Associative routing through neuromorphic nanowire networks

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ABSTRACT  
Resistance in neuromorphic nanowire networks can be decreased when activated by voltage as multiple pathways of low resistance interconnected nanowires form, increasing nanowire to nanowire connectivity. We show that high connectivity regions are retained for a few minutes after the energy source is switched off. We have used this property to devise an associative device. With a multielectrode array, we send current through the network to connect together areas that are spatially associated with a given electrode combination forming a pattern. We correctly retrieve the stored patterns by passing a small current through the network at a later time even when we input a faulty or incomplete pattern as the network groups stored patterns into cluster of high associativity, in analogy with semantic memory association in the human brain.  
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Networks are formed by polymer coated Ag nanowires. They were routinely synthesized by following the well-established polyol method \cite{22,23} and drop-casted on a glass substrate with pre-patterned gold electrodes. These nanowires have a typical length around 10 μm and diameter around 0.3–0.5 μm, forming a continuous interconnected network, as shown in the inset of Fig. 1. The network conductance changes upon application of consecutive I–V cycles, as shown in Fig. 1(a). The electrode distance was 2.5 mm. When the voltage reaches a given threshold, the current starts to increase as low resistance bridges form between nanowires, \cite{24} creating a pathway of connected nanowires throughout the network. The state of lower resistivity is preserved for a short time so that, in a second I–V cycle, new parallel pathways can be formed, increasing network conductance until reaching a final value in the third cycle. Unlike a single filament-like atomic switch, network conductance is not typically reset by applying a large voltage as the current spreads across many parallel junctions in the network. If voltage bias is reduced below the threshold value, random thermal breakage of individual nanowire junctions within conductance pathways occurs, \cite{15} after which it decays to a disconnected state.

Even though conductance (or short-term memory) is lost between seconds, the connectivity (or long-term memory) between nanowires forming pathways is retained longer in neuromorphic networks. In Fig. 1(b), the evolution of network conductance is inspected when applying consecutive square waves with varying duty cycles. Each square wave is composed of 30 high-voltage pulses of 10 V and 15 s each. This voltage is about 3 times larger than typical threshold values [Fig. 1(a)]. In the time between high-voltage pulses, \( t_{bp} \), zero voltage bias is applied. We have gradually increased \( t_{bp} \) from 1 up to 1500 s while keeping high-voltage duration and magnitude constant (15 s, 10 V). Between two consecutive square wave pulses, we waited one hour to ensure the network completely loses connectivity. Figure 1(c) shows a comparison of the average conductance per square wave when the network is active (black dots) and the initial conductance when the voltage of the square wave changes from low (0 V) to high (10 V) voltage (red squares). Figure 1(c) is split into four quadrants with center \( t_{bp} = 300 \) s. The initial and the average conductance are almost similar in the upper quadrant. The network slightly increases the conductivity between successive pulses as the time between pulses is short enough so that the short-term memory of the network does not decay, and new pathways can be added in new high-voltage cycles. However, when \( t_{bp} \) equals 50 s [third point in Fig. 1(c)], the average conductance during high-voltage pulses starts to decay. This implies that \( t_{bp} \) is larger than the short-term memory of the networks, which has been found to be typically 35 s \(^{-1}\) for Ag networks with similar density and size. Thus, at this \( t_{bp} \), conductance starts to decay as new pathways cannot be added. At the cross point between the two dashed lines (300 s), the network reaches a steady-state average conductance value (approximated by the blue dashed line) and initial conductance starts to diverge from the average conductance. This indicates that when \( t_{bp} \) is typically above 300 s, the network loses information about the connectivity of previous high-voltage pulses and need to reactivate in every high-voltage pulse. In this regime, the average conductance value obtained in each new high-voltage cycle reflects the maximum number of pathways that can be opened within the network for 10 V during 15 s. The magnitude of the high-voltage pulse could, thus, be controlled to modulate the time for which connectivity is retained within a network.

We have used this property to design an associative device with nanowire networks, as we can write new information to the network from a given open current pathway (by strengthening connections) to later readout with smaller currents while connectivity is retained. The device has an array of nine electrodes [Fig. 2(a)] at each end of the network. A voltage bias is applied on the left array (input channels). The right electrode array (output channels) is connected to a home-made amplification system (Fig. S1). We use electromagnetic relays to control which input/output channels are operative at any given time. As sketched in Fig. 2(a), whenever a given combination of input/output channels is selected and voltage bias is applied, pathways form between the electrodes, and current is acquired at the output channel. This is considered a training cycle. An example of training is shown in Figs. 2(a) and 2(b) for one input and one output configuration. The voltage difference is ramped up until the current

\[ \text{FIG. 1. (a) Consecutive I–V cycles applied to the Ag nanowire network shown in the inset. Conductance increases in successive cycles (order numbered and marked by an arrow) as connections are strengthened. Inset scale bar: 10 μm. (b) A 30 cycle square wave is applied to the nanowire network every hour (red arrow). High-voltage is 10 V for 15 s. Low voltage is 0 V for varying time. The average conductance and the initial conductance when voltage changes from 0 V to 10 V are plotted in (c) as the time between high-voltage pulses increases.} \]
achieves a target value. Upon reaching the target, selected channels are closed by operating on the relays so that no current flows through the network.

After training, the previously used inputs and all nine outputs are opened simultaneously, with an equal voltage in every input channel, and current is acquired for a short time (testing process), as shown in Figs. 2(c) and 2(d). We further process the acquired currents by taking the average on each channel during the testing time. Results are presented as a bar graph, inset of Fig. 2(d), in which the amplifier noise with magnitude less than 0.5 nA is observed in outputs 1-to-8, which have not been trained. In the case of the ninth output, a weak but distinguishable nA current is visible.

Applying subsequent cycles of training and testing will strengthen the local connectivity between the selected channels. We, thus, create dedicated current pathways as a response to the voltage difference in the localized areas of the network. In Fig. 3, we show the procedure to store a pattern in the network. As voltage is equal in every input channel during training and testing, the input is considered binary, and every individual channel is a bit. We have represented the nine channel input/output arrays as $3 \times 3$ matrices, as shown in Figs. 3(a), 3(b), 4, and 5. The input channels to be trained are shown in green. The averaged network current per output channels is represented as a matrix with a gray colormap. To train the 2-bit input pattern shown in Fig. 3, the same input/output channels are selected and trained by increasing the voltage difference until the target current is achieved. This procedure is repeated with each pair of 1-bit input/output channels conforming to the 2-bit pattern to promote the creation of lateral connections (Fig. S2). The pattern is tested after each cycle. As can be seen in Fig. 3(b), in the first training/testing epoch, the response of the network is flat, and connections between channels are not strong enough. However, if we keep applying the training procedure continuously after each testing cycle, it takes a short number of epochs to retrieve a clear network response from the trained channels during the testing procedure [Figs. 3(c) and 3(d)]. This is an indication that the 2-bit pattern is stored as an ensemble of higher connectivity pathways between the selected input/output channels.

Figure 3(e) shows the Zero-Mean Normalized Cross-Correlation (ZNCC) operation applied to the average current for each testing epoch of Fig. 3(d). ZNCC is a method generally adopted for pattern matching between two images that is insensitive to brightness.24 We have used ZNCC to assess whether a channel has been trained after a given number of epochs. We compare the average current per channel of any given testing epoch with the binarized target input that is trained. A score of 1 indicates a perfectly correlated match. As seen in Fig. 3(e), the pattern trained in Fig. 3 evolves from having poor fidelity to the target pattern and a low signal-to-noise ratio toward an almost perfect score in the tenth epoch [Figs. 3(b) and 3(d)].

We can train multiple patterns in the same network. In Fig. 4, we have simultaneously trained one 2-bit pattern [pattern 1 in Fig. 4(a)], two 2-bit patterns with one overlapping bit (patterns 2 and 3), and one 1-bit pattern (pattern 4). The four patterns are trained sequentially, with each pattern tested after its corresponding training cycle. An epoch finishes when all four patterns are trained and tested, and the next epoch repeats the same training/testing order. Figure 4(a) shows the results of testing after 100 epochs. The input target pattern is compared with the average current for each pattern in the matrix form as well as a bar graph. The ZNCC score is displayed in Fig. 4(b), while the averaged ZNCC score up to the
The ZNCC score for patterns 2 and 3 has the larger integrated ZNCC response of both patterns converges to a slightly minor output. In Fig. 4(c), the integrated ZNCC score has a marked tendency to 1. Finally, the network response during the last epoch is evident from Fig. 4(a). The correct retrieval of patterns 1 and 4 in the last epoch is evident from Fig. 4(a). As observed in Figs. 4(b) and 4(c), the 1-bit pattern has the strongest response and a perfect score for the entire training/testing cycles. It is readily seen that the network clearly retrieves the target pattern 1 after all epochs, although with dissimilar weight between the two outputs and a noisier ZNCC score, as indicated in the corresponding bar graph of Fig. 4(a). The integrated ZNCC score has a marked tendency to 1. Finally, the network response during the last epoch is the same for target patterns 2 and 3, that is, the composition of both 2-bit patterns forming a 3-bit output. In Fig. 4(c), the integrated ZNCC response of both patterns converges to a slightly minor score of 0.9. The ZNCC score for patterns 2 and 3 has the larger amount of fluctuations per epoch. It is possible to explain fluctuations on the ZNCC by taking into account the dynamic of the network during the testing protocol. The scores in some epochs are correlated and in others anti-correlated, signaling that the creation of shared pathways in the network produces a strong association between both patterns. For a 2-bit pattern, all 2-bit and 1-bit input/output combinations conforming to that pattern are trained for many epochs. Therefore, we promote the creation of the most topologically suited pathways as the training cycles increase. We are able to form several dedicated pathways for different electrodes in the network, and this rely on the high degree of homogeneity that must be achieved during the deposition. However, it is to be noticed that even if we create multiple stable connectivity pathways between the selected input/output electrodes, we are testing the patterns at a voltage less than the network threshold. As investigated recently, in the sub-threshold regime, there is a competition between pathway formation and dissolution, and the network adapts its conductance even when the random breakage of a single junction disrupts the entire pathway. In the case of having multiple current sinks, as with a 2-bit pattern, the random disruption of a single pathway could redistribute the current to only one of the output channels, thus creating the noisy ZNCC score. Despite random fluctuations in the ZNCC score per epoch, the average of the ZNCC shows the correct clustering of patterns into separate categories corresponding to the trained patterns. The process of memory association and retrieval in the human brain utilizes the same mechanism of grouping semantically equivalent words into clusters of associations with very fast retrieval as they are linked together conceptually.

We further explore this property of our networks in Fig. 5. During the train/test protocol of Fig. 4, the set of trained patterns must be known to probe stored routes from input electrodes to output electrodes. We have used the associative property of the network to design a post-training test which probes, using the automatic routing and clustering induced by pattern association, which electrodes are correlated or sharing connections within the network without any prior knowledge of the stored routes. After each epoch for every pattern in Fig. 4, we obtained the current through all nine output patterns for every possible 1-bit input pattern for a short time. We compose a $9 \times 9$ matrix in which every slot has been colored proportionally to the averaged response for that 1-bit pattern during all testing epochs, as shown in Fig. 5. There are three clusters in the matrix outlining regions of shared connectivity in the network or, equivalently, correlated patterns. The network only responds whenever the 1-bit input pattern that is tested is part of a previously trained pattern. Thus, it associates incomplete sections of the trained patterns to the whole patterns. More interestingly, the size of the clusters is proportional to the number of overlapping patterns. The strength of the different 1-bit connections naturally arises as the testing patterns are averaged, and thus, the matrix gives an indication of the degree of connectivity in topologically connected pathways of the network between any two particular electrodes, thus transforming correlated bits of information into spatially interconnected regions.

In summary, we have used fundamental properties of neuro-morphic nanowire networks such as resistive switching and connectivity retention to create an associative device with nanowire networks. The device was tested with 2-bit patterns, which were stored by creating dedicated spatial connections using a multielectrode...
array. We have proved that patterns sharing electrodes develop association that can be later retrieved even by testing with incomplete or faulty input patterns. This research draws important parallels with the basic mechanism whereby human memory works and establishes a promising venue to design neuromorphic devices which can automatically group bits of spatio-temporally correlated input information as shared connectivity pathways within the nanowire network, which could find relevant applications in highly automatized clustering or data-mining applications.

The supplementary material includes two sections: first, the multielectrode array setup is described, including a figure with the schematics of the measurement system. Second, the complete algorithm used for a 2-bit pattern training is shown.

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