Supporting Information

Cobalt-doped Zinc Oxide Based Memristors with Nociceptor Characteristics for Bio-inspired Technology

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Introduction

The goal of neuromorphic computing, which seeks to develop hardware circuits that can process data similarly to the human brain, has seen a major push in recent years [1, 2]. The neuromorphic chip is a type of energy-efficient information processing technology that draws inspiration from the brain to do complex tasks. The algorithms and physical implementation of computing systems that are created by humans differ greatly from those found in brains. Both the inference phase, which is when a network is given an input and computes the outcome, and the training phase might be sped up with neuromorphic circuits. Constructing systems that function with the current generation of most powerful neural networks' hierarchical layered architecture, where the synaptic inputs of the next layer are naturally fed by the neuron outputs of the previous layer, is a problem. Vast electrical energy is needed to process vast volumes of data. Furthermore, the issue gets substantially worse when artificial intelligence (AI) and its relatives machine learning and deep learning are involved. All of this might change with the development of neuromorphic chip architectures. These chips can perform numerous jobs at once and handle difficult tasks efficiently and effectively because they are particularly intended to mimic the functions of the human brain [3]. The demand for other strategies and technologies that can offer improved capabilities above and beyond what conventional CMOS technology can supply is growing as AI develops and Moore's Law encounters limitations in order to serve the changing requirements of AI applications [4, 5]. Memristor-based nanoelectronic devices that concurrently implement data processing and storage enable the construction of matching computer architectures for artificial intelligence systems that go beyond the von Neumann bottleneck. For a wide variety of synapses, neural networks, neuromorphic computing, AI systems, and computer chips for AI applications, memristors exhibit considerable potential [6-8]. One of the ongoing challenges in AI systems is figuring out how to create a memristor-based system with integrated brain-like multifunctional applications. Currently, memristor-based artificial intelligence systems only perform tactile and visual tasks; additional human brain-like capabilities remain uncommon [9].

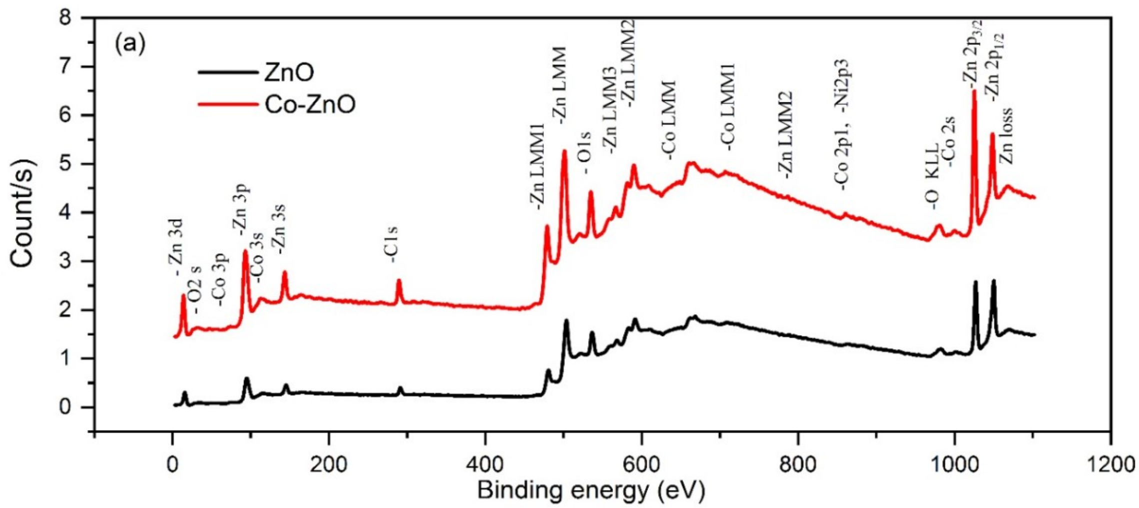


Figure-S-1. (Supporting information) XPS analysis of ZnO and Co-doped ZnO films

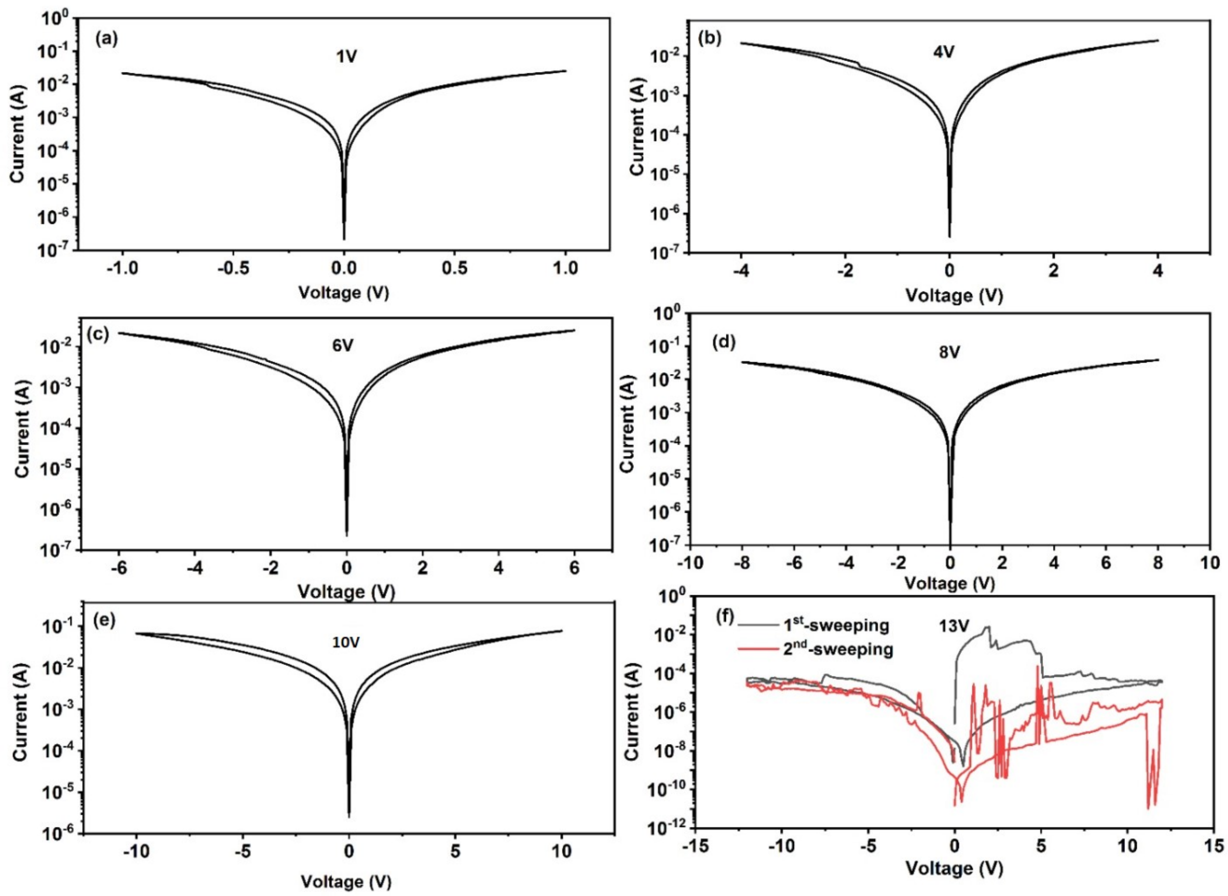
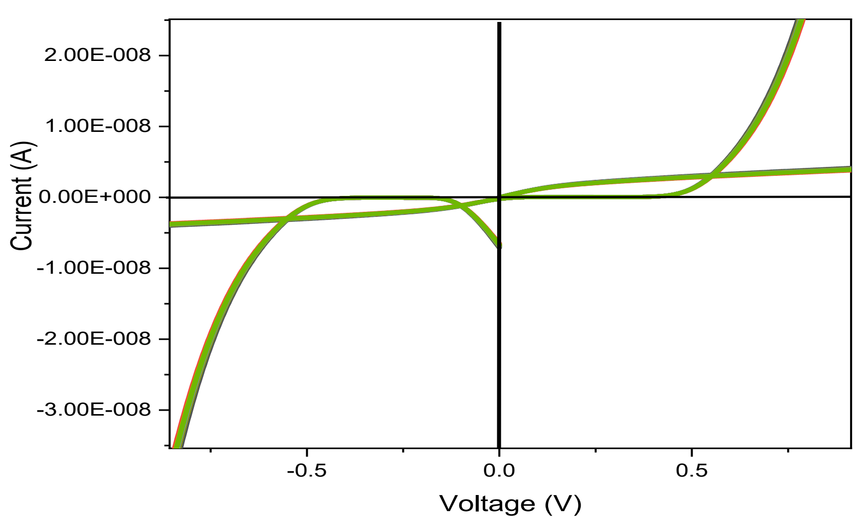


Figure-S-2. Sweeping behavior for P++-Si/Zno/Au under sweeping voltages. (a) 1 V, (b) 4 V, (c) 6 V, (d) 8V, (e) 10 V. (f) 13 V,on a semi-logarithmic scale.



S3: The enlarged part of the I-V showing non-zero crossing.

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