process of human learning, AILife follows pre-defined activities (similar to human instincts) to interact with virtual/real worlds. By doing so, AILife can evolve independently to solve various complicated tasks without the need for training data.

2 ARTIFICIAL INTELLIGENT LIFE

AILife develops intelligence by mimicking the learning process of human intelligence. We define AILife as an artificial life that interacts with the virtual/real world based on pre-defined activities to develop intelligence. AILife includes a neuron system to learn from interactions, a sensory system to perceive the world, and actuators to perform activities. The sensory signals and actuator actions form the input-to-output circle for the neuron system to learn, similar to the conditioned stimulus.

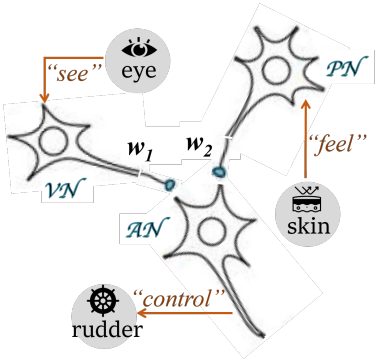

Figure 1: The neuron system of $\mathcal{P}$.

We provide a toy example (*smart pinball*) to explain AILife. We define a virtual one-dimensional world, which has two barriers. A pinball lives between barriers, and its predefined activity (instinct) is to constantly move with an invariant speed. The physical rule of this world is that barriers cannot be crossed, and thus the pinball has to change direction when hits them. We expect the pinball to be "smart" to realize this rule, so that it changes direction before hitting the barriers.

To achieve that, we design *smart pinball* ($\mathcal{P}$) based on the principle of AILife. Specifically, $\mathcal{P}$ contains: 1) a neuron system implemented by spiking neural networks (SNN) Nunes et al. (2022), which is capable of mimicking the biological learning process Taherkhani et al. (2020); 2) a sensory system that includes an "*eye*" to see a short distance in the front and a tactile "*skin*" to feel the hit; and 3) an actuator ("*rudder*") to change direction. By convention, we assume the neuron system with fixed neurons and adjustable connections Wang et al. (2020). A neuron in SNN has inputs to receive signals from other neurons and outputs to fire signals. The signals are transmitted as discrete spikes. When a neuron receives a spike from another neuron, its *membrane potential* increases, based on the weight of the connection. The neuron fires when the *membrane potential* reaches a threshold. After firing, the *membrane potential* returns to the initial value. The learning of SNN is based on Spike-Timing Dependent Plasticity (STDP) Shouval et al. (2010), which mimics the strengthen/weaken mechanism of connections among biological neurons.

The neuron system of $\mathcal{P}$ (Fig. 1) contains three neurons: 1) a vision neuron ($\mathcal{VN}$) that fires when the "*eye*" sees a barrier; 2) a pain neuron ($\mathcal{PN}$) that fires when the "*skin*" feels hitting a barrier; and 3) an action neuron ($\mathcal{AN}$) that fires with threshold δ to control the "*rudder*" to change direction. The connection of the three neurons are $\mathcal{VN} \rightarrow \mathcal{AN}$ (with weight w_1) and $\mathcal{PN} \rightarrow \mathcal{AN}$ (with weight w_2). We set the initial $w_1 \ll \delta$ assuming there is no causal relationship between vision and action in the beginning, and the initial $w_2 > \delta$ as feeling pain naturally drives $\mathcal{P}$ to change direction.

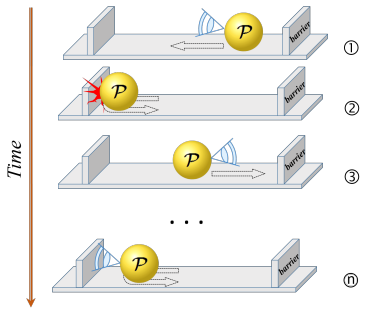

Figure 2: The learning process of $\mathcal{P}$.

The learning process of $\mathcal{P}$ is shown in Fig. 2. Initially, $\mathcal{P}$ does not know barriers cannot be crossed, even though it can see them before the hit occurs. Thus $\mathcal{P}$ keeps moving in one direction (Fig. 2 ①) till it hits a barrier. The hit causes $\mathcal{PN}$ to fire, which further causes $\mathcal{AN}$ to fire, due to $\mathcal{PN} \rightarrow \mathcal{AN}$ with large w_2; and that makes $\mathcal{P}$ change the moving direction (Fig. 2 ② and ③). The key point is that, at the same time, $\mathcal{VN}$ also fires as $\mathcal{P}$ can see the barrier in front. According to STDP, the connection $\mathcal{VN} \rightarrow \mathcal{AN}$ is strengthened (w_1 increases) because $\mathcal{VN}$ and $\mathcal{AN}$ express a causal relationship. After a few rounds, when $\mathcal{VN} \rightarrow \mathcal{AN}$ grows strong enough ($w_1 > \delta$), the firing of $\mathcal{VN}$ can cause $\mathcal{AN}$ to fire to change direction (Fig. 2 ⓝ). That means, $\mathcal{P}$ has learned to change direction when it sees a barrier.

3 Discussion

In this paper, we propose AILife as a new perspective to approach AGI. As preliminary work, we provide a toy example to explain AILife. We envision that approaching AGI in the way of AILife involves three milestones: 1) AILife can interact with more complex worlds, in order to process high-dimensional sensory feedback and perform complicated activities; 2) AILife is capable of interacting with other AILife instances and expressing social behaviors; and 3) AILife develops high-level intelligence and cognitive abilities by learning from highly abstractive information, such as language. Apart from the possibility of approaching AGI, we believe AILife can progress neuroscience. In comparison to the human brain, which has hundreds of billions of neurons, AILife provides a platform that allows for customized construction of neuron systems to discover the essential mechanism of high-level cognition and intelligence.

URM STATEMENT

The authors acknowledge that at least one key author of this work meets the URM criteria of ICLR 2023 Tiny Papers Track.

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