NEURAL MODELING

Memristive stochastic plasticity enables mimicking of neural synchrony: Memristive circuit emulates an optical illusion

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The human brain is able to integrate a myriad of information in an enormous and massively parallel network of neurons that are divided into functionally specialized regions such as the visual cortex, auditory cortex, or dorsolateral prefrontal cortex. Each of these regions participates as a context-dependent, self-organized, and transient subnetwork, which is shifted by changes in attention every 0.5 to 2 s. This leads to one of the most puzzling issues in cognitive neuroscience, well known as the “binding problem.” The concept of neural synchronization tries to explain the problem by encoding information using coherent states, which temporally patterns neural activity. We show that memristive devices, that is, a two-terminal variable resistor that changes its resistance depending on the previous charge flow, allow a new degree of freedom for this concept: a local memory that supports transient connectivity patterns in oscillator networks. On the basis of the probability and distribution of the resistance switching process of Ag-doped titanium dioxide memristive devices, a local plasticity model is proposed, which causes an autonomous phase and frequency locking in an oscillator network. To illustrate the performance of the proposed computing paradigm, the temporal binding problem is investigated in a network of memristively coupled self-sustained van der Pol oscillators. We show evidence that the implemented network allows achievement of the transition from asynchronous to multiple synchronous states, which opens a new pathway toward the construction of cognitive electronics.

INTRODUCTION

Consciousness and perception are, without doubt, one of the most fascinating functionalities of the human brain and result from massively parallel computing in a huge self-organizing dynamical neural network (1, 2). Neural synchrony is an elegant concept that tries to explain the underlying computing scheme by using dynamical network behaviors (1, 3–5). It assumes that information is encoded into coherent states via temporally correlated neural pattern activity (6). Thus, neural synchrony can cope with the “binding problem” by providing a dynamic functional relation between different descriptive attributes of the same object (3, 7–10). First experimental evidences of these concepts have been reached from sensorimotor networks (11, 12), whereas more recent studies have shown the universality of these concepts for the entire brain (4, 6). In particular, their role in neural communication across spatially distributed brain areas through phase synchronization of the underlying neuronal firing activities was investigated. Although the underlying mechanisms of neuronal synchrony are currently under debate, it is still believed that this concept is an essential tessera explaining higher cognitive brain functions, in accordance to experimental and theoretical evidences (4, 13, 14).

The aim of neuromorphic engineering is to emulate cognitive functionalities using artificial neural networks (ANNs) (15). Although machine learning approaches date back to the early beginning of serial, binary computing based on the von Neumann architecture (16), today’s approaches are only partially able to mimic cognitive functionalities. The biggest challenge in this context rises from the massive parallel working and highly complex interconnection of neuronal networks and requires a close cooperation between modeling and experiments. However, software-based neural network models have difficulty coping with the highly complex interconnection to provide a real-time and parallel computing scheme. The use of neuromorphic circuits might overcome these restrictions and has recently gained new momentum with the advent of memristive devices (16, 17). Memristive devices are resistors with memory and have been proven to enable the emulation of synaptic functionality in a detailed and efficient manner (18–20). So far, important local biological synaptic mechanisms such as the Hebbian learning rule, including spike timing–dependent plasticity (18, 20, 21), short-term potentiation and long-term potentiation (LTP), and long-term depression (LTD) (22–30), have been realized. Recently, the potential of memristive devices to cause locally synchronous oscillations has been presented (31).

Here, we show that memristive devices allow a new degree of freedom for the concept of neural synchrony: a local memory that supports a transient connectivity pattern in ANNs. In detail, we show that the use of memristive devices arranged in an oscillator network allows the integration and storage of coincident information in a manner where distinct information is combined and long-lasting associations are formed. By using a 4-inch wafer device technology, electrochemical metallization (ECM) cells with the layer sequence Al/TiO2–/Ag are fabricated and used for the coupling of self-sustained van der Pol oscillators (32). To illustrate the performance of the proposed computing paradigm, the temporal binding problem of a “bistable” object is investigated, in which selective attention to the same object forces the binding of different attributes. For this purpose, a context-dependent partial synchronization of the memristive network is experimentally realized using the inherent stochastic nature of the resistive switching devices. On the basis of the probability and distribution of the resistance switching process, a local plasticity model is proposed, which causes an autonomous phase and frequency locking of the participatory oscillators, that is, a transition from an asynchronous state to a synchronous state. We show evidence that the use of memristive devices allows the realization of active self-organized and transient ANNs, and opens a new pathway toward the realization of cognitive electronics.

RESULTS

The temporal binding problem
In Fig. 1, an archetypical example of neural synchronization is indicated (33, 34). It illustrates the temporal binding of different attributes of the...
One of the most important properties of synapses is their ability to respond to specific neural activity patterns with long-lasting increase or decrease in synaptic efficacy. This process is known as LTP or LTD, respectively, and is believed to be the fundamental precondition for memory and learning (2). This process is known as LTP or LTD, respectively, and is believed to be the fundamental precondition for memory and learning (2). This process is known as LTP or LTD, respectively, and is believed to be the fundamental precondition for memory and learning (2). This process is known as LTP or LTD, respectively, and is believed to be the fundamental precondition for memory and learning (2). This process is known as LTP or LTD, respectively, and is believed to be the fundamental precondition for memory and learning (2). This process is known as LTP or LTD, respectively, and is believed to be the fundamental precondition for memory and learning (2).
Here, $\beta$ is a device-dependent constant and $\theta_{thr}$ is the voltage where $f_N(V) = 0.5$ (HRS and LRS are equally probable). In Fig. 2E, the distribution function $f_N(V)$ for the switching after $N = 5, 10,$ and 50 pulses is shown together with experimental data. The solid lines correspond to the prediction made from Eq. 1, whereas the black dots are the measured data. The following procedure was used to compare the recorded data with the distribution function $f_N$: Pulse trains of 60 positive voltage pulses with amplitudes ranging from 200 mV to 2 V are used. Before each pulse cycle, the device was set in the HRS. The pulse number at which the switching occurs, $N_{sw}(V)$, are divided by the total number of voltage pulses $N$ in the pulse train (that is, $N = 5, 10,$ and 50). If no switching was observed, then a value of 1 has been taken for the $N_{sw}(V)/N$ ratio. The corresponding ratios are subtracted from 1 [$1 - N_{sw}(V)/N$] to obtain the distributions shown in Fig. 2E (black dots). We found that for a $\beta$ value of $12.5 \text{ V}^{-1}$ and $\theta_{thr}$ values of 1.65, 1.48, and 1.2 V for $N = 5, 10,$ and 50 pulses, the distribution functions $f_N(V)$ agree with our experiment. This shows that the resistance switching is predictable, although the underlying processes are random (38, 40–43). The inherent stochastic nature of the memristive devices offers the possibility of emulating synaptic plasticity by the number of applied voltage pulses. As shown in Fig. 2F, for voltage pulses with a fixed amplitude of 1.5 V, the probability of switching is increased from 13 to 98% (blue curve). This is associated with a decrease of $\theta_{ thr}$ [voltage, where $f_N(V) = 0.5$; Eq. 1] from 1.65 to 1.2 V (red curve).

The probability that switching from the low to high conductance state occurs for a given voltage amplitude within a pulse train, which contains $5, 10,$ and 50 voltage pulses. Solid lines are the prediction made by the distribution function $f_N(V)$ of Eq. 1; points are measured data. (F) Probability of emulating synaptic plasticity by the number of applied voltage pulses. For a fixed voltage pulse amplitude of 1.5 V, the probability of switching is increased from 13 to 98% (blue curve). This is associated with a decrease of $\theta_{thr}$ [voltage, where $f_N(V) = 0.5$; Eq. 1] from 1.65 to 1.2 V (red curve).

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The temporal binding problem can be divided into two parts. The first part contains the mechanism of information storage (plasticity). For the second part, a mechanism is searched, which combines distinct information in a single process (association of information). The model of neural synchrony copes particularly with the second part, that is, the mechanism of association of information. The extension of this model with stochastic memristive devices provides an excellent opportunity to combine both parts of the binding problem into a single compact model. In this model, self-sustained relaxation oscillators, which are pulse-coupled with memristive devices, are used. Mathematically, the self-sustained oscillators can be described by the following set of $n$ non-linear van der Pol equations (31)

$$\frac{d^2 x_i}{dt^2} - \mu (1 - x_i^2) \frac{dx_i}{dt} - \omega^2 x_i (x_i + \gamma)^2 = 0$$

$$\sum_{i=1}^{n_0} \sum_{j=1}^{n_1} \delta_{ij} \left( \frac{dx_j}{dt} - \frac{dx_i}{dt} \right)$$

Fig. 2. Stochastic plasticity. (A) Sketch of the formation of LTP. LTP is activity-dependent, that is, it depends on the number of action potentials appearing in a time interval in the presynaptic neuron. (B) I-V curve of an Ag-doped TiO$_2$-based memristive device. Inset: Simplified cross-sectional view graph. (C) Distribution of the set voltage obtained from 1700 identical voltage sweeps. The sweep rate for positive and negative voltages are 0.74 and 0.49 V/s, respectively. For the measurement, a current compliance of 0.1 mA is used. The red line is a Gaussian distribution fitted to the data. (D) Measured conductance variations of the device by applying a voltage train (see sketch in the inset) containing 1 ms voltage pulses with amplitudes of 1.1 V (blue points) and 1.3 V (red points). (B) Probability that switching from the low to high conductance state occurs for a given voltage amplitude within a pulse train, which contains 5, 10, and 50 voltage pulses. Solid lines are the prediction made by the distribution function $f_N(V)$ of Eq. 1; points are measured data. (F) Probability of emulating synaptic plasticity by the number of applied voltage pulses: For a fixed voltage pulse amplitude of 1.5 V, the probability of switching is increased from 13 to 98% (blue curve). This is associated with a decrease of $\theta_{thr}$ [voltage, where $f_N(V) = 0.5$; Eq. 1] from 1.65 to 1.2 V (red curve).
Here, \( x(\vartheta) \) are the position coordinates of the oscillator \( i(j) \); \( \mu, \gamma \), and \( \omega_0 \) are positive constants that define the damping, nonlinearity, and frequency behaviors of the uncoupled oscillators; and \( n_O \) is the number of object oscillators (background or the body of the hippo in the example of Fig. 1). Further, \( g_{ij} \) is the \((n_O \times n_a)\) coupling matrix that contains the topology of the complete network from \( n \) oscillators to the couplings between \( n_O \) object oscillators and \( n_a \) attribute oscillators (Fig. 1E). This coupling matrix contains the conductivities of \((n_O \times n_a)\) memristive devices and affects the network dynamic in the following manner: If a memristive cell connecting two oscillators is in its LRS (highly conductive), then an autonomous frequency and phase locking of those oscillators is achieved. However, in the case where the memristive cell is in the HRS, the connecting oscillators do not affect each other. The basic idea of the memristive couplings used here is that these couplings allow coping with the temporal binding problem by changing the respective device conductivities. In particular, the switching between the different representations, as indicated in Fig. 1, is carried out by a sensory input to the particular synaptic connection. We define the change in conductance by the sensory input matrix \( S \), which takes the switching probabilities of the individual memristive couplings into account. Thus, the updating rule of the memristive \((n_O \times n_a)\) coupling matrix \( g_{ij} \) in our model is given by

\[
\frac{dg_{ij}}{dt} = S(\vartheta_j(N, V)), \quad i = 1, \ldots, n_O, j = 1, \ldots, n_a \tag{3}
\]

Here, \( \vartheta_j \) is the voltage pulse trains applied to the memristive devices. According to Eq. 1, the probability of switching the resistance of a single memristive cell is given by the distribution function \( f_{ij}(V) \) and depends on the pulse number \( N \) and fixed voltage amplitude \( V \) of the voltage pulse trains. Thus, \( S \) contains voltage pulse trains to decode temporal attention to particular aspects of an object by enabling stochastic plasticity at the particular memristive couplings. This mechanism is discussed in detail below.

An example of a network with two memristively coupled neurons is shown in Fig. 3 (named \( N_1 \) and \( N_2 \)). In Fig. 3A, a sketch of two memristively coupled self-sustained relaxation oscillators is shown. In the initial state, the memristive device is in the HRS. Both oscillators oscillate in their own angular frequencies \( \omega_1 \) and \( \omega_2 \), and are uncoupled. It is important to note that the oscillator-induced voltage pulses have to retain a small amplitude to prevent an unwanted resistance switch (Eq. 1). To synchronize the oscillators, the external signal \( S \) is applied to the small network. In accordance to Eq. 3, \( S \) consists of voltage pulse trains \( \vartheta_j \), where the resistance switching probability is determined by the number of equivalent pulses (Fig. 2). In the high-activity case, that is, high number of voltage pulses, the memristive device transitions from the HRS to the LRS. This leads to an autonomous phase and frequency locking of both oscillators. Hence, because of the pulse-dependent memristive, coupling synchronization is expected.

The implemented technical realization of two memristively coupled relaxation oscillators with stochastic plasticity is shown in Fig. 3B. The key devices for the electrical implementation of the relaxation oscillators are programmable unijunction transistors (PUTs; 2N6027) (44, 45). These transistors exhibit a negative differential resistance (NDR) and belong to the class of silicon-controlled rectifiers. Because of \( I-V \) nonlinearity, the constant voltage source \( V_{BB} \) charges the capacitor \( C_{BB} \) below the NDR threshold voltage via the resistor \( R_A \) at the anode side \( A_x \) of the PUT (circuits yellow shown in the black frames in Fig. 3B). If the voltage

across the capacitor exceeds the NDR threshold, the PUT switches to its low-resistance branch and \( C_{BB} \) is discharged to the ground. Here, the transition point, that is, the NDR threshold voltage, is defined by the voltage \( V_{G} \) at the gate terminal \( G_s \) of the PUT. To implement the memristively coupled van der Pol system of Eq. 1, the two oscillators are coupled through their gate terminal \( G_a \). In addition, two capacitors at the respective gate terminals are used to achieve a dc potential decoupling of the oscillator circuits and to obtain the pulse coupling scheme defined in Eq. 1. Thus, the obtained circuit represents a threshold-coupled oscillator system. The input signal \( \vartheta \) which allows the emulation of plasticity, is applied to the output knot of the first oscillator (labeled \( N_1 \) in Fig. 3B). In the \( S \) subcircuit (blue frame in Fig. 3B), two linear resistances, \( R_P \) and \( R_C \), are used to obtain the desired voltage pulse amplitude, which allows us to change the resistance of the memristive device according to the learning condition discussed. The capacitance \( C_P \) is used to eliminate a dc voltage offset, which can be caused by generating \( \vartheta \) through the voltage pulse generator.

The recorded phase and frequency dynamics of the oscillator circuit are shown in Fig. 3C. In the top panel of Fig. 3C, the gate voltages of both oscillators are represented by \( V_{G1} \) and \( V_{G2} \) respectively. Here, \( V_{G1} \) are the constant offset voltages caused by the voltage dividers \( R_{BB} \) and \( R_{GB} \) and the supply voltage \( V_{BB} \). In the bottom panel of Fig. 3C, the applied voltage pulses through the \( S \) subcircuit are shown. In this regard, in the beginning, the oscillators follow their own angular frequencies (\( \omega_1 = 1190 \text{ s}^{-1} \) and \( \omega_2 = 1680 \text{ s}^{-1} \)). However, after the application of the voltage pulse, oscillator 1 adapts its frequency to oscillator 2. This is caused by the increased coupling as a consequence of the changed resistance state of the memristive device. Because of the increased connectivity between the oscillators, every discharge of the integrating capacitor of oscillator 2 triggers the discharge of the integrating capacitor of oscillator 1. The mechanism and consequence of the memristively forced synchronization are detailed in Fig. 3D. In the figure, a phase portrait is shown, in which \( V_{G1} \) is plotted as a function of \( V_{G2} \) (gray dots). The blue and red lines correspond to oscillation cycles where the memristive device is in the HRS (blue lines) and LRS (red lines). Although initially an “L”-like symmetry is obtained, which accounts for the digital nature of the gate voltage spikes, in the final state a nearly straight line is observed, which represents frequency and phase locking of the system. The observed hysteresis in the LRS state in the phase portrait indicates a small prevailing phase shift. Because of this, we are able to synchronize memristively coupled oscillators.

Apart from synchronization, desynchronization is required to account for the bistable nature of the temporal binding problem, as shown in Fig. 1. For this purpose, it is required to return to the uncoupled network, in which the memristive devices are in their inertial high-ohmic states. However, in contrast to the set process, the switching characteristics of the reset process show a more continuous switching behavior. The stochasticity of the reset process can be analyzed by regarding the cumulative probability of the resistance states at different negative voltages. Figure 3E shows the cumulative probability of the resistances for two different voltages (gray data points), as well as the HRS (blue data points) and LRS (red data points). A voltage-dependent multilevel switching, rather than a binary switching, is observed in the reset process, that is, the probability of resetting the device resistance completely increases with decreasing voltage (gray data points in Fig. 3E). Thus, an appropriate low voltage ensures that the device resistance resets completely. Within the network environment, a negative sensory input signal through the \( S \) subcircuit can be used to reset the device resistance. An example of desynchronization of the two oscillator networks is...
shown in Fig. 3E. Initially, the memristive device is in the LRS. This causes the synchronization of the two oscillators, as discussed above. However, if a voltage of $-1.6 \text{ V}$ is applied for 5 ms, the device resistance is increased back to the initial HRS and the coupling between the two oscillators is decreased. Consequently, the oscillators are decoupled and returned to their own angular frequencies (Fig. 3F). The synchronization scheme is applied to the binding model, as shown in Fig. 1.

The memristive binding model
The circuit of two memristively coupled relaxation oscillators of Fig. 3 has been extended to a system of six oscillators and eight memristive devices to simulate the system of Fig. 1. The implemented circuit is indicated in Fig. 4. In particular, the circuit consists of two object oscillators $n_A$ representing the body (A) and background (B) of the bistable image shown in Fig. 1. These oscillators are memristively coupled to four attribute oscillators $n_B$ representing the different special features of the bistable image of the hippo. In accordance to Eq. 3, depending on the input stimuli, the $n_B$ oscillators are coupled during learning to the first or second object oscillator or to neither of them. The voltage traces of the gate potentials of the network oscillators in a typical binding case are shown in Fig. 4C. Initially, all memristive devices are in their HRS and the network oscillators are uncoupled. Because all the oscillators of the network differ in their frequency, no synchrony between them can be observed (Fig. 4C). During the learning phase, oscillators 1 and 2 have been associated to oscillator A (body of the hippo), whereas oscillators 3 and 4 have been bound to the background of the image mimicked by oscillator B. In this case, an increased attention has been given to attributes 1 and 2 of the hippo image (Figs. 1C and 4B). In
according to Eq. 3, this has been reached by eight voltage pulses, which were applied to the memristive devices $m_{a1}$, $m_{a2}$, $m_{b3}$, and $m_{b4}$ (Fig. 4B). This corresponds to a sufficient pulse activity to decrease the respective device resistances and to partly couple the network oscillator. As a result, oscillators 1 and 2 are synchronized with oscillator A, whereas object oscillator B is synchronized with oscillators 3 and 4.

An important aspect of the temporal binding problem is that it is selective, that is, a slightly changed perspective on the image or a reduced level of attention enforces the association of other attributes. This requires the formation of context-dependent, self-organized, and transient subnetworks, which are shifted by changes in attention. This attention-dependent process can be emulated by the stochastic behavior of the memristive devices, which is described in Eq. 1. According to Eq. 3, in the oscillator circuit model, the attention to specific attributes of the same object is encoded by the number of pulses applied to the specific memristive device. The changed input activity locally shifts the switching probability of the particular devices and thus the synchronization of the different oscillators. This leads to different self-organized subnetworks. In Fig. 5, the frequencies of the individual network oscillators are compared for three subnetwork configurations. We used pulse trains of eight voltage pulses with an amplitude of approximately 1.8 V as shown in Fig. 2E. We would like to mention that a voltage divider is responsible for the voltage $V_{M}$ across the memristive cell (Fig. 3). Therefore, the voltage across the memristive device is reduced when the transition from HRS to LRS occurs (see, for example, Fig. 3C). For all three configurations, we started from a completely uncoupled network, that is, all memristive devices are initially in their HRS. The case of Fig. 4 is shown in Fig. 5A, in which oscillators 1 and 2 (red curves) have been bound to oscillator A, which represents the body of the hippo, whereas oscillators 3 and 4 are associated to the background (oscillator B, blue curves). In Fig. 5B, the situation is flipped: Oscillators 3 and 4 are associated to the body of the hippo, whereas oscillator B is coupled to oscillators 1 and 2. In Fig. 5B, the case is presented, in which oscillator 1 is associated neither to the background nor to the body of the hippo. This reflects the scenarios in Fig. 1, in which perceptual situations switch among each other (B to C) but are mutually exclusive. As in the scenario in Fig. 1C, the hippo seems to be only correctly configured in the emulation shown in Fig. 5A.

**DISCUSSION**

We have shown that the proposed model of memristively coupled van der Pol oscillators allows the incorporation of plasticity into the concept of neural synchronization. For this purpose, the nonvolatility of memristive devices provides a long-lasting association of learned attributes. Higher-level assemblies, which might correspond to the temporal sensory input, are required for switching between the different representations. This is due to the fact that the brain is an active and dynamic system, which binds at any moment the environmental information from several sensory modalities to a coherent conscious perception. For this amazing computing process, three fundamental processing stages are necessary: selective attention, segregation, and integration (46–48).

Selective attention acts as a kind of an effective input filter of the nerve system to extract the relevant information from a tremendous amount of permanently received environmental information by the
Fig. 5. **Context-dependent self-organized network formations.** Change in the input activity locally shifts the switching probability of the particular devices and the synchronization of the different oscillators. The frequencies of the network oscillators for the subnetwork configurations are shown. (A) Oscillators 1 and 2 (red curves) are bound to oscillator A (body of the hippo), whereas oscillators 3 and 4 are associated to the background (oscillator B). (B) Oscillators 3 and 4 are associated to the body of the hippo, whereas oscillator B is coupled to oscillators 1 and 2. (C) Oscillator 1 is not associated to the background or to the body of the hippo.

sensory receptors. Only items that are deemed relevant to the existing task are considered. It is widely believed that, at the neural level, the strength of attention serves as the input to sensory neurons and is translated into a firing rate of action potentials. Similar to this mechanism, the number of voltage pulses emulates the level of attention in our model: Depending on the number of applied pulses, the probability of a resistance change for a single memristive device increases (Fig. 2A). This allows us to cope with the initial processing step, where the outer world is being perceived rather than copied.

Segregation stands for the necessity of encapsulating and composing the incoming information in distinct neuronal ensembles (motifs) to maintain their individual response profiles (for example, for color and shape of an object). To emulate the mechanism of segregation, we used van der Pol oscillators, which differ in their frequencies. This is of particular importance for the representation of different motifs, for example, in the case of the bistable image of the hippo shown in Fig. 1. In particular, the frequency difference is important for the mechanism of desynchronization: By reverting the resistances of the memristive devices that were changed before, the particular oscillators return to their own frequencies. In our memristive circuit, this was obtained by a global reset of the individual memristive devices whenever the attention is changed. Alternatively, this can also be locally obtained by applying negative voltage pulses via S. Therefore, the stochasticity of the reset process, for example, can be used. It is important to mention that in the case that all oscillators have the same frequency and only differ in their phases, desynchronization process cannot be achieved. Thus, the presented model differs from the concept of phase synchronization, which is currently intensively discussed in terms of memory formation in the brain (4).

Finally, integration means the temporal binding of the motifs and coincides with a partial loss of specialization. In this respect, the inherent stochasticity of memristive devices offers an elegant possibility of defining a local plasticity model that causes a partial phase and frequency locking of the network oscillators.

It is worthwhile to compare our memristive model in terms of its biological realism, that is, how it reflects the general understanding of visual perceptions in the brain. This is connected to the fundamental question of how we see or, more precisely, perceive our environment. A widely accepted theory believes that vision is processed by three parallel pathways in the brain, namely, processing motion, depth/form, and color (47). This has been followed from the finding that cells in different areas of the visual cortex respond to different perceptual attributes of objects. In line with the image of the hippo shown in Fig. 1, the processing of vision into coherent states is based on various features from different pathways, visual areas, and modalities. The memristive binding model presented might not cover this. In particular, the information flow from the high-level input (sensory input) to the local level (oscillator synchronization) was realized locally by S: Every coupling is individually addressed and the sensory input is directly linked to the individual activities of the particular aspects of the drawing (number of voltage pulses). However, compared to the complexity of the brain, in which the relevant information is selected from a myriad of information, our approach represents a strong simplification of that complexity. To account more effectively for the complexity of the problem, a global selection mechanism, which takes into consideration the higher-level down-streaming of information, is required. Nevertheless, the model has clear advantages in terms of its technical feasibility, which, in the future, may allow the realization of complex electrical circuits with cognitive functionality and the justification of the reductionist approach. In this respect, a reductionist model is important for the emulation because, during visual perception, the brain has to process several objects and control multiple actions concurrently. However, this requires a whole number of binding problems to solve and a dedicated interaction mechanism among them (7, 47). Neural synchronization, in conjunction with a local memory, may support this communication mechanism, and it has been shown that synchronization is based on two major functions: neural communication and plasticity (4). Thus, a thorough consideration of memory processes seems to be important for the binding problem and is coped with the memristive model presented. Furthermore, by extending the proposed network with memristive circuit elements such as memcapacitors or meminductors (49), more complex network behavior might be feasible. In this respect, the memristive binding model presented here provides a new pathway toward the realization of cognitive electronics.

**MATERIALS AND METHODS**

**Device preparation**

For the memristive couplings, Ag-doped TiO$_2$−$_x$−Al memory devices, which were fabricated on a 4-inch Si wafer using a three-step photolithography process, were used. The device stack consisted of Nb (5 nm)/Ag (40 nm)/TiO$_2$−$_x$ (10 nm)/Al (40 nm) and was defined in a mesa structure. To prevent micro-shorts, the stack was isolated by evaporated SiO. An upper 500-nm-thick Nb layer was sputtered to complete the devices. To obtain a set behavior of the current-voltage characteristic in quadrant I while ensuring standard conditions for ECM cell measurements, the layer sequence of the device stack was inverted in Fig. 2B.
Electrical characterization

To characterize the resistance state of every single memristive device and to analyze its stochastic properties, the bias voltage was swept, whereas the current of the devices was measured simultaneously. For this purpose, an Agilent E5263A source measurement unit (SMU) was used. A current compliance of 100 μA was set for the current-voltage measurements (I-V curves) to protect the devices from high electrical stress. Controlled pulse schemes with defined voltage amplitudes and durations were also provided by the SMU to define the conductance variation of the devices. A constant supply voltage \( V_{\text{pp}} \) was delivered from the SMU. The gate potentials of every six oscillators were simultaneously recorded with a Tektronix oscilloscope. The voltage traces of \( \text{vdP}_A \) and \( \text{vdP}_B \) were recorded with a TDS2002B oscilloscope, and a TDS7104 oscilloscope was used for the other voltage traces.

Circuit layout

The complete circuit was developed on a printed circuit board. The layout of the circuit was designed with the EAGLE software developed by Cadsoft by using the devices from the library. The photoresist of the two processed eurocards can be patterned with the eagle layout consisting of conductive tracks and pads by using UV Exposure Unit (RS stock no. 196-5251) for 300 s. A developer fluid consisting of sodium hydroxide and water was used to develop the patterned photoresist. The eurocards were finally etched in a plastic sink filled with ferric chloride. The etching time was 600 s under steady movement of the etching bath. The cards were etched simultaneously recorded with a Tektronix oscilloscope. The voltage traces \( \text{vdP}_D \) were generated by two Agilent E5263A source measurement units (SMU) whereas the current of the devices was measured simultaneously. For this purpose, an Agilent E5263A source measurement unit (SMU) was used. A current compliance of 100 μA was set for the current-voltage measurements (I-V curves) to protect the devices from high electrical stress. Controlled pulse schemes with defined voltage amplitudes and durations were also provided by the SMU to define the conductance variation of the devices. A constant supply voltage \( V_{\text{pp}} \) was delivered from the SMU. The gate potentials of every six oscillators were simultaneously recorded with a Tektronix oscilloscope. The voltage traces of \( \text{vdP}_A \) and \( \text{vdP}_B \) were recorded with a TDS2002B oscilloscope, and a TDS7104 oscilloscope was used for the other voltage traces.

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