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A novel memristive cellular neural network with time-variant templates☆

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Summary A cellular neural network (CNN) is a massively parallel analog array processor capable of solving various complex processing problems by using specific templates that characterize the synaptic connections. The hardware implementation and applications of CNN have attracted a great deal of attention. Recently, memristors with nanometer-scale and variable gradual conductance have been exploited to make compact and programmable electric synapses. This paper proposes and studies a novel memristive CNN (Mt-CNN) with time-variant templates realized by memristor crossbar synaptic circuits. The template parameters are estimated analytically. The Mt-CNN provides a promising solution to hardware realization of real-time template updating processes, which can be used to effectively deal with various complicated problems of cascaded processing. Its effectiveness and advantages are demonstrated by practical examples of edge detection on noisy images.

Introduction

A cellular neural network (CNN) (Chua and Yang, 1988a,b) possesses the neuromorphic property of local connectivity with a topographic array of simple processing cells, thus suitable for very-large-scale integration (VLSI) chip implementation (Adamatzky et al., 2013). Executing various tasks by using specific cloning templates at a high speed, more than a thousand times faster than regular digital processors (Zarándy, 1999), makes the CNN widely adopted in image and video processing, biological and robotic version, and a variety of other real-time applications (Chua and Roska, 2002). Furthermore, CNN with time-variant templates can execute cascaded processing operations in a one-layer array via real-time template updating. Therefore, it is quite suitable for image processing of multiple tasks (Harrer, 1993).

However, although some small operational CNN chips have been developed (Cruz and Chua, 1998; Dominguez-Castro et al., 1997), their VLSI implementation by using the conventional CMOS-based integration technology remains a big challenge. Even if CNN hardware circuit can be built,

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its synaptic connections cannot be easily updated. That is another factor restricting the practical use of CNN chips today.

The memristor was predicted by Chua in 1971 (Chua, 1971) and physically developed by HP researchers in 2008 (Strukov et al., 2008). Possessing desirable characteristics such as small size, automatic memory and low power consumption, the memristor has been incorporated into a variety of technologies, including the nonvolatile memory (Hu et al., 2012; Zidan et al., 2013), ultra-high density Boolean logic and signal processing (Borghetti et al., 2010), as well as nonlinear circuits (Hu et al., 2014), to name just a few. In particular, memristors exhibit a remarkable similarity to biological synapses in variable conductance subject to external excitations and thus become one prospective candidate of electric synapses in neuromorphic computing systems (Alibart et al., 2012; Alibart et al., 2013). Notably, memristors have also been proposed to realize the templates of CNNs (Corinto et al., 2014; Duan et al., 2014; Kim et al., 2012; Wen et al., 2014; Yilmaz and Mazumder, 2013). Apart from circuit compactness and nonvolatility, the greatest advantage of memristive templates lies in its good programmability. Utilizing these special advantages of memristors, our objective in this paper is to design an efficient compact memristive CNN with time-variant templates.

Specifically, in this paper a compact memristive CNN (Mt-CNN) model with time-variant templates is proposed and studied. A memristor-based synaptic circuit is used to realize the time-variant template where the template parameters are estimated analytically. Furthermore, its application to edge detection of noisy images is discussed. Illustrative examples and comparative analysis show its effectiveness and advantages over its traditional counterparts.

Memristor synaptic circuit

Preliminaries

The acclaimed HP titanium dioxide memristor can be modelled by a combination of two variable resistors in series made respectively from two materials of pure TiO_2 with very low conductivity and oxygen-deficient TiO_{2-X} with much higher conductivity which are sandwiched in between two metal electrodes (e.g. Pt) (Hu et al., 2014; Kim et al., 2012; Strukov et al., 2008). Its operating mechanism is primarily described through the change of the conductance state caused by the movement of the doping front between these two material regions under externally applied stimuli.

The relationship between the input u and the output y of the memristor is described by

$$y = M\left(\frac{w}{D}\right)u, \quad y = G\left(\frac{w}{D}\right)u, \tag{1}$$

for the current-controlled case, namely $u=i$ and $y=v$, or for the voltage-controlled case with $u=v$ and $y=i$. Here, w and D are the width of the TiO_{2-X} region and the overall titanium dioxide thin-film, respectively. The memristance (memristor-resistance, M) and memconductance (memristor-conductance, G) are respectively defined by

$$M\left(\frac{w}{D}\right) = \frac{w}{D}R_L + \left(1-\frac{w}{D}\right)R_H, \tag{2}$$

$$G\left(\frac{w}{D}\right) = \frac{G_L G_H}{(w/D)G_H + (1-(w/D))\,G_L}, \tag{3}$$

where $R_L (G_L = R_L{}^{-1})$ and R_H $(G_H = R_H{}^{-1})$ denote the limiting resistance (conductance) when the doping front at the boundaries of the device is at $w=D$ or $w=0$, respectively. The width w is chosen as the internal state variable and its dynamics are described by

$$\dot{w} = i\frac{\mu_v R_L}{D} f(w, v) \tag{4}$$

where μ denotes the average mobility of the oxygen vacancies, the window function $f(w,u)$ is an estimation of the oxygen vacancy drift. In this paper, the window function associated with the so-called BCM (boundary condition memristor) model is adopted because of its simple, accurate and flexible expression (Corinto and Ascoli, 2012), as

$$f(w, v) = \begin{cases} \gamma, & \text{if } C_1 \text{ or } C_2 \text{ holds,} \\ 0, & \text{if } C_3 \text{ or } C_4 \text{ holds,} \\ \alpha, & \text{if } C_5 \text{ holds,} \end{cases} \tag{5}$$

where $\gamma \in \mathrm{R}_{0,+}$ and $\alpha \in \mathrm{R}_{0,+} (\gamma > \alpha)$ describe the degree of nonvolatility of the device, and

$$\begin{cases} C_1 = & \left\{w \in (0, D)\,\&\,((v > v_{to}) \text{ or } (v < -v_{t1}))\right\}, \\ C_2 = & \left\{(w = 0\,\&\,v > v_{tho}) \text{ or } (w = D\,\&\,v < -v_{th1})\right\}, \\ C_3 = & \left\{w = 0\,\&\,v \le v_{tho}\right\}, \\ C_4 = & \left\{w = D\,\&\,v \ge -v_{th1}\right\}, \\ C_5 = & \left\{w \in (0, D)\,\&\,(v \le v_{to})\,\&\,(v \ge -v_{t1})\right\}. \end{cases} \tag{6}$$

It is noted that $v_{tho} \in \mathrm{R}_{0,+}$ and $v_{th1} \in \mathrm{R}_{0,+}$ denote the boundary thresholds for releasing the memristor state from its limiting values near the device boundaries, and $v_{to} \in \mathrm{R}_{0,+}$ and $v_{t1} \in \mathrm{R}_{0,+}$ represent the programmability thresholds, namely the magnitudes that an input voltage needs to exceed in order to provide a (much) bigger velocity of the state change.

The memristor synaptic circuit

In artificial neural networks, the weighted summation of input data and synaptic weights is the most critical part and also a key issue hindering their VLSI implementation. In the Mt-CNN design, the synaptic connection is realized by a crossbar-based memristor synaptic circuit, as shown in Fig. 1, where the weighted summation can be executed in an efficient compact manner.

In this synaptic circuit, voltages $V_1, V_2, \ldots, V_k$ are either the memristor conductance programming excitations or the input data to be weighted by the memristive weights. Each pair of memristors represents a synaptic weight and the weighting operation is carried out in a simple way via Ohm's Law. Taking for example a pair of memristors with conductance G_i^+ and G_i^-, respectively, the synaptic weight that they represent is given by

$$\omega_i \propto G_i \equiv G_i^+ - G_i^-, \tag{7}$$