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Neuromorphic terahertz imaging based on carbon nanotube circuits

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We propose a neuromorphic THz imaging system based on the integration of carbon nanotubes (CNTs) circuits and the spin-transfer torque magnetic tunnel junctions (STT-MTJs). Utilizing the photothermoelectric effect of CNTs and constructing the monolithic 3D circuit, the system realizes the sensing, perception, memory and binary code waveform classification of simple THz images. The content of our systematic research extends the field of artificial intelligence image sensing to the terahertz frequency range, developing an innovative concept of "intelligent terahertz eyes", which has great development potential in the field of the Internet of Things applications, fast and intelligent image processing.

Among the potential applications of CNTs, their applications in THz sensing are highly anticipated [1–4]. Among several mechanisms that have been reported, the photothermoelectric effect of CNTs has been demonstrated to enable room temperature THz detection [3]. CNTs can detect a terahertz range from 0.14 to 39 THz, with a responsivity as high as 2.5 V/W and a polarization radio as high as 5:1 [1–4]. So CNTs can effectively absorb THz waves over a broad frequency range and achieve detection at room temperature with hyper pixel THz image sensing.

STT-MTJs are promising for not only the higher degree of integration compared with dynamic random access memory but also for higher reading speeds and writing compared with static random access memory [5, 6]. In the system, a memory unit of STT-MTJs is combined with a CNT field-effect transistor (CNTFET) by interconnecting different layers to form non-volatile logic gates to achieve sufficient parallel speed and energy efficiency of information processing. It is expected to realize information processing with ultra-low power consumption and short interconnected delay [5, 6].

The system integrates the sensing layer, memory layer, and processing layer, while the device architecture proposes a monolithic 3D integration through the nanometer vertical interconnections. Figure 1(a) illustrates the system integrating perception, memory, and neuromorphic processing. The THz image of the letter "n", for example, is radiated to the sensing layer, and the top of the figure presents the schematic of the CNTs sensing layer. The carbon nanotube array is designed as a grid structure in the sensing module, with different electrode materials (Ti and Al), and the CNT of n-type and p-type forms p-n junctions vertically, which are the pixel points [7]. We simulate and verify the CNTs as the sensing layer material, which is feasible and supported by the experimental reference basis. Specific information can be viewed in the supplementary file. A 3 × 3 pixels square array is simulated where the diameter of the CNTs is 10 nm, and the total area of the sensing layer is 25 μm^2. The photoelectric response currents of the CNTs array are generated, combined, and read when an image is projected onto the sensor layer.

In the memory layer that is composed of STT-MTJs, the response voltage of each p-n junction is introduced into the STT-MTJs, which is analyzed and used to adjust the synaptic weight (from W_{11} to W_{nm}) for the next training cycle in the image classification layer. After processing, the data is delivered in the form of voltage to the image classification layer's circuit. In Figure 1(b), the corresponding data is read from the STT-MTJs of the memory layer and processed in the classification processing circuit layer in rows or columns, and the encoded data signals (from $V_{\text{in}1}$ to $V_{\text{in}M}$) are input into the circuit in the form of voltage (high or low level) controlled by the microcontroller unit (MCU), and the signal generates an oscillation waveform signal V_{osc1} through the oscillating circuit, then input rectangular signal V_{pulse1}. The V_{pulse1} performs an "AND" gate circuit with the reference signal V_{ref1}, and generates the output signal V_1. Finally, the M dynamic signals (from V_1 to V_M) are input into the full-adder logic circuit, while the classified signal V_{OUT} is the output [8]. In the classification circuit layer, a letter image of 3.11 THz with 1 mW is irradiated to the perception layer. Figure 1(c) shows the waveform of each node in the circuit. Each projected letter delivers a 3-bit unique binary code signal pattern at the output.

The circuit processes three coded signals and outputs

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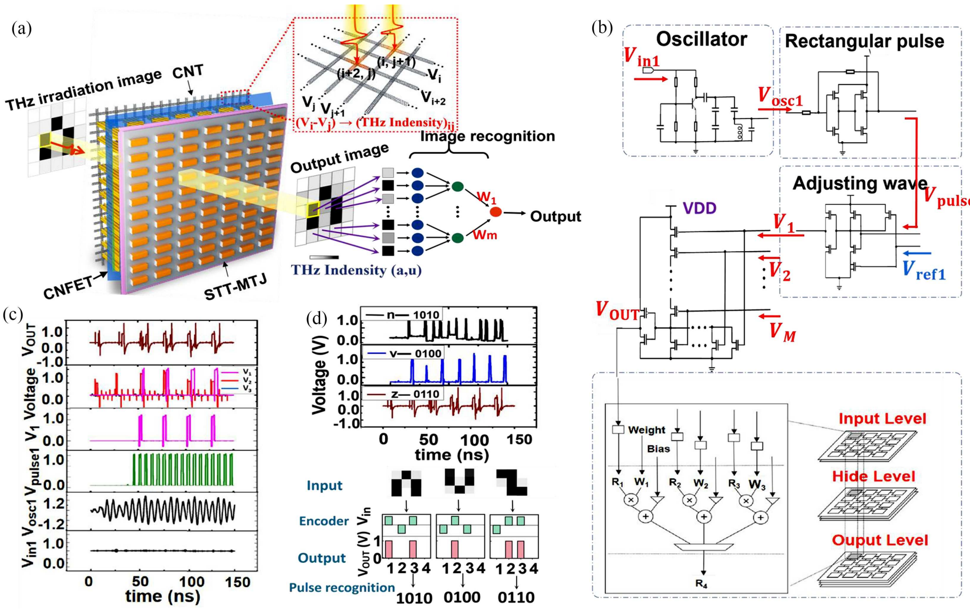

Figure 1 (Color online) (a) Schematic diagram of sensing, memory, and image recognition based on CNTs under THz irradiation. The THz irradiation image is radiated to the sensor layer, causing the voltage difference between V_i and V_j due to the thermoelectric effect of CNT. Then the STT-MTJs of the corresponding memory layer can capture the corresponding image information. After the image recognition circuit which is composed of CNTFET and MTJ, each image information will be recognized by W_1 to W_m in the neural network to output a unique waveform. (b) The schematic circuit of the image data in the classification circuit layer, including the oscillator, rectangular pulse module, adjusting wave module, and neural training module. The input voltage ($V_{\text{in}1}$–$V_{\text{in}M}$) is converted to V_{osc1}–$V_{\text{osc}M}$, V_{pulse1}–$V_{\text{pulse}M}$, V_1–V_M, and then the output voltage V_{OUT} through the circuits. Then the neural network training which includes weight training (W_1–W_3) in the input level and bias adjusting in the hidden level can obtain the result of image letters R_4. (c) The waveforms of signals in the circuit modules in the case of THz irradiation image 'n'. (d) The output waveforms of the images of 'n', 'v', and 'z', with their encoding and decoding flowchart.

three different dynamic waveforms. The output waveform of THz irradiated image letters "n", "v", and "z" is shown in Figure 1(d), from which we can see that different graphic information has different dynamic waveforms, and the waveform signal can be further processed. The binary codes will be used as inputs for a three-layer fully-connected pre-trained neural network, which is composed of an input layer, a hidden layer, and an output layer. The input layer is directly connected with the output port of the image classification layer. The hidden layer is composed of 12 neurons, and the weight is stored in the MTJ. The output layer is composed of three neurons, which will be inspired by the three different inputs "n", "v", and "z", respectively. Through the training, which includes weight training (from W_1 to W_3) at the input level and bias adjusting at the hidden level, the classified results of the three different image letters R_4 are obtained. In fact, the simulation indicates that the different image signals can be classified within 100 ns, so the system could achieve a throughput of 10 million to classify and process images in 1 s. Furthermore, the system can realize a larger image resolution with larger pixels through parallel processing.

Conclusion. In this study, we design an integrated system of perception, memory, and classification for THz images. We handle the simple image classification by unique binary output waveform. Through cascading, larger pixel recognition can be achieved. The system can classify $N \times N$ pixels of images by processing $N+1$ input data in the circuit layer. And the system can achieve a throughput of 10 million to classify and process images in 1 s. It would have great potential for expanding the smart applications of THz imaging.

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