## High-density CNT/HfO<sub>2</sub>/CNT nano-junction memristors for reservoir computing

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Recently, the research on brain-inspired computing is gaining tremendous interest to overcome the obstruction on von Neumann architecture [1]. Reservoir computing is a novel artificial intelligence (AI) computing method that utilize the complex physical system [2]. An array of numerous memristors has been demonstrated that could be exploited as a physical reservoir to run various AI applications with low power consumption, high data bandwidth, and low training cost. However, the main issues of conventional reservoir based on memristor array is the limit in the memory density. The higher number of memristors in the reservoir provides a better computing output. Here, we report the utilization of high-density memristors based on nanojunctions formed by carbon nanotubes (CNTs) for the application in physical reservoir computing.

Figure 1a shows the scanning electron micrograph image (SEM) of fabricated CNT reservior device with multiple terminals. The random network structure of a CNT thin film could generate high-density memristor at the cross-junctions of CNTs. To form the memristor structure, we inserted thin HfO<sub>2</sub> of 10 nm between two CNT thin films. Multiple electrodes were connected to the top and bottom CNT films. The memristors were formed between the bottom and top CNT films. Consequently, each combination of two electrodes pairs can represent a memristor because the current path of each combination is different in the random CNT networks. In this fashion, numerous memristors can be obtained through the random network of CNTs in a ultra-small area and independently trained.

Figure 1b represents the *I-V* characteristics of a single combination of the CNT/HfO<sub>2</sub>/CNT memristors. The hysteresis indicates a clear memristor function. The change of the memristor's conductivity by the pulse input voltages is shown in Figure 1c. The sequential pulse input voltages of +5 V increased the memristor's conductivity while the -5 V input voltage decreased the conductivity. These behaviours correspond to the potentiation and depression of synapse connections. We also confirmed that the memristors formed from each electrodes pair can be trained individually from other memristor combinations. Moreover, we demonstrated the Pavlov's dog training for the memristors. Interestingly, each memristors combination behaved differently by the Pavalov's dog training regime. Thus, by merely changing the electrode combination, we could operate the numerous memristors even in a ultra-small footprint. These results suggest that our proposed high-density memristors is very promising for the pyhsical reservoir computing applications.



**Figure 1.** (a) SEM images of CNT/HfO<sub>2</sub>/CNT memristors. (b) Typical *I-V* characteristic of CNT/HfO<sub>2</sub>/CNT transistors. (c) Potentiation (red shaded) and depression (blue shaded) of memristors' conductivity by multiple voltage pulses.

## **Reference:**

[1] P. Merolla et al. Science, **345**, 668 (2014).

[2] C. Du et al. Nat. Comm. 8, 2204 (2017).