Bridging Neuroscience and AI: A Comprehensive Investigation of Brain-Inspired Computing Models

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Abstract. Artificial Intelligence (AI) has reached new heights, supported by advancements in hardware and algorithm theory. Areas like robotics and autonomous driving have made significant strides, but brain-inspired computing remains a distinctive field. Although there were early hopes of AI closely connecting with brain science, this integration has been minimal. Neuroscience has mostly inspired some early algorithms, while most neural networks only adopted the idea of neuron connections without fully replicating real neural signals. However, brain-inspired algorithms, such as Spiking Neural Networks (SNNs), have shown promising results, often outperforming traditional algorithms in specific tasks and offering lower power consumption. These advancements could inspire new AI models or improve existing ones. This review explores the development of successful brain-inspired algorithms, starting with the structure and function of neurons, including cerebellar structures. It then discussed spiking neural networks, their principles, and recent research, as well as cerebellar-inspired models. Finally, the article summarizes methods for building these models and their applications in fields like robotics.

1 Introduction

Since the first artificial neuron network came to the world, scientists have always been seeking for answer from human brain about how to make Artificial Intelligence (AI) perform better. Unfortunately, even though much effort has been put into this, most of the progress of nowadays' deep learning models are not direct outcomes of the neuron science research but mathematical tricks and skills to upgrade the structure and components. Also, improvement of hardware's performance also plays an important role in this.

At most case, the brain knowledge and the neuron science are served as a kind of inspiration instead of an intact way to build the whole artificial intelligence models. The reason might be that attempting to replicate the brain's structure in a computer could lead to suboptimal performance on silicon-based chips, given that the original biological structure is the result of billions of years of evolution and is finely tuned to its tasks. But this does not indicate that brain and neuroscience won't be beneficial to AI development, as nowadays Artificial Neural Networks (ANNs) can all trace back to the basic networks proposed decades

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years ago, and modern Spiking Neural Net (SNNs) can also have a better performance on some kind of tasks than ANNs. The key to how much the brain and neuroscience can do is the balance of rebuilding and model performance.

This article aims to server as a review of some kinds of brain-inspired AI techniques. Next to the first part, basic knowledge about brain and neuroscience is stated. This includes neuron's basic structures and dynamic models. Then this paper would like to introduce synapse's properties and introduce Spiking Neural Networks and applications of this kind of networks. Furthermore, other brain-inspired models will also be introduced. New applications and comparisons will be included. Imitate neuron's behavior is the most intuitive and direct ideas when coming to the brain's inspiration. In the third part it is an introduction to researches about cerebellum-like structures and their inspiration on AI models. Cerebellum-like structures include human's cerebellum and mushroom-body of insects. In most situations it's difficult to use computer to rebuilt brain's structure and recover its advanced cognitive function. This not only because till now a complete comprehension is limited (In fact, very little) of how the brain process the information and generate the cognitive activities but also a consideration about its complexity in terms of the computer. However, the brain also has different parts which in charge of different neuron system abilities. Telencephalon (including the cerebral cortex) nearly commands all the advanced cognitive activities like logical thinking as well as creation. And the cerebellum process much sub-conscious information then helps humans with balance and motor coordination. Compared to Telencephalon, cerebellum's structure is rather simple and clear. Besides, balance and coordination also play an important role in robots. Therefore, scientists try to build some cerebellum-based AI model to help settle these problems. In the fourth part it is knowledge about cerebellum-like models. The fifth part will consider the related issues including summary of how these researches can inspire people build better and practical models, the physical and mathematical conception that can help better describe the dynamic properties of neurons and finally some concrete application related to these researches.

2 Basical biological knowledge

This part provides some basic knowledge about the nervous system of human, especially the basic structure and dynamical properties of the neuron. The structure of the cerebellum is also included as a main part.

2.1 The structure of the human nervous system

Nervous system of human can be divided into two main parts: central nervous system, which includes the brain as well as spinal cord, and the remain parts of other neuros consist of the peripheral nervous system. The whole system is based on a kind of cell: neuron. And this cell can also be classified into two parts: the soma (neuron body) which mainly plays the role of receiving impulse information from other nervous cells (not only neurons because other sensory receptor cell may also generator such signals) and also generates its own never impulse. Another part is the axion which assumes the role of transmitting nerve impulses. In simple terms, nerve impulse generated from one neuron's soma is transmitted through the axion to another neuron's soma, and one neuron can be connected with more than one axon. Therefore, the information can also be transmitted in such way and one neuron can integrate them. Then with complex physiological processes the neuron can "determine" whether to continue to generate impulse.

For neural impulses, they also often called as action potentials. This is because under normal conditions, neurons maintain a relatively stable membrane potential. However, when an electrical signal stimulus changes the membrane potential to a certain extent, it will release a neural impulse, causing the potential to rise briefly and then fall back. This impulse travels along the axon. The Hodgkin-Huxley model describes this process.

What mentioned above is the basic structure and process of how the nervous system work. With these elements and their interaction, human can have consciousness and advanced cognitive activities. However, even though now a rather clear view about this system from the elements and consistence can be obtained, it is still too difficult to find how each part of the system can make difference when they active together. Therefore, most works that try to simulate and rebuilt the function of human nervous system pay more attention to change the neuron and their connection or information interaction methods, through which the whole network can more closely resemble the workings of human nervous system. And this leads to the Spiking Neural Network (SNN), which will be stated in the third section.

Though comprehensive understanding of brain seems challenging, some part of the brain can be easier to research. Cerebellum with a rather clear structure and simple impulse transmission may give an inspiration to existing Artificial Neural Network (ANN) and some related researches already have valuable outcomes. These will be stated in the 4th part.

The following contents will introduce knowledge about neuron's dynamic properties which is the base to build SNN and then the structure about cerebellum which is also the base to build related network structures.

2.2 Neuron dynamic properties

The main work about neuron's dynamic properties comes from Alan Hodgkin and Andrew Huxley in their famous Hodgkin-Huxley Model [1-3]. They carried out experiments on the squid giant axon and research their reactive to input current.

In this model, the axon with its outer ionic solution environment is considered as a circuit. The cell membrane can be modeled as capacitance. Besides, there is an ionic concentration difference across the cell membrane and this difference provide electric potential difference so that it can be modeled as power. On the membrane of the axon there are proteins named ion channel which controls the movement of ions in and out of cells to help maintain or change the inner-outer ionic concentration difference. These proteins are considered as variable resistor in the model. Then, the model describes how the membrane potential be maintained and modeled the process of how the active potential formed with dynamic differential equation.

The ion concentration difference inside and outside the neuron forms the membrane potential. Using the Nernst Equation, the potential difference corresponding to each ion can be obtained.

$$E = \frac{RT}{zF}\ln\left(\frac{[X]_{out}}{[X]_{in}}\right) \tag{1}$$

Then this is the value of the whole membrane potential：

$$V_m = \frac{RT}{F}\ln\left(\frac{P_{Na}[Na^+]_{out}+P_K[K^+]_{out}+P_{Cl}[Cl^-]_{in}}{P_{Na}[Na^+]_{in}+P_K[K^+]_{in}+P_{Cl}[Cl^-]_{out}}\right) \tag{2}$$

R, T, F, P_{Na}, P_K, P_{Cl} are constant. And the parentheses represent the concentration of the corresponding ions inside and outside the membrane (indicated by subscripts). In the absence of neural impulses and external currents, according to the circuit model, there should be:

$$c\frac{dV_m}{dt} = -g_{cl}(V_m - E_{cl}) - g_k(V_m - E_k) - g_{Na}(V_M - E_{Na}) \tag{3}$$

The variable c represents the capacitance of the cell membrane, and V_m is the membrane potential obtained earlier. The variable g represents the conductance of the ion channels corresponding to each ion.

For an action potential, the membrane potential no longer maintains a stable state. When a sufficiently high neural impulse is received, the ion channel proteins change, causing the ion concentrations inside and outside the membrane to change accordingly. At this time, the conductance of each ion channel in the equation changes and can be modeled as a function of the potential difference.

2.3 Structure of cerebellum

If someone wants to have a model that focuses on a higher level, the cerebellum is a wise choice. Generally speaking, when trying to rebuild the function of such an organ, it's useful to pay more attention on the abstract structure than the detail anatomical structure. Fortunately, cerebellum is mainly formed of a large number of repetitive units which can be abstracted to a circuit.

This circuit starts from the mossy fibers which are the axons from the cerebral cortex, spin cord or other nervous structures. These axons are connected with granule cells. The grannle cell has an axon with a considerable length, and there cells's axons form the parallel fibers, just like its name, these fibers are lined parallel. Another kind of neuron in the unit named Purkinje cell, which has a dendritic tree branching very profusely, is connected with many parallel fibers and receives their synaptic inputs. And finally, Purkinje cells' axons projects to the deep part of the cerebellum. Notably, the Purkinje cell has a very large number of branches which may indicate they have the capability of integration of information [4].

Cerebellum play an important role in human's activity precision and body balance maintenance [5], which may help inspire better idea of robot learning algorithms. Besides, cerebellum's also relates to human's advanced cognitive function [6].

3 Preliminaries of spiking neural net

This part concentrate on the basic concepts, structure, and development of the SNN.

SNN is firstly proposed as the 3rd generation of neural network models. As for the first generation of neural network, it's based on the McCulloch-Pitts neurons as computational units (can also be refereed to perceptrons) and can be universal for computations with digital input and output, and the second generation is based on computation units applying an "activation function" with a continuous set of possible output values to a weighted sum of inputs. Most of latter developed neuron networks are from this generation. Along with such kind of networks, learning algorithm with backprop is developed and have a good performance.

Then it comes to the SNN. Compared with former two kinds of networks, this kind of network put the imitation of nature neuron structure deeper. This is reflected in the inclusion of neuron spiking activity. A neuron unit in such a model will produce a spiking when its potential P_v reaches a certain threshold. This potential is the sum of so-called excitatory postsynaptic potentials ("EPSPs") and inhibitory postsynaptic potentials ("IPSPs"), which is the result of other neuron units' spiking. Consider two neurons u with its axon connected to v , the spiking of **u** contribute to the potential of v is $P_v = w_{u,v}\varepsilon_{u,v}(t - s)$, where $w_{u,v}$ is a weight ≥0 and $\varepsilon_{u,v}(t - s)$ is the response function. The weight w reflects the strength of connection between two neurons and can be analogous to the weight in ANNs in some degree.

For a spiking in a neuron of SNN, it depends on the threshold function $\Theta_v(t)$, this function defines the threshold with time. However, the neuron has a property that if it has fired at time **t'**, then it will not fire again for a few msec after **t'**, no matter how large its current potential P_v is. Then for a few further msec it is still "reluctant" to fire. To model this, the threshold function can be upgraded to $\Theta_v(t - t')$, where the **t'** is the time the most recent firing of this neuron. Then the value of this function can be manipulated (e.x. using the Hodgkin-Huxley model's dynamical equation or its simplified form) to fit the properties of a real neuron mentioned above. A typical shape of threshold function is shown in Fig. 1.

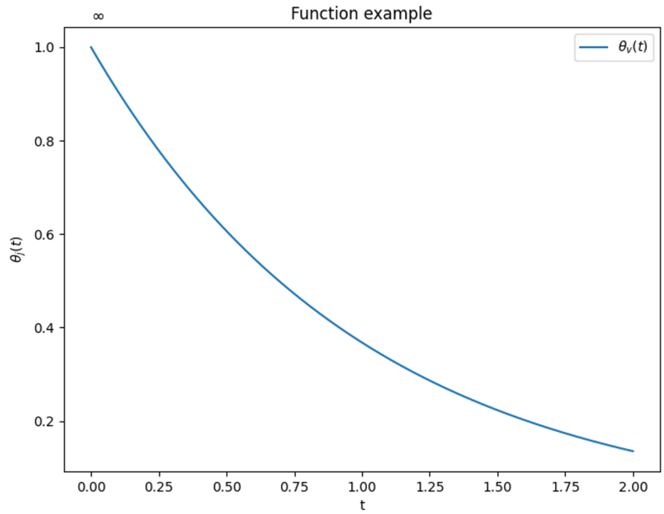

Fig. 1. An example of function Θ (The initial value of this function needs to be set high enough. And the final value is near 0) (Photo/Picture credit: Original).

A formal model can be sated as below: A finite set V of spiking neurons, a set $E \subseteq V \times V$ of synapses, a weight $w_{u,v} \geq 0$, response function $\varepsilon_{u,v}: R^+ \quad R$ for each synapse $< u, v > \in E$ and a threshold function $\Theta_v \; R^+ \quad R$ for each $v \in E$. These neurons can also be gathered to build layers then come into a network [7].

Although this model made a progress on imitation to nervous system, there are still lots of works to do to address its inherent problems. Two of them play major roles: First is about how to train such a network. As it has been stated, the threshold function is a non-differentiable function, which means that it can't directly apply traditional gradient descent backpropagation to train a model. Besides, other complex dynamic properties also make it too difficult to compute such kind of model. Second, an algorithm that behaves rather efficiently on training may ignore the inner connection between the time and space and pay more attention to one side, which won't play out the advantage of SNNs.

There are mainly three kinds of methods to train SNNs: (1) unsupervised learning, which uses the idea of weight modification in biological synapses but performs not well. (2) indirect supervised learning, which firstly trains an ANN, and thereupon transforms it into its SNN version with the same network structure where the rate of SNN neurons acts as the analogy activity of ANN neurons. (3) direct supervised learning, which tries to overcome the obstacles mentioned above and find a way to apply modified descent backpropagation to train the model.

Generally speaking, the third king of method has a greater chance to have a better performance to train a comprehensively well-behaved model. In a work trying to improve the spatial domain and temporal domain comprehensive information use, the widely used simplified SNN neuron model:

$$\tau \frac{du(t)}{dt} = -u(t) + I(t) \tag{4}$$

where $u(t)$ is current potential and $I(t)$ is input current, is modified to the:

$$u(t) = u(t_{i-1}) e^{\frac{t_{i-1}-t}{\tau}} + \hat{I}(t) \tag{5}$$

Therefore, it can transform the original linear differential equation into a kind of iteration one, which greatly descends its computation complex. Besides, it also modified the connected part. The input integration of this part is the sum of all the output current of current timestep from neurons connected to this neuron multiplied by a weight w. Then, replace $\hat{I}(t)$ in equation (5) with this integration and the outcome potential of next iteration of current neuron can be obtained. And the next step, compare the potential $u(t)$ with threshold to decide whether fire an impulse or not. This fire will help next neuron's iteration.

Through this way the model can make better use of both the spatial domain and temporal domain properties of SNN. This model makes a better performance than most of the previous methods on the dynamic dataset test, which can provide rich time-related information [8].

Based on this work, the model is further developed in a way that expands the range of traditional normalization operation, which applies the normalization on the time dimension. Besides, it also conducts the normalization depending on the threshold of the spiking neuron to balance the threshold and the pre-synaptic inputs. Finally, the model can reach a performance better than all the previous performance on the dataset ImageNet [9].

Recent years, there are also many kinds of strategies concentrating on the overall structure of SNNs. Shrinking SNN (SSNN) is a model which uses a main strategy called timestep shrinkage to decrease the network's latency then achieve highly efficient. This strategy divides the SNN into Multiple stages, and the timestep is shrinking with each stage. In the former stages, the time step is rather big, which can extract enough comprehensive information. Then in the latter stages the time step becomes shorter, but as there is enough information get in the former stage, it can also have a good performance with a shorter total latency [10].

4 Preliminaries of cerebellum-based models

For the cerebellum, there are also different models concentrating on different properties of this organ.

4.1 Control system model

First there is a kind of model that stresses the advanced control ability to accomplish comprehensive movement of the cerebellum, which usually combined with System Control science and techniques. In such models, cerebellum' s separate structure will correspond to the phase space of a dynamical system and synapses of neurons will help transfer the information as well as compute them.

Here is a concrete example of such model [11]: In this model, the parallel fibers with its Granular cell bodies can represent the parameters in the phase space of dynamical systems, and the Golgi cell can transmit this information on parallel fibers to the body of other Granular cell, which can help this cell refine the parameter value it represents. Purkinje cells play the role of transmitting the phase space data represented by the parallel fibers to the actuators like limbs of organisms.

This work uses a second-order control system to demonstrate its model. In such a system, there are 3 variables: x, $\dot{x}$, $\ddot{x}$, each variable is represented by a Granular cell and it axon, the parallel fiber. With the Hamilton' s theory about the dynamical system, the change of these 3 variables can be determined by a iteration form: $x_{i+1} = x_i + \dot{x}_i$, $\dot{x}_{i+1} = \dot{x}_i + \ddot{x}_i$, $\ddot{x}_{i+1} = -w^2 x_i$. There are 3 Golgi cell help this iteration by transmit each parallel fiber's signal to corresponding Granular cell body. Besides, the Granular cell that transmit x to $\ddot{x}$ will also consider the coefficient w^2 and transmit the data computed with it to the cell body. And Purkinje cells will integrate the information of parallel fibers, which will finally reach the actuator like musule of limbs. As for the mossy fibers, which is a main source of the input to

Granular cell, will help computing the system state's iteration and in charge of clocks in this model.

It is rather obvious that this model stresses the feedforward mechanism compared to traditional feedback mechanism like Backpropagation. In this way it may lack the ability to conduct complex learning tasks.

4.2 Pattern separation model

The second kind of model will focus on the separation ability of cerebellum-like structure, which can help solve a general problem of learning and memory networks: pattern separation [12]. Actually, this cerebellum-like structure is the mushroom body in the Drosophila which has been thoroughly researched due to the simple behavior of Drosophila and its smaller scale compared to cerebellum. Like the basic structure of cerebellum, it also has input transmitted to a parallel axons structure. What makes it suitable to separation is that the amount of these parallel neurons is far richer than the inputs. In the mushroom body of Drosophila, there are 50 inputs, but they project to 2000 neurons. In this way, it has the ability to separate the similar input data into different ones by a dimensionality lifting operation (compared with the dimensionality reduction in other king of ANNs).

A classic example of this kind of model is the Cerebellar Model Articulation Controller (CMAC) model [13]. In this model, each element in the input space will project to more than one element in a middle layer whose space is larger than the inputs. Different inputs will project to different middle element sets but can share some of the elements. Take a concrete example: input S_1 projects to m_1, m_4, m_7 and inputS_2 projects to m_1, m_3, m_7. The middle layer sets of these two inputs can be distinguished as they are not completely same, but both projects to $m_1$and$m_7$in the middle layer.

In such a model, not only the input information can be specified in the middle layer but also their association information is also stored in it. Thus, this kind of structure and its model may help develop learning algorithms that better suit association learning or contribute to new information processing techniques.

4.3 Reinforcement model

Reinforcement progress is very common in human body, especially in the nervous system. Definitely, the cerebellum and Mushroom body also have such reinforcement progress.

In the cerebellum-like Mushroom body, the reinforcement process is conducted by the Dopaminergic neurons (DANs) with dopamine transmission. Dopamine will help manipulate the connection strength of synapses between the parallel axons and the final output neurons, which represents reward information [12].

But this process seems to be rather complex, and the progress of how the information in the parallel axons be integrated in the output neurons still need further research to completely understand this. It is supposed that such research may contribute to reinforcement learning based on cerebellum-like structure.

Well-developed AI model basing on dopamine system hasn't come out, but there are related researches to this concept: Researchers from DeepMind found the relationship between the distributed reinforcement learning and dopamine-reward system. This research shows evidence for a neural realization of distributional reinforcement learning [14]. Furthermore, another investigation also conducted an in-depth analysis of the connections between the reinforcement learning and biological basement [14].

5 Discussion

5.1 Model building

This article shows a way from the basic elements in the Nervous System to the model basing on the dynamical properties of single neuron then the model basing on a higher level of structure-the cerebellum.

Just like other kind of mathematical models, it is necessary to consider which kind of part should be included or detailed reproduction, and which part that should simplify of juts omit them due to the computational complexity or generalization. Then determining the key factors for conducting this becomes crucial, and it is vital to analyze them based on existing models.

As it has been stated before, if completely rebuild the Hodgkin-Huxley model, the computation consumption is very huge. There are higher-order variables with the exponent of 3 or 4 and there are also complex differential equations. Generally speaking, using a computer to simulate such a system cannot match the efficiency of the original system, as the simulation is based on a completely different platform, lacking many of the system's intrinsic dynamic characteristics. However, when considering AI application, the purpose is never loyally stimulating such one-to-one restored model like what the biology scientists do. What matters is that whether it is possible to abstract basic rules about intelligence and what structure or what process contribute to such intelligence. Convolutional Neural Networks (CNN), for example, originated from researches related to the visual system which discovers receptive fields and feature extraction process. Basing on this work, Fukushima proposed the first network with convolution and pooling operation. Then, with other effort towards model improvement and training efficiency refinement, nowadays CNNs can perform better than human on certain tasks. It is obvious that certain tasks like feature extraction of the visual system don't need to be conducted on organism. It is the system's structure that matters.

This will help guidance how to better build a practical model from organism body: one can first simplify the original description with detailed biological properties and abstract the most obvious parts of them. As for what parts can be considered as obvious, take the SNNs as example: models retain the concept of impulse: a sudden change of membrane potential, and this change is caused by other cell's impulse transmitted here, thus a network can be built. As for the detailed information of the impulse and membrane potential change, like how long the impulse will remain, which level of voltage the potential will get or the speed of potential's rise and decline during the impulse, these elements won't be pay much attention or just ignored in the model. Therefore, a clear structure has remained. Then, as stated in part 2, similar to the development of CNNs, more effort was put on finding a better way to train such a model.

The model building of cerebellum can also reflect such a rule. These organs contain so many kinds of elements, even it has a rather clear and repetitive structure, they also consist of different kinds of neuron with different properties. If rebuilding them completely with the HH model, it is easy to imagine the complexity. Conversely, it is the sparse coding network and the dimensionality increase, which do not dependent on a specific physiological structure, that determines parts of the separation ability of cerebellum. Therefore, it is possible to just build network resembling the structure and then shift to mathematically refine it, which would result in a practical model.

5.2 Physical method

This part will discuss the mathematics usage in the model.

Though it is obvious that computers more fits linear computation than nonlinear computation, nonlinear dynamics can better describe the dynamical properties of neurons. Even though in the last part it is stated that building a model with such a detailed description can be unpractical, it is still useful to learn about related knowledge.

The core of neuron dynamic system is a mathematical conception named Attractor. Attractor is used to describe the final stable states of a dynamic system. For example: If throwing a little ball into a bowl, it will first move along the wall of the bowl, but finally enter the state of staying at the bottom of the bowl quietly. This state in the dynamic system of the ball with the bowl is an attractor, as no matter how you throw the ball and how the initial state could be, it will all be 'attract' to this stable state. Besides, attractors also have different sorts. Another kind of attractor is like gravitational capture, when a celestial body pass by another body with huge mass, there is a chance that this small body will be captured and rolls with an elliptical orbit around the massive one. If there is no energy consumption, this state will remain, and different from the still ball in the bowl, there is also movement in this system.

Back to the nervous system, attractors also exist in this dynamic system. Even though the action potential of neurons is widely known, the firing patterns of different neurons in different situations or with different kinds of stimulation also differ. All of this reaction can be considered as a deviation from an attractor with outer influence and then back to one kind of attractor.

Therefore, it can inspire the idea that even though existing computer systems may not fit such kind of computation, is it possible to build hardware elements that fit the dynamic systems with attractors? In this way, it's not necessary to conduct approximation of the dynamic system, in which situation developing a system consists of elements resembling the exact attractors can reach a better simulation and efficient performance of brain-inspired AI models.

5.3 Applications

This part is about application of brain-inspired AI models.

Benefiting from its dynamical properties, SNNs especially fit some kind of timing dynamic issues. There is a work that gets inspiration from SNNs and further invites a model named Continuous Integrate-and-Fire (CIF) to address automatic speech recognition problems [15], which achieves a word error rate of 2.86%.

Robot related intelligence also represents one of the files with a wide range of applications of brain- inspired methods. In the control system part, there are methods based on the excitation properties of muscle. This model [16] utilizes both phasic and tonic muscle synergies to characterize the coupling relationship of the structure and function among muscles more sufficiently and then designs a radial basis function neural network to modulate muscle synergies. With the similarity to the structure of the nervous system, this model behaves well on the tasks of learning generalization and robustness. There are also control or decision-making models learning from cerebellum. This work [17] also provides a model based on cerebellum, it builds an echo state network to achieve a feedforward regulation. This model also shows significant improvement in learning efficiency and robustness.

Another beneficial application is reinforcement learning. This work [18] proposes a model, which has a population-coded spiking actor network trained in conjunction with a deep critic network using deep reinforcement learning. The performance of this model shows its population coding scheme inspired by brain structure will increase the representation capacity of the network. Besides, it also combines the efficiency advantage of SNNs and training strength of deep reinforcement learning. If considering a higher level than basic neurons, this model named BIMR [19] has a novel multi-layer architecture along with brain-inspired memory module helping agents quickly adapt to new tasks within a few episodes than traditional methods.

Reviewing these models, it also provides an idea about the application of brain-inspired models: try to improve or refine existing AI models with porting brain-inspired computation models. Like the BIMR, it tries to use brain-inspired methods to help improve deep reinforcement learning. This may help reduce the workload and make it more practical to build the model.

6 Conclusion

The advancements in brain-inspired computing demonstrate the potential to bridge the gap between biological systems and technological models. While artificial intelligence has mostly relied on mathematical techniques and hardware improvements, brain-inspired algorithms like SNNs offer a more biologically aligned approach, showing efficiency in specific tasks such as low power consumption. These models, despite not fully replicating brain functions, have drawn useful inspiration from neuroscience. By further exploring the structure and behavior of neural systems, such as cerebellum-like models, researchers can develop more sophisticated and efficient AI applications, particularly in areas like robotics and reinforcement learning. These developments open up new avenues for creating algorithms that mimic the complex dynamics of the human brain, offering promising improvements for AI models.

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