Memristor-based Bionic Decision-making Circuit Inspired by Self-awareness

Zilu Wang (wangzilu@hit.edu.cn)
School of Mechanical Engineering and Automation
Harbin Institute of Technology (Shenzhen)
Shenzhen, 518055 China

Abstract

Advancing intelligent systems requires efficient computational architectures built on emerging electronic computing devices, as well as effective biomimetic function simulation to improve overall intelligence. Here we design a memristor-based circuit inspired by self-awareness concepts. It effectively achieves bionic adaptive decision-making by mimicking habituation learning mechanisms. Memristors serve as foundational units in the circuit, facilitating the simulation of functions akin to biological neurons and synapses. They help implement key features such as information filtering, integration, and synaptic plasticity through concise circuit structures and efficient computing methods. Experimental results indicate that our circuit is capable of rapid and efficient information processing through in-memory analog computing, and it can make more reasonable and intelligent adaptive decisions by incorporating self-awareness concepts and biomimetic mechanisms. Extending this work to large-scale decision-making systems holds potential for intelligent platforms aiming to achieve advanced cognitive capabilities.

Keywords: self-awareness; memristor; bionic circuit; adaptive decision-making; habituation learning

Introduction

The recent advancements in Artificial Intelligence (AI) have largely focused on leveraging efficient, high-speed computation to replicate bionic perception and cognitive functions. However, more research is required to simulate advanced cognitive abilities, such as intelligent learning, decision-making, and reasoning (Xie, 2023; Kugele & Franklin, 2020). Achieving such intelligent functions often entails high energy consumption, in stark contrast to the biological brain's capacity to perform intelligent behaviors with ultra-low power usage (Kaushik, Akhilesh, & Priyadarshini, 2019). Thus, there is a need to find an effective way to achieve more efficient and biomimetic cognitive function simulations.

Memristors, as emerging two-terminal elements, have shown potential in implementing novel compute-in-memory architectures due to their inherent in-memory computing characteristics (Zhang et al., 2020). Their biomimetic properties, such as memory capacity and plasticity, demonstrate advantages in simulating biological neural network structures (S. Chen, Zhang, Tappertzhofen, Yang, & Valov, 2023) like neurons, synapses, etc. In light of this, researching an appropriate approach to map the realization of these cognitive functions onto memristor-based computational modules or hardware circuits is expected to lead to the effective achievement of more advanced biomimetic functionalities.

The self-aware computational framework (Lewis et al., 2015), an architecture inspired by the concept of self-awareness in psychology, is a promising approach that can guide the aforementioned mapping. Self-awareness is a fundamental concept in psychology refers to an individual's ability to reflect upon and recognize their own thoughts, emotions, and behaviors (Diener & Srull, 1979; Morin, 2006). When endowing computational systems with capabilities such as adaptability, autonomy, etc., concepts of self-awareness are often involved (Schlatow et al., 2017; Elhabbash, Salama, Bahsoon, & Tino, 2019). That is, by integrating the self-awareness concepts into a unified framework, AI systems that are not only more capable and adaptive but also more transparent and reliable can be created. This will ultimately enhance human-AI collaboration and provide valuable insights for future research on more biomimetic and efficient intelligent systems. As a result, by incorporating the self-aware computational framework into the design of memristor-based biomimetic functional circuits (Xia & Yang, 2019; Zhang et al., 2020), it is possible to realize an intelligent system that possesses both efficient computational capabilities and reliable biomimetic functionalities. Therefore, in this work:

1) Inspired by the concept of self-awareness in psychology and incorporating the self-aware computational framework, we implement an adaptive decision-making circuit using a bionic circuit design approach based on memristors.

2) A habituation learning mechanism is introduced in our circuit supported by the memristor-based bionic modules at the underlying circuit, aimed at delivering more efficient and reasonable intelligent decision-making.

3) Experimental results show that our circuit can adaptively make intelligent decisions during task execution. It also excels in processing speed, hardware overhead, and power consumption thanks to the in-memory analog computing capabilities of the underlying memristive circuit.

Non-volatile Memristor Model

As an important member of the emerging non-volatile memory, memristor is a two-terminal ionic device that uses resistance states to represent information (J. J. Yang, Strukov, & Stewart, 2013). It possesses rich switching dynamics which make it a suitable element to mimic the functions of neurons and synapses in the biological neural network (S. Chen et al., 2023). Additionally, it exhibits inherent capabilities such as

In L. K. Samuelson, S. L. Frank, M. Toneva, A. Mackey, & E. Hazeltine (Eds.), *Proceedings of the 46th Annual Conference of the Cognitive Science Society.*

computing-in-memory and analog computing, enabling the realization of efficient parallel in-memory analog computing systems (X. Yang, Taylor, Wu, Chen, & Chua, 2022).

Since HP Laboratory first presented the TiO_2 memristor model (Biolek, Biolek, & Biolkova, 2009), there emerged various physical and mathematical memristor models such as metal-oxide memristor model (Prezioso et al., 2015), *VTEAM* model (Kvatinsky, Ramadan, Friedman, & Kolodny, 2015), etc. But these models cannot well describe the information integration or weight plasticity of neurons or synapses in biological neural networks (Wang, Hong, & Wang, 2019). Therefore, a non-volatile memristor (*NVM*) model is used (Z. Chen, Zhang, Wen, Li, & Hong, 2021) in our work, which matches the conductive property of the AgInSbTe memristor (Li et al., 2014). Compared with the above memristor models, the *NVM* model can be used to mimic synaptic behavior based on resistance plasticity, and can also simulate behaviors of neurons such as information integration and filtering by using memory and threshold features. Thus, by referring to the structure and mechanism of the biological neural network, this *NVM* model is beneficial for simulating corresponding bionic functions in the following decision-making circuit, while also providing efficient in-memory analog computing capability. Of course, other memristor models with similar functions as above are also suitable for the design of our circuit. The *i*-*v* relationship of this *NVM* model can be described as the following (Z. Chen et al., 2021):

$$v(t) = (R_{off} - x \cdot \triangle R) \cdot i(t), \tag{1}$$

where the state variable x is a normalized width of the conducting layer, whose derivative is matched to memristor current-voltage data, and its range is [0, 1]. In addition, $\triangle$R=(R_{off}-R_{on}), R_{off} and R_{on} indicate the maximum resistance and minimum resistance of the memristor, that is, the bounds of device resistance. And the corresponding state variable is x=1 and x=0. Therefore, the derivative of the state variable x can be expressed as follows:

$$\frac{dx}{dt} = \begin{cases} k_{on} \cdot \triangle R \cdot i(t) \cdot f(x), & v(t) > v_{on}, \\ 0, & v_{off} \leq v(t) \leq v_{on}, \\ k_{off} \cdot \triangle R \cdot i(t) \cdot f(x), & v(t) < v_{off}, \end{cases} \tag{2}$$

$$f(x) = \begin{cases} (a_{on} \cdot (1-x))^{p_{on}}, & v(t) > 0, \\ (a_{off} \cdot x)^{p_{off}}, & v(t) \leq 0, \end{cases} \tag{3}$$

where $f(x)$ is a speed adaptive state variable function. v_{on} and v_{off} represent positive and negative threshold voltages, only when the applied input voltage meets the threshold condition, the state of the memristor will be changed. a_{on}, a_{off}, p_{on} and p_{off} are scaling parameters, which determine the indirect effect drift speed. k_{on} and k_{off} represent the average ion mobility of oxygen vacancies, similar to μ_v in HP model (Biolek et al., 2009).

Based on the roles of above parameters in *NVM* model and the functions to be realized in our decision-making circuit, the parameter settings of *NVM* model are shown in Table 1. The detailed uses of these two kinds of parameter settings of *NVM* model in Table 1 will be introduced in the following section.

Table 1: The Parameter Settings of *NVM* Model

Parameters	a_{on}	a_{off}	k_{on}	k_{off}	p_{on}	p_{off}	$V_{on}(V)$	$V_{off}(V)$	$R_{on}(\Omega)$	$R_{off}(\Omega)$
Setting1	80	80	10	100	1.9	1.2	0.6	-0.6	1e2	5e3
Setting2	30	30	10	100	1.9	1.2	0.6	-0.6	1e2	5e3

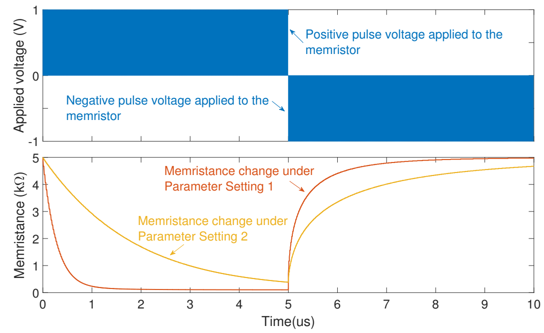

Figure 1: Memristances change of *NVM* model with two kinds of parameter settings. The orange and yellow curves indicate the change of memristances based on the parameters of *Setting1* and *Setting2* in Table 1 respectively. The blue curve represents the pulse that applied to the memristor.

The memristance change curves of *NVM* model under parameter settings in Table 1 are shown in Figure 1. When the memristor is applied to a positive pulse that satisfies the threshold condition voltage (V_{on}), the resistance of the memristor starts to drop and stabilizes when it reaches R_{on}. After that, a negative pulse that satisfies the threshold condition (V_{off}) is applied at 5μs, and the resistance of the memristor begins to rise to R_{off} to stabilize. Therefore, the resistance of memristor can be written to an appropriate value by controlling the duration of the applied input pulse across the memristor. The orange and yellow curves in Figure 1 correspond to the parameters of *Setting1* and *Setting2* in Table 1 respectively, which reflect that different parameter settings can change the memristance change rate of the memristor, and can be used to realize corresponding functions in the following circuit.

Memristor-based Bionic Circuit Design

In real-life driving, drivers can quickly decide how to avoid obstacles based on their perceptions and past experiences. Inspired by this scenario and functionality, we have implemented a memristor-based circuit based on the self-aware computational framework (Lewis et al., 2015). This circuit can adaptively learn and make reasonable decisions based on the corresponding perception information, guiding the car to successfully avoid obstacles. The scenario schematic and specific circuit are shown in Figures 2-4.

In the scenario depicted in Figure 2, we have set up a task where a smart car equipped with decision-making circuit modules enters a circular area and needs to make decisions based on distance information perceived by the front sensor. The smart car controls actions such as advancing, reversing,

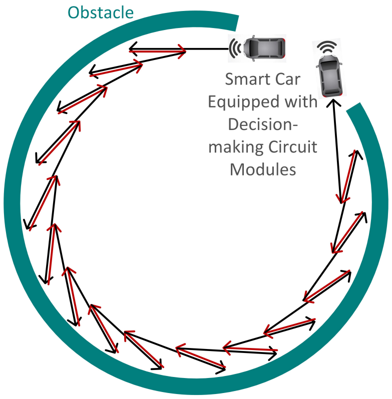

Figure 2: The schematic of the scene for a smart car obstacle avoidance navigation (*Experiment 1*). The smart car is equipped with decision-making circuit modules, so as to make decisions adaptively based on the corresponding perception information. The circuit implementation is shown in Figure 3, it can adaptively learn and make reasonable decisions based on the perceived distance information between car and obstacle, thereby guiding the car to navigate out of the circular area.

and changing direction in order to gradually navigate out of the circular area. Specifically, once the smart car enters the circular region, it will first be guided to move forward. Its front distance sensor continuously detects the distance to the obstacle ahead. When the smart car is about to hit the circular wall, it will first be guided to back up a certain distance, then the steering gear will control the car's direction to make it rotate counterclockwise by a certain angle. After this, the drive will continue to guide the smart car to move forward. This cycle repeats until the car exits the circular area.

As shown in Figure 3, the overall decision-making circuit is designed based on the self-aware computational framework (Lewis et al., 2015). *Modules 1-5*, highlighted in dashed boxes of different colors, represent modular circuits inspired by corresponding elements of the framework. The *stimulus awareness element* (i.e., inspiring the design of *Module 1*) is modeled after the dendritic neuron structures in Biological Neural Networks (BNNs), which is used to filter, integrate, and process analog signals from external sensors into spiking signals circulating within the system. The *time awareness element* (i.e., inspiring the design of *Module 4*) is based on soma/axon structures in BNNs, performs spatio-temporal fusion of external and internal feedback information. This enables the system to learn from historical events and predict future occurrences. The *interaction awareness element* (i.e., inspiring the design of *Module 2*) draws inspiration from synapse structures in BNNs, processes external and internal feedback information using brain-inspired learning rules. The *self-expression element* (i.e., inspiring the design of *Module 3*) generates intelligent decision outputs based on task objectives and the processed information from previous elements, aided by external processors. It is inspired by neuron structures in BNNs. The *internal actuator element* (i.e., inspiring the design of *Module 5*) processes signals from the *self-expression element* and feeds them back to the other three elements/modules to complete system-level tasks, functioning similarly to synapse structures in BNNs.

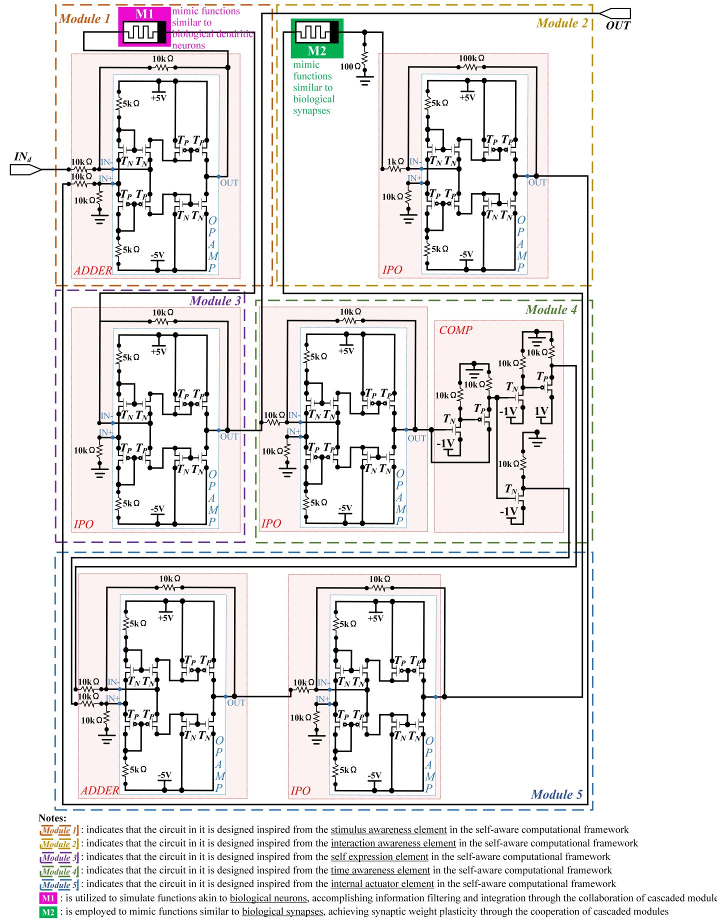

Figure 3: The schematic of the memristor-based decision-making circuit. Inspired from the self-awareness in psychology, the overall design of our circuit follows the self-aware computational framework (Lewis et al., 2015). Memristors *M1* and *M2*, through collaboration with their respective cascaded modules, simulate functions akin to biological dendritic neurons and synapses. This enables the circuit to achieve the required bionic functionalities with a concise circuit structure and efficient in-memory analog computing. In this way, a bionic habituation learning mechanism can be easily introduced. That is, by adjusting the parameter settings of *M1* and *M2*, the circuit can enter a state of habituation learning, resulting in more intelligent navigation trajectories as shown in Figure 4.

Memristors *M1* and *M2* are used to simulate functions similar to biological dendritic neurons and synapses respectively. When combined with related modules, they enable the circuit to process information, learn, and make decisions. This is achieved through a concise circuit structure and efficient in-memory analog computing. In addition, we also introduced

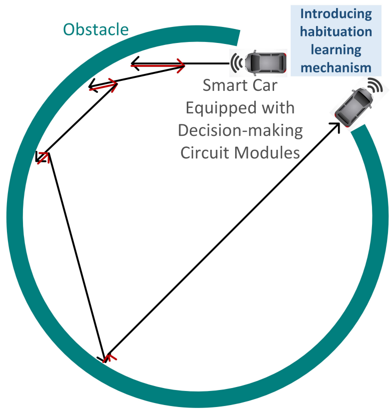

Figure 4: The schematic of the scene for a smart car obstacle avoidance navigation (*Experiment 2*). The habituation learning mechanism in there is introduced, which can more intelligently guide the smart car to drive out of the circular areas. In other words, after executing several cycles of "forward-backward-turn" operations, it appears to realize that it is in a circular area. As a result, the car no longer explores along the wall but instead reverses for a shorter distance and turns at a larger angle, thereby quickly exiting the circular area.

a bionic habituation learning mechanism (Boisseau, Vogel, & Dussutour, 2016) in the circuit. This means that by adjusting the parameter settings of the memristors *M1* and *M2*, the circuit can enter a state of habituation learning easily. The habituation learning posits that organisms will gradually adapt to repeated similar stimuli, becoming less sensitive than when they first encountered such stimuli. Specifically, we take the signals from the distance sensor as the circuit's input (i.e., IN_d signal in Figure 3). When the smart car continuously checks the distance while navigating around the circular area, the circuit repeatedly receives similar stimuli. With the introduction of habituation learning, the circuit's output gradually reflects this habituation to the input information, that is, the circuit's output (i.e., *OUT* signal in Figure 3) will gradually decrease. Since we control the car's backing distance and turning angle based on the strength of the circuit's output signal, the introduction of habituation learning will cause the corresponding output signal strength to gradually decrease when the circuit repeatedly receives similar stimuli. As a result, the car's trajectory during circular navigation will become more intelligent, as shown in Figure 4.

The circuit schematic shown in Figure 3 involves three discrete components: memristors, transistors, and resistors. The memristors used in the circuit are the *NVM* model mentioned in above section, where the parameter setting for the memristor *M1* is specified as *Setting1* in Table 1, and for *M2* as *Setting2* in Table 1. The introduction of habituation learning mechanism by adjusting the parameter settings of memristors *M1* and *M2* primarily involves tuning the parameters V_{on}, V_{off}, etc., as indicated in Table 1, which leads to corresponding changes in memristance. The specific parameter settings should be adjusted based on the desired degree of habituation learning and the current state of the circuit, among other circuit factors. The transistor models primarily consist of T_N (*N-channel enhancement type*, e.g., 2N7000) and T_P (*P-channel enhancement type*, e.g., 2N6806). The remaining components are resistors, whose parameter settings are determined based on the desired computational functions to be implemented. These functions mainly include *IPO* (Inverse Proportional Operation), *ADDER* (Addition Operation), *COMP* (Voltage comparator), and others shown in Figure 3. These functions are achieved through the collaboration between transistors and resistors, which are utilized to implement the corresponding peripheral circuits to assist the relevant memristor-based circuit modules in performing the required bionic functions. Additionally, the parameter settings of resistors in Figure 3 also consider the resistance range of the associated memristors, compatibility with transistor components, and overall power consumption of the circuit.

Experimental Result and Analysis

We first conduct *Experiment 1* without introducing the habituation learning mechanism into our implemented decision-making circuit. As shown in Figure 2, a smart car enters a circular area and needs to navigate and avoid obstacles under the guidance of the equipped decision-making circuit modules in order to exit the circular area. Assuming the diameter of this circular ring is 10 meters, if we follow conventional thinking (i.e., without introducing the habituation learning mechanism), the car will adaptively navigate and avoid obstacles along the path shown in Figure 2.

Specifically, as the car starts moving, the distance sensor mounted on the front of the car continuously detects distance information. When it reaches the predefined threshold (i.e., the distance between the car's front and the circular wall is smaller than our defined safety distance), the sensor generates a fixed-duration spiking pulse signal (as shown in the small figure on the right of the upper subgraph in Figure 5(a)) to engage the car's motor and apply brakes, thus preventing the car from colliding with the circular wall. Simultaneously, this spiking pulse signal is input to the equipped decision-making circuit for processing. Based on the output signal of the circuit (as shown in the lower subgraph in Figure 5(a)), the car's motor controls the car to reverse a corresponding distance, and after completing the backward movement, the circuit further controls the steering servo to turn the car at the appropriate angle. This completes the first round of "forward-backward-turn" actions.

Subsequently, the distance sensor of the car is reset, the spiking pulse signal disappears, and the car's motor continues to control the car to move forward under the guidance of the equipped decision-making circuit. The process repeats the similar "forward-backward-turn" actions of the first round until the car successfully exits the circular area. As shown in the lower subgraph in Figure 5(a), we can observe that the output intensity generated by our circuit is similar every time it receives a spiking pulse signal from the distance sensor.

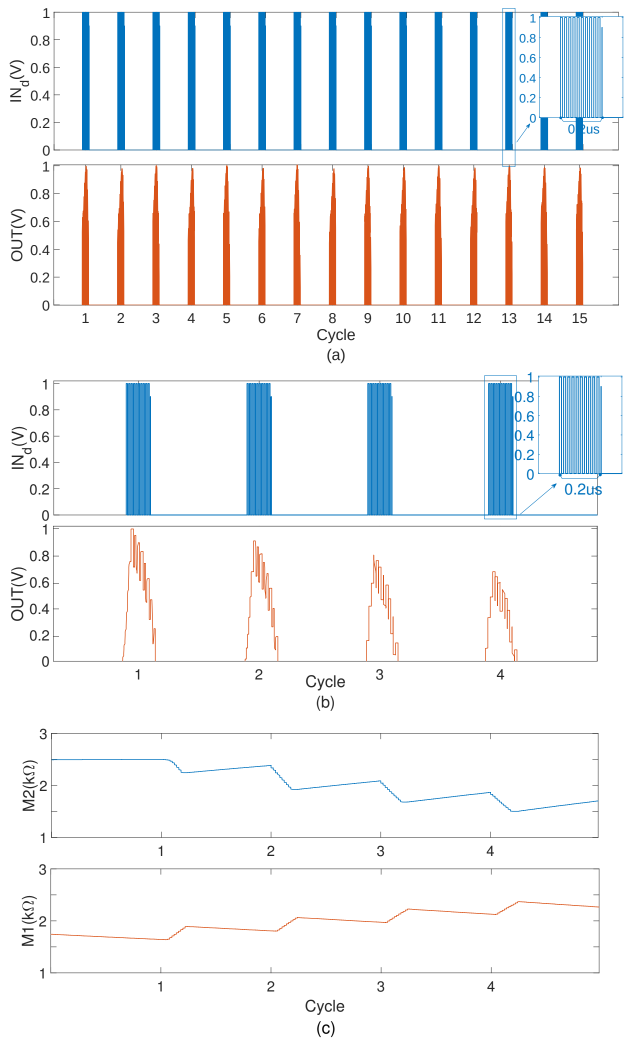

Figure 5: The experimental results of the decision-making circuit for the scene of the smart car avoidance navigation. (a). The results of *Experiment 1*, where the habituation learning mechanism is not introduced in the circuit. (b). The results of *Experiment 2*, where the habituation learning mechanism is introduced in the circuit. It can be observed that due to the introduction of habituation learning, our circuit gradually exhibits habituation to similar input signals IN_d after receiving them repeatedly, i.e., the output signal OUT strength of the circuit gradually decreases as shown in (b). (c). Adjusting the parameters of *M1* and *M2* allows the circuit to incorporate a habituation learning mechanism for smarter decision-making. With this mechanism, *M2*'s memristance decreases, causing *M1*'s memristance to increase and signal output strength to diminish, enabling intelligent, energy-efficient car movement. Without it, *M2*'s memristance remains unchanged, leading to conventional movement decisions.

Experiment 1			
Forward	**Backward**	**Turning**	**Cycle**
3m	1.5m	15°	1
3m	1.5m	15°	1
⋮	⋮	⋮	⋮
3m	1.5m	15°	15
3m	/	/	16
Experiment 2			
Forward	**Backward**	**Turning**	**Cycle**
3m	1.5m	15°	1
3m	0.75m	30°	2
4m	0.325m	60°	3
7m	0.1625m	120°	4
9m	/	/	5

Figure 6: The navigation data from *Experiment 1* (its navigation trajectory shown in Figure 2) and *Experiment 2* (its navigation trajectory shown in Figure 4). According to the statistical results, it can be observed that both sets of experiments are capable of making decisions based on the corresponding input information and successfully navigating the car out of the circular area. The difference lies in that, in *Experiment 2*, due to the introduction of habituation learning, the car can be able to exit the circular area in just 4.5 cycles, which is a 58.82% reduction compared to the 15.5 cycles required in *Experiment 1*, which demonstrate a more efficient and reasonable intelligent decision-making.

This is because habituation learning was not introduced in our circuit for *Experiment 1*. Thus, even if the signal is similar each time, the circuit responds to it with the same intensity as it did when it received the signal for the first time. Consequently, under the guidance of such output signals, the car backs up the same distance and turns at the same angle each time, resulting in a trajectory as shown in Figure 2. In our experiments, we normalized the range of the output signal OUT to be between 0V and 1V. Based on the magnitude of the output signal, starting from 1V, the distance for the car to reverse decreases by half compared to the previous reverse distance for every 0.1V reduction in the output signal (the initial reverse distance for the car is set to 1.5m). Similarly, the angle for the car to turn in place increases by double compared to the previous turning angle for every 0.1V reduction in the output signal (the initial turning angle for the car is set to 15°).

Next, we conduct *Experiment 2* by introducing the habituation learning mechanism into our decision-making circuit. The experimental results are shown in Figures 4 and 5(b). From Figure 5(b), it can be observed that due to the introduction of habituation learning, our circuit gradually exhibits habituation to similar input signals after receiving them repeatedly. This means that the output signal intensity of the circuit gradually decreases with each repetition of the received signal, instead of producing similar intensity output as in the previous *Experiment 1* where the circuit did not incorporate habituation learning. Therefore, based on the output signal OUT shown in Figure 5(b) and according to the rules we have set for the reverse distance and turning angle, the car follows the trajectory depicted in Figure 4. It can be observed that the smart car, as if possessing self-awareness, after a few rounds of "forward-backward-turn" operations, seems to realize that it is in a circular area. As a result, it no longer explores paths along the walls, but instead reverses for a shorter distance and turns at a larger angle to quickly exit the circular area. The reason for these results is precisely due to the memristors in our circuit. As shown in Figure 5(c), by adjusting the parameters of *M1* and *M2*, our circuit can incorporate a habituation learning mechanism to facilitate smarter decision-making. That is, after introducing the habituation learning mechanism, the memristance of *M2* gradually decreases during the process. This, in collaboration with other circuit modules, causes the memristance of *M1* to gradually increase. The increase in *M1*'s memristance leads to a gradual reduction in signal output strength, enabling more intelligent and energy-efficient decisions regarding the movement of the car. Conversely, without the habituation learning mechanism, the memristance of *M2* remains unchanged throughout the process and does not affect *M1*'s memristance and the signal strength output. Thus, the decision-making regarding car movement remains conventional.

We statistically analyzed the driving data from *Experiment 1* and *Experiment 2*, as shown in Figure 6. It can be seen that by introducing the habituation learning mechanism into the circuit, the adaptive decision-making behaviors become more efficient and reasonable. That is, in *Experiment 1*, the circuit is able to make adaptive decisions based on the corresponding input information and successfully navigate the car out of the circular area. However, in *Experiment 2*, the car only required 4.5 cycles to exit the circular area due to the incorporation of habituation learning, which is a 58.82% reduction compared to the 15.5 cycles in *Experiment 1*. This demonstrates that such adaptive decision control is more intelligent and resembles human-like decision-making behavior.

In addition, in terms of computational speed during the decision-making process, it can be seen from Figure 5 that the execution time for each cycle is 0.2μs. It follows that our circuit can make decisions within microseconds. The primary factor determining the decision-making speed is the operating frequency of the memristor-based circuit. In our experiments, the circuit operates at a frequency of 50MHz, enabling it to make decisions within microseconds. The read and write speeds of the memristor determine the operating frequency of the circuit. That is, the faster the read and write speeds, the higher the frequency at which the circuit can operate, allowing for quicker and more effective responses (Choi et al., 2016).

In terms of hardware overhead and power consumption, we estimated them by counting the number of the main components used in our circuit (Shi, Minku, & Yao, 2022). From Figure 3, it can be seen that approximately 92 two-terminal components (including memristors, resistors, and transistors) are needed in the circuit. Assuming each two-terminal component has a size of 10 *nm* (nanometre) (Shi et al., 2022), the area of one component would be about 100 nm^2. Therefore, 92×100 $nm^2 = 0.0092$ (μm^2) (square microns), so we can see that the area of this system is roughly $0.01\mu m^2$. Moreover, according to the power measurement data of the circuit simulation platform, by calculating the average power consumption of two-terminal components like memristors, transistors, and resistors in the circuit, it can be estimated that the average power consumption of the entire circuit is approximately 1.05*m*W. In general, it can be observed that the hardware overhead of our circuit is on the order of square micron and the power consumption is on the order of milliwatt, indicating good hardware efficiency.

Conclusion

In this work, based on a self-aware computational framework, we have effectively mapped memristor-based circuit design with biomimetic module simulation, which can achieve a bionic circuit with adaptive decision-making capabilities. When this circuit was applied to a simulated obstacle avoidance navigation scenario, it was found to not only make rapid and effective adaptive decisions based on current information but also to introduce a bionic habituation learning mechanism by adjusting circuit parameters, thereby enabling more efficient and reasonable intelligent decision-making. Furthermore, through hardware overhead and power consumption analysis, our circuit exhibits hardware-friendliness. In the future, we will further optimize the performance of our circuit, so as to realize a larger scale and higher performance autonomous decision-making hardware system.

Acknowledgments

This work was supported by the Young Scientists Fund of the National Natural Science Foundation of China (Grant No. 62206121), the Shenzhen Higher Education Stable Support Program General Project (Grant No. GXWD20231130200138001), and the Science Center Program of National Natural Science Foundation of China (Grant No. 62188101).

References

Biolek, Z., Biolek, D., & Biolkova, V. (2009). SPICE model of memristor with nonlinear dopant drift. *Radioengineering*, *18*(2), 210-214.

Boisseau, R. P., Vogel, D., & Dussutour, A. (2016). Habituation in non-neural organisms: evidence from slime moulds. *Proceedings of the Royal Society B: Biological Sciences*, *283*(1829), 20160446.

Chen, S., Zhang, T., Tappertzhofen, S., Yang, Y., & Valov, I. (2023). Electrochemical-memristor-based artificial neurons and synapses—fundamentals, applications, and challenges. *Advanced Materials*, *35*(37), 2301924.

Chen, Z., Zhang, J., Wen, S., Li, Y., & Hong, Q. (2021). Competitive neural network circuit based on winner-take-all mechanism and online hebbian learning rule. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, *29*(6), 1095–1107.

Choi, B. J., Torrezan, A. C., Strachan, J. P., Kotula, P., Lohn, A., Marinella, M. J., ... Yang, J. J. (2016). High-speed and low-energy nitride memristors. *Advanced Functional Materials*, *26*(29), 5290–5296.

Diener, E., & Srull, T. K. (1979). Self-awareness, psychological perspective, and self-reinforcement in relation to personal and social standards. *Journal of Personality and Social Psychology*, *37*(3), 413.

Elhabbash, A., Salama, M., Bahsoon, R., & Tino, P. (2019). Self-awareness in software engineering: A systematic literature review. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)*, *14*(2), 1–42.

Kaushik, R., Akhilesh, J., & Priyadarshini, P. (2019). Towards spike-based machine intelligence with neuromorphic computing. *Nature*, *575*, 607–617.

Kugele, S., & Franklin, S. (2020). Conscious multi-modal perceptual learning for grounded simulation-based cognition. In *Proceedings of the 42th Annual Meeting of the Cognitive Science Society, (CogSci2020)* (pp. 1–7).

Kvatinsky, S., Ramadan, M., Friedman, E. G., & Kolodny, A. (2015). Vteam: A general model for voltage-controlled memristors. *IEEE Transactions on Circuits and Systems II: Express Briefs*, *62*(8), 786–790.

Lewis, P. R., Chandra, A., Faniyi, F., Glette, K., Chen, T., Bahsoon, R., … Yao, X. (2015). Architectural aspects of self-aware and self-expressive computing systems: From psychology to engineering. *IEEE Computer*, *48*(8), 62–70.

Li, Y., Zhong, Y., Zhang, J., Xu, L., Wang, Q., Sun, H., … Miao, X. (2014). Activity-dependent synaptic plasticity of a chalcogenide electronic synapse for neuromorphic systems. *Scientific Reports*, *4*(1), 1–7.

Morin, A. (2006). Levels of consciousness and self-awareness: A comparison and integration of various neurocognitive views. *Consciousness and Cognition*, *15*(2), 358–371.

Prezioso, M., Merrikh-Bayat, F., Hoskins, B. D., Adam, G. C., Likharev, K. K., & Strukov, D. B. (2015). Training and operation of an integrated neuromorphic network based on metal-oxide memristors. *Nature*, *521*(7550), 61–64.

Schlatow, J., Moostl, M., Ernst, R., Nolte, M., Jatzkowski, I., Maurer, M., … Herkersdorf, A. (2017). Self-awareness in autonomous automotive systems. In *Design, Automation & Test in Europe Conference & Exhibition (DATE2017)* (pp. 1050–1055).

Shi, X., Minku, L. L., & Yao, X. (2022). Adaptive memory-enhanced time delay reservoir and its memristive implementation. *IEEE Transactions on Computers*, *71*(11), 2766–2777.

Wang, Z., Hong, Q., & Wang, X. (2019). Memristive circuit design of emotional generation and evolution based on skin-like sensory processor. *IEEE Transactions on Biomedical Circuits and Systems*, *13*(4), 631–644.

Xia, Q., & Yang, J. J. (2019). Memristive crossbar arrays for brain-inspired computing. *Nature Materials*, *18*(4), 309–323.

Xie, H. (2023). The promising future of cognitive science and artificial intelligence. *Nature Reviews Psychology*, *2*(4), 202–202.

Yang, J. J., Strukov, D. B., & Stewart, D. R. (2013). Memristive devices for computing. *Nature Nanotechnology*, *8*(1), 13–24.

Yang, X., Taylor, B., Wu, A., Chen, Y., & Chua, L. O. (2022). Research progress on memristor: From synapses to computing systems. *IEEE Transactions on Circuits and Systems I: Regular Papers*, *69*(5), 1845–1857.

Zhang, Y., Wang, Z., Zhu, J., Yang, Y., Rao, M., Song, W., … others (2020). Brain-inspired computing with memristors: challenges in devices, circuits, and systems. *Applied Physics Reviews*, *7*(1), 011308.