The human brain is a sophisticated biological processing unit based on hierarchical nervous meshes, interconnecting “slow” and “inaccurate” neural components (notably neurons and synapses). Yet, it is capable of outperforming most of the existing software/hardware computing platforms in terms of energy efficiency and error tolerance. Beyond the great success of artificial neural networks (ANNs) for artificial intelligence (AI), spiking neural networks (SNNs) were innovated to emulate the way the biological nervous system performs information processing. The main differences between ANNs and SNNs are the signal representation and coding strategy: While the typical ANNs focus on tuning the real-valued vectors representing connective weights, the biological plausible SNNs synergistically encode the information flow and the connective weight, enfolding a larger volume of information into correlated sequences of the pattern. Though the fundamental mechanism of the biological neural network is still under active research, recent investigations provide evidence that SNNs shows superior advantage in terms of speed and power efficiency when processing complex spatiotemporal data with additional noise and sparsity in an event-driven computing paradigm.[1,2] To implement SNNs, emerging devices are being researched to emulate artificial synapses or neurons.[3–8] Great effort has been made to enhance the performance at the device level (notably synaptic devices), including engineering the linearity and symmetry of the analog behavior.[9–13] There have been several demonstrations of SNNs based on nanoionic devices with multiple internal dynamics, such as resistive devices and ionic-gated devices.[2,6] These hardware-based neuromorphic computing systems were realized with well-established coding schemes and learning rules: rate and spatiotemporal coding with translated ANN parameters or principles of spiking-time-dependent plasticity (STDP) and spiking-rate-dependent plasticity (SRDP). To obtain enhanced energy/area efficiency, one critical metric/criterion for SNN hardware design is to leverage the spike coding principle that orchestrates the information flow in SCNNs can be greatly enlarged by taking advantage of the synergy between the rate coding and the neuronal correlations. This proof-of-concept work provides the potential to achieve high-volume information processing with the simplified circuitry of neuromorphic computing systems.
Biologists have revealed that neuronal cooperativity may contribute to high-level brain functions by enabling a high-density information flow within a small group of correlated neurons. As a result, the volume of information flow can be greatly enlarged with relatively few neurons, thus further enhancing the energy/area efficiency.

Biological neurons are the active nodes in the complex nervous mesh. The essential function of a neuron is to receive a weighted action potential through connections of dendrites and to fire a unanimous action potential through an axon when the stimulus exceeds the threshold. The connections of dendrites and axons are bridged by numerous synapses. The previous hardware emulations of biological neural networks focus on exploiting either the spike representation or the temporal and spatial coding scheme in SNNs. The correlations of the neurons are somehow overlooked; therefore, they fail to exploit the potential to envelop additional information. Figure 1a shows the schematic of an elementary neural system with correlated neurons. Inspired by the neuronal correlation between neurons, which is the subpatterns of the neuronal cooperativity, we proposed a spiking correlated neural network (SCNN) based on a dual-gated MoS₂ neuristor for the first time. In the SCNN, the multiterminal neuristor synchronously integrates the spatial and temporal spiking patterns generated from the multilayer synaptic connections and the temporal gating signal, respectively. Finally, the correlated spike patterns are formulated through wiring the three neurons in an “OR” mode. By decoding the firing rate and cross-correlation of the output spike sequences, the SCNN succeeded in recognizing the rotated patterns and their rotation angle at the same time. This proof-of-concept work provides the potential to achieve high-volume information processing with a simplified circuitry in brain-inspired computing paradigms.

Two-terminal and three-terminal artificial neurons excel in terms of cell footprint area and integration complexity. However, it remains a great challenge to simultaneously integrate multiple control signals in these devices. Here, to facilitate the modulation of correlated neurons, a dual-gated MoS₂ neuristor is used to emulate the integrate-and-fire (IF) feature of the biological neuron. Figure 1b shows the schematic of the device structure. Several MoS₂-based multiterminal (typically three terminals) devices have been put forward to emulate the biological neuron and synapse. The mechanisms of these devices are based on defect-migration-induced modulation of the Schottky-barrier height at the source/drain. Instead, in a dual-gated MoS₂ neuristor, the IF process is enabled by regulating the channel conductance through the cooperation of the ionic gate (i.e., the top gate, TG) and the electronic gate (i.e., the back gate, BG). The TG controls the integration process through ionic relaxation and the BG control the firing process through electronic relaxation so that signal patterns can be summed up and transcended by the synthetic ionic/electronic dynamics. For example, when a positive pulse (V_{TG}) is applied to the TG, the positively charged Li⁺ ions are driven toward the MoS₂ channel, whereas the negatively charged ClO₄⁻ ions are extracted from the MoS₂ channel. The accumulated Li⁺ ions at the surface of the channel will cause the electrochemical doping effect (Figure S1, Supporting Information, shows the first-principle simulation results of the Li⁺ electrochemical doping effect), realizing the n-type doping of the MoS₂ channel. As the migration rate of Li⁺ ions is relatively small (mass transport process), the relaxation time of this process will be longer than that of...
the electronic process. The spike will be triggered immediately once the threshold voltage is decreased below the amplitude of the BG sampling signal (i.e., the channel doping is high enough). As a result, the threshold voltage of the BG will be adjusted according to the signal at the TG, where high/low $V_{\text{TG}}$ will accelerate/decelerate the electrochemical doping process. As only a limited number of Li$^+$ can be intercalated between layered materials, the thickness of the channel material also influences the electrochemical doping process. A more detailed discussion can be found in our previous work.[7,13] With these behaviors, the double gates act as receiving ports of control signals of synaptic connections and timing. The signals on the TG/BG can be simultaneously integrated by the device’s internal dynamics.

To obtain a comprehensive understanding of the MoS$_2$ neuristor, the $I$–$V$ characteristics were measured first. The typical transfer characteristics under $V_{\text{TC}} = 0 \, \text{V}$ and $V_{\text{TC}} = 1 \, \text{V}$ were measured to investigate the influence of the electrochemical doping on the BG threshold voltage (Figure 2a,b). During measurement, a 100 mV bias voltage was applied to the drain electrode to monitor the drain current spikes ($I_{\text{ds}}$), which can be seen as the membrane current of the neuron. Under the same $V_{\text{BG}}$, the drain current under $V_{\text{TC}} = 1 \, \text{V}$ was $\approx 20$ times larger than that under $V_{\text{TC}} = 0 \, \text{V}$, demonstrating the strong dependence of $I_{\text{ds}}$ on $V_{\text{TG}}$. A numerical model was developed in our previous work to capture the device characteristics as well as to gain insight into the mechanism (the Supporting Information note 3 shows the derivation process of the formula). The drain current ($I_{\text{ds}}$) can be calculated as

$$I_{\text{ds}} = A e^{BV_{\text{BG}}} \sqrt{C - DV_{\text{TG}}}$$

where $A$, $B$, $C$, and $D$ are positive constants. These parameters can be obtained by fitting our model with the experimental data ($A = 6.999 \times 10^{-9}$, $B = 0.5853$, $C = 8.968$, $D = 8.892$). Figure 2c shows the typical current spike ($I_{\text{ds}}$) trains of the neuristor under different combinations of $V_{\text{TC}}$ and $V_{\text{BG}}$. The upper and middle graphs (Figure 2c) were obtained under the same $V_{\text{BG}}$ but with different $V_{\text{TG}}$. The bottom graph (Figure 2c) shows that the current spikes cannot be generated by solely applying $V_{\text{TG}}$. The device will not fire any spikes even with increased $V_{\text{TG}}$ if $V_{\text{BG}} = 0$. The results indicate that the $V_{\text{TG}}$ and $V_{\text{BG}}$ can jointly modulate the output spikes. Figure 2d shows the output spike trains of the neuristor as a function of the TG voltage (amplitude increases from 0 to 2.0 V, frequency: 5 Hz, pulse width: 50 ms). The red dots represent the average value of the spike number obtained from 30 measurements, and the blue line is the fitting curve. It is worth noting that the output spike frequency of the MoS$_2$ neuron approximates a sigmoid function of the input pulse amplitude. Consequently, a single neuristor can be a

![Figure 2](https://www.advancedsciencenews.com/)

**Figure 2.** a,b) A schematic of the electrochemical doping process and the corresponding transfer characteristic of the device with $V_{\text{TC}} = 0 \, \text{V}$ and $V_{\text{TC}} = 1 \, \text{V}$. With the electrochemical doping process introduced by the TG voltage, the conductance of the channel has been enhanced $\approx 20$ times under the same $V_{\text{BG}}$. c) The IF function of the MoS$_2$ neurons. The sampling clock applied to the BG can be used as the enable signal. When the neuron is enabled, the amplitude of the sampling clock signal is set to 5 V, and the frequency and pulse width of input signals and clock signals are 5 Hz and 50 ms. The time difference between the input signal and the clock signal is set to 100 ms. When the neuron is disabled, although a large input signal (3 V, 100 ms) is introduced, any current spikes cannot be found. d) The relationship between the number of output spikes in 10 s and the amplitude of input pulses. Red dots represent the average value of the spike number of 30 experiments and the blue line shows the fitting curve.
functional encoder to synthesize the cooperative signals on TG and BG, laying the foundation to enable the neuronal correlation by synchronously devising the control signals and the connective topology of the neuristors.

To demonstrate the capability of neuronal correlation in expanding the information flow, we constructed an SCNN capable of recognizing the rotated patterns and their rotation angle at the same time, but with a reduced number of output neurons. Figure 3a shows a schematic diagram of the SCNN. The SCNN consists of three main functional layers: the spatial configuration layer (SCL), which is emulated by a multilayer perceptron (MLP), the temporal gating layer (TGL), which is formed by multiterminal MoS$_2$ neurons, and the selective output layer (SOL). In general, the neuronal correlations in this network are jointly encoded by the SCL and the TGL. The spatial (synaptic connection) information is generated by the SCL. The TGL correlates the spatiotemporal information by encoding the TG and BG input signals through the internal dynamics of the MoS$_2$ neurons and fires spike trains containing the correlated information. Within a fixed time range, the nodes in the SOL selectively collect spike trains from their corresponding MoS$_2$ neurons. Finally, the spike trains can be decoded by the SOL through cross-correlation analysis.

Figure 3b shows the schematics of the correlated coding scheme in the SCNN. In the first stage, the correlation between spatial and temporal information is accomplished by the multiterminal MoS$_2$ neuron in the TGL. All neurons’ TGs receive the spike trains generated by the preneurons that are encoded by the SCL, while all neurons’ BGs are controlled by the enable signal generated by the gating clock. The I$_{ds}$ of a MoS$_2$ neuron integrates the spatial and temporal patterns and fires sequentially in a fixed time range (30 s in this work) to form the subpatterns. Neuronal cooperativity is then realized by wiring three MoS$_2$ neurons to formulate the final sequence pattern. For instance, node I ($N_i$, Figure 3b) can be seen as a neuron that is sensitive to the rotation angles of the input patterns. The rotation angles of the input patterns are coded by the firing rate of $N_i$ (i.e., the number of spikes in 30 s). Therefore, the larger the rotation angle, the higher the firing rate of $N_i$. Due to the collaborative control of the spatiotemporal correlation (signals of the TG and BG) and the neuronal correlation (wiring three neurons), the interval of the burst-firing pattern will always fall into a time range between 10 and 20 s. In contrast to $N_i$, the firing rate of selective node II ($N_{II}$, Figure 3b) is constant, while the interval of the burst-firing pattern will shift according to a certain type of input pattern. In Figure 3b, the burst-firing period of $N_{II}$ is between 20 and 30 s, which is defined to represent the pattern C in Figure 3c. The signal of $N_{I}$ (or $N_{II}$) accumulates the firing pattern of neurons 1, 2, and 3 (or neurons 4, 5, and 6) in a fixed time range.

The SCL is constructed to emulate the spatial distribution of pre/postneurons in the complex neural network. Figure 3c shows the input signals contain three types of patterns: bars (pattern A), obtuse angles (pattern B), and right angles (pattern C). There are four rotation angles of each pattern (0°, 45°, 90°, 135° for pattern A and 0°, 90°, 180°, 270° for pattern B and C). d) The input signal amplitude ($V_{TG}$) of the six MoS$_2$ neurons ($N_1$–$N_6$) under all types of input patterns.
the input patterns. The input patterns are divided into three types: bars (pattern A), obtuse angles (pattern B), and right angles (pattern C). There are four rotation angles of each pattern \(0^\circ, 45^\circ, 90^\circ, 135^\circ\) for pattern A and \(0^\circ, 90^\circ, 180^\circ, 270^\circ\) for pattern B and C. These patterns are formed by a 3 × 3 matrix. For each input signal, the black pixels correspond to a voltage pulse (1 V) and the white pixels correspond to null (0 V). All input patterns can be found in Figure 3c. As the exact spatial connection of correlated neurons is still under debate, an MLP with a topology of \(9 \times 8 \times 7 \times 6\) was constructed to intake these patterns and emulate the synaptic connections between correlated neurons. The elusive link configuration of pre/postneurons was translated into the TG input signals of the MoS\(_2\) neurons in the TGL. To generate the training set of the MLP, 1% Gauss noise was added to the input patterns. For each pattern, there were 50 noised training samples in the training set, and there was a total of 600 training samples in the training set. The generated signals can serve as the input TG signals of the MoS\(_2\) neurons in the TGL. Figure 3d enumerates the input signals for the MoS\(_2\) TG.

The TGL integrates the spiking signals from the SCL and the temporal gating signals to establish the spatiotemporal correlation. The generated control patterns for each neuron in TGL are shown in Figure 4a. To calculate the output spikes from each neuron, a modified sigmoid function was used to simulate the output characteristic of the MoS\(_2\) neuron

\[
S_{\text{out}} = \frac{21.19}{1 + \exp(-26.56 \times (V_{\text{TG}} - 1.06))} + 26.73
\]

where the \(S_{\text{out}}\) and \(V_{\text{TG}}\) represent the number of output spikes and the TG voltage, respectively. The device has a stochastic output characteristic, which may result from the spontaneous electrochemical doping process (the concentration of Li\(^+\) near the channel has a fluctuation with time). A probability-based method was adopted in this work to incorporate the stochastic behavior of the neuristor. The firing probability \(P_{\text{fire}}\) can be calculated by \(P_{\text{fire}} = S_{\text{out}}/S_{\text{clock}}\), where \(S_{\text{clock}}\) represents the spike number of the BG enable signal (\(S_{\text{clock}} = 50\)). Thus, the output spike trains can be calculated by the relationship between \(P_{\text{fire}}\) and \(V_{\text{TG}}\). In this work, the working period of one neuron was gated by the enable signal. For example, neuron 2 (\(N_2\)) and neuron 5 (\(N_5\)) were only active from 10 to 20 s in a period (Figure 3b).

![Figure 4. a) The input signal amplitudes of six MoS\(_2\) neurons under all input patterns, which are derived from the SCL. b) The output signals of node I (\(N_I\)) and node II (\(N_{II}\)) when fed the input patterns A1, B2, and C3. The firing probability \(P_{\text{fire}}\) is calculated by the average number of spikes in five BG sampling periods. c) The joint distribution function of \(N_I\) and \(N_{II}\) fire together \(P_{fi}\) under the input patterns A1, B2, and C3. The red squares show the high-probability regions.](image-url)
In the biological neural system, some neurons are only sensitive to a specific type of signal. For instance, the ganglion cells located in the retina are generally sensitive to the edge between light and dark. These neurons with particular preferences may interact through selectively spatial and temporal correlation in the cognitive process. In the SCNN, N_I and N_{II} in the SOL are set up to receive and reassemble the incoming signals from the TGL. Figure 4b shows the reconstructed output signals of neurons 1, 2, and 3 (connected to N_I) and neurons 4, 5, and 6 (connected to N_{II}) when fed patterns A1, B2, and C3 (the output signals of N_I and N_{II} under all input patterns are shown in Figure S5, Supporting Information). By comparing the three pulse trains of N_I (i.e., all green spikes), it can be found that the burst-firing pattern constantly appears among pulse number 50–100, and the firing rate increases with the rotation angles. In contrast, the burst-firing pattern in N_{II} (i.e., all blue spikes) shifts from the first 50 clock pulses to the last 50 clock pulses, and the firing rate is almost unchanged. Analysis of the joint distribution of spikes regarding N_I and N_{II} agrees well with the results (Figure 4c). The cross-correlation functions are the most intuitive method to decipher the information coded by spike trains on N_I and N_{II}. All the generated spike trains (corresponding to all input patterns) were analyzed by the cross-correlation function to decipher the underlying information encoded by the correlations. Figure 5a shows the cross-correlation functions of the complete output spike trains (all input patterns). Each spike train from N_I and N_{II} has a total number of 150 spikes. The histograms in Figure 5a show the cross-correlation between all pairs of spike trains. The spike shift is benchmarked with spike trains from N_{II}. Cross-correlograms were calculated from all output spike trains. The y-axes are normalized to represent the proportional probability that two spike trains from N_I and N_{II} are separated in spike shifts by the amount indicated on the x-axes. The cross-correlation functions show different patterns when the input differs from pattern A, B, or C. In Figure 5a, the types of the patterns

Figure 5. a) The cross-correlation analysis of the output spike trains between N_I and N_{II}. The types of patterns (patterns A, B, and C) are coded by the deciphered cross-correlation results (i.e., orange, blue, and green correlation patterns represent patterns A, B, and C, respectively). b) The rotation angles (patterns 1, 2, 3, and 4) of each type of input pattern are coded by the spiking rate (i.e., the number of spikes) of node I.
(patterns A, B, and C) are coded by the cross-correlation of the output spike trains (i.e., orange, blue, and green correlation patterns). The orange correlation patterns show an up trend from −150 to +150 s, which means that the spikes in train II (spike train on node II) are more likely to appear before the spikes in train I (spike train on Node I). The blue correlation patterns are approximately axisymmetric patterns, which means that the spikes in train II and train I are more likely to appear at the same time. The green correlation patterns show a downturn from −150 to +150 s, which means that the spikes in train II are more likely to appear after the spikes in train I. In this work, the type of pattern (A, B, and C) is encoded by the correlation of the output spike trains, while the firing rate of $N_1$ indicates the rotation angle of each pattern. In the radar chart (Figure 5b), the patterns and their rotation angles can be unambiguously identified.

In summary, a correlated SNN is proposed and demonstrated based on a multiterminal MoS$_2$ neuristor to enable recognition of rotated patterns and their angles at the same time. The integration of spatiotemporal signals is realized by exploiting the internal ionic dynamics of the multiterminal MoS$_2$ neuristor, while the neuronal correlation, which is the subpattern of the neuronal cooperativity, is accomplished by selectively wiring three neurons to form preferring nodes. By calculating the cross-correlation functions and the firing rate, we demonstrated that the different patterns can be coded by different correlations of the neuronal spike trains and the features of the pattern (i.e., the rotation angle) can be coded by the firing rate of a specific neuron. Compared with conventional spiking-based artificial neural networks (spiking-ANNs), the SCNN has potential in saving the numbers of neurons/synapse devices by implementing the correlated spatiotemporal structure of the spike train as well as the neuronal cooperativity. This proof-of-concept work aligns emerging device technology with a bioplausible coding strategy to provide a new perspective that leverages neuromorphic circuitry to enhance computing functionality.

**Experimental Section**

**Device Fabrication:** Device fabrication started from heavily n-doped silicon wafers with 100 nm thermally grown silicon dioxide, which was heated at 170°C for 10 min to expel water molecules absorbed on the SiO$_2$ surface. The MoS$_2$ nanosheet was transferred onto the substrate by mechanical exfoliations, where the suitable channel materials were selected based on observations using optical microscopy and atomic force microscopy measurements. Electron-beam lithography was used to pattern the electrodes. Electron-beam evaporation followed by the lift-off process was used to make electrodes. The electrodes used in this study were Au (30 nm)/Pd (5 nm), with a source–drain distance of ≈2 μm. To fabricate the polymer electrolyte, a spin-coating process was used. Polyethylene oxide (PEO, 100,000 g mol$^{-1}$) was first mixed with LiClO$_4$ in a mass ratio of 9:1. The mixture was then dissolved in methanol by 2 wt% to form an ion gel. Electron-beam lithography was used to pattern the gate region and the ion gel was dropped above the substrate. Then, the substrate was spun on at a rate of $\approx$100 r s$^{-1}$ for 80 s. The devices were subsequently heated at 50°C for 10 min to fully evaporate the methanol and the absorbed water molecules. After 30 min cooling under room temperature, the lift-off process was used to make the ionic gate in the end.

**Electrical Measurements:** The device was heated at 60°C for 5 min to expel water before electrical measurements. The tests were conducted using the Agilent B1500A semiconductor parameter analyzer.

**First-Principle Calculation:** The ab initio calculation was conducted using the Cambridge Sequential Total Energy Package (CASTEP) and data from Accelrys Materials studio 2016. A cutoff energy 300 eV was used in all calculations. The band structure and density of states were obtained using a plane-wave pseudopotential method within the generalized gradient approximation functional of Perdew, Burke, and Ernzerhof. A mixing ratio of 0.5 and a range separation parameter of 0.05 Å$^{-1}$ were used in all calculations.

**Neural Network Simulation:** The neural network simulation was conducted in MATLAB 2019B. The simulation code files are available at Github: https://github.com/LinBaoPKU/SCNN-Network.git.

**Supporting Information**

Supporting Information is available from the Wiley Online Library or from the author.

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**Conflict of Interest**

The authors declare no conflict of interest.

**Keywords**

artificial neurons, dual gate devices, ionic gate devices, neural signal correlation, neuromorphic computing, 2D materials

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