Preliminary results from an analog implementation of first-order TDCNN dynamics

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SUMMARY

This work falls into the category of linear cellular neural network (CNN) implementations. We detail the first investigative attempt on the CMOS analog VLSI implementation of a recently proposed network formalism, which introduces time-derivative 'diffusion' between CNN cells for nonseparable spatiotemporal filtering applications—the temporal-derivative CNNs (TDCNNs). The reported circuit consists of an array of Gm-C filters arranged in a regular pattern across space. We show that the state-space coupling between the Gm-C-based array elements realizes stable and linear first-order (temporal) TDCNN dynamics. The implementation is based on linearized operational transconductance amplifiers and Class-AB current mirrors. Measured results from the investigative prototype chip that confirms the stability and linearity of the realized TDCNN are provided. The prototype chip has been built in the AMS 0.35 μm CMOS technology and occupies a total area of 12.6 mm sq, while consuming 1.2 μW per processing cell. Copyright © 2010 John Wiley & Sons, Ltd.

KEY WORDS: cellular neural network implementations; continuous-time filtering arrays; spatiotemporal filtering; analog signal processing

1. INTRODUCTION

Since its introduction in 1989, the cellular neural network (CNN) has expanded itself as a mainstream subject branch in the CAS community [1]. Applications of CNNs include, but are not limited to, computer vision [2, 3], robotic control [4] and nonlinear modeling [5, 6], with numerous contributions to date covering a healthy blend of theory and implementation issues. In particular, CNNs operating in its linear region—all input/output neighboring interactions are governed by linear equations and each cell implements a set of linear differential equations (DEs), are useful for linear spatiotemporal filtering where the input to the CNN is an image that changes over time. These classes of CNNs are often called 'linear CNNs'. Recently, the authors presented a network formalism as an extension to the linear CNN. The proposed network introduces the temporal-derivative coupling (earlier work on temporal derivatives in neural networks can be found in [7]) between the original CNN cells and has been termed as temporal-derivative CNNs (TDCNNs). The additional connections provided by TDCNNs facilitate a potentially large class of linear spatiotemporal filters 0 [8]. Owing to the novelty of the time-derivative connections at each cell with its immediate neighbors, the practical implementation of TDCNNs or networks of similar nature are

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not well attempted and studied. In this contribution, we aim to report the first attempt of implementing TDCNNs in analog-VLSI and we hope that our work would be useful for researchers that are interested in realizing practical TDCNNs and similar networks. Specifically, this contribution presents results from an analog-VLSI implementation attempt of a previously described TDCNN architecture [9]. A useful transistor-level extension of Gm-C continuous-time filters for implementing the required TDCNN dynamics is articulated based on the fact that the capacitor current relates to the derivative of the filter’s output voltage. The paper aims at verifying the practical implementability of TDCNN networks, in particular this paper’s scope is to confirm their stability and linearity in the temporal domain. The remainder of the paper is organized as follows. Section 2 details the Gm-C implementation of TDCNNs at block level. Section 3 presents the transistor-level topologies for the implementation outlined in Section 2. Section 4 presents measured results from a prototype chip. Section 5 concludes the paper.

2. GM-C AND TDCNNS

The TDCNN formalism, like the original CNN, comprises cloning templates for describing intercell coupling. Specifically for TDCNNs, we have introduced the $L$-th-order derivative coupling feedforward and feedback templates [8]. Templates are essential for network implementation as they describe the inter-cell coupling strength at which the electronics need to be tuned. On the other hand, the designer could start with a TDCNN compatible spatiotemporal transfer function (STTF) for a top-down approach where the templates are subsequently derived. Consider a typical first-order pole-only STTF describing a first-order (temporal) TDCNN filter with $E(z_x, z_y, p_t)$ and $S(z_x, z_y, p_t)$ denoting the filter’s input and output, respectively, each being a function of discrete spatial location $(x, y)$ and time $t$ with $z_x$, $z_y$, and $p_t$ denoting the $z$ and Laplace domain variables of $x$, $y$ and $t$, respectively

$$\frac{S(z_x, z_y, p_t)}{E(z_x, z_y, p_t)} = \frac{1}{\alpha(z_x, z_y) + \beta(z_x, z_y) p_t} \quad (1)$$

The quantities $\alpha(z_x, z_y)$ and $\beta(z_x, z_y)$ are polynomials of the spatial $z$-domain variables $(z_x, z_y)$ given by

$$\alpha(z_x, z_y) = \alpha_{0,0} + \sum_{n,m} \alpha_{n,m} z_x^n z_y^m \quad (2)$$

$$\beta(z_x, z_y) = \beta_{0,0} + \sum_{n,m} \beta_{n,m} z_x^n z_y^m \quad (3)$$

where $(n, m)$ are integers and $(\alpha_{n,m}, \beta_{n,m})$ are real constants. Equation (1) yields the frequency-domain representation of a spatiotemporal filter, which operates on moving images with discrete sampled grids denoted by the $(x, y)$ pair of variables and evolving continuously with the continuous-time variable $t$. The STTF is sometimes referred to as a mixed-domain STTF due to its discrete-space/continuous-time nature. Designing with first-order (temporal) TDCNNs results in filters with STTFs in the form of Equation (1). It is precisely the mixed-domain nature of the STTF that facilitates convenient nonseparable 3D filter synthesis [9]. Rearranging Equation (1), bearing in mind (2)–(3) and subsequently taking the inverse $z$-and-Laplace transforms yields:

$$\beta_{0,0} \frac{d}{dt} s(x, y, t) = e(x, y, t) - \alpha_{0,0} s(x, y, t) - \sum_{n,m \neq 0,0} \alpha_{n,m} s(x-n, y-m, t)$$

$$- \sum_{n,m \neq 0,0} \beta_{n,m} \frac{d}{dt} s(x-n, y-m, t) \quad (4)$$

Equation (4) characterizes the dynamics of a first-order (temporal) TDCNN implementing the filter function (1). An analog-VLSI implementation calls for an array of analog components arranged regularly across space, each implementing Equation (4) in continuous time. Equation (4) suggests that the output derivative \( \frac{d}{dt} s(x, y, t) \) at each spatial location \((x, y)\) evolves with the right-hand-side of the equation, which includes the sum of scaled neighboring cell outputs \( s(x-n, y-m, t) \) and their derivative \( \frac{d}{dt} s(x-n, y-m, t) \). The interaction of each array component with its neighbors is governed by the spatially dependent terms in Equation (4). Let us contrast the dynamics of a typical Gm-C integrator (Figure 1) and compare it with Equation (4); it holds:

\[
\frac{d}{dt} V_{\text{out}}(t) = \frac{g_m}{C} [V_{\text{in}}(t) - V_{\text{out}}(t)]
\]  

for the respective input and output voltages \( V_{\text{in}}(t) \) and \( V_{\text{out}}(t) \) and for a capacitor value of \( C \), respectively. If we assume that the spatiotemporal filtering output \( s(x, y, t) \) is pre-scaled by a constant factor \( 1/\beta_{0,0} \), then Equation (5) implements exactly the first line of Equation (4) when \( g_m/C = 1/\beta_{0,0} \). The next task is to introduce the spatially dependent terms appearing in Equation (4) over Equation (5). Observe that the RHS of Equation (5) relates to the output current of the operational transconductance amplifier (OTA). To modify the RHS of Equation (5) in such a manner that spatial coupling terms are introduced, one could inject appropriate spatially dependent currents into the capacitor node. This is illustrated in the shaded part of Figure 1.

Considering KCL at the capacitor node:

\[
\frac{d}{dt} V_{\text{out}}(t) = \frac{g_m}{C} [V_{\text{in}}(t) - V_{\text{out}}(t)] - G V(n, m, t) - G_d \frac{d}{dt} V(n, m, t)
\]  

The quantity \( V(n, m, t) \) denotes the output voltage of a neighboring Gm-C filter at spatial location \((n, m)\) in the array, whereas the constants \( G \) and \( G_d \) denote circuit-dependent parameters of appropriate dimensions. Now the Gm-C circuit enables the implementation of the TDCNN dynamics codified by Equation (4). What remains is the generation of the respective terms \( G V(n, m, t) \) and \( G_d (\frac{d}{dt}) V(n, m, t) \) from each cell at position \((n, m)\) for distributing them to neighboring cells. The \( G V(n, m) \) term denotes a typical ‘voltage to current conversion with gain’ and can be implemented with standard transconductance amplifiers. The derivative term \( G_d (\frac{d}{dt}) V(n, m, t) \) can be realized by copying the capacitor current at position \((n, m)\), which is proportional to the derivative of the output voltage. This can be achieved by means of a class-AB current mirror that acts as a buffer for the summation of injected currents and current distribution (with gain or attenuation) to neighboring cells and into the capacitive node of the local cell. Note that it can be argued that our top-down approach starting from an STTF filter description suggests further implications than simply demonstrating the implementability of specific TDCNNs: since our starting point is a STTF, which can be synthesized by means of a variety of methods (such as TDCNNs [8], multilayer CNNs [10] or 3D recursive filter design [11]), then the transistor-level circuits and Gm-C-based architecture presented here should be equally useful for the direct implementation of stable, spatially general-support STTFs reached by such methods.
3. CIRCUIT BUILDING BLOCKS

3.1. Output voltage ‘diffusion’

The output voltage ‘diffusion’ to neighbors is achieved by means of OTAs. For this operation, a linearized differential pair OTA structure has been employed. Two classical linearization techniques reported in the literature are exploited: (a) source degeneration with two diode connected transistors per side and (b) ‘bump’ linearization [14] which further enhances the linear range of the OTA. The linearized OTA is illustrated in Figure 2.

3.2. Output derivative ‘diffusion’

As described in Section 2, the derivative of the output voltage in Gm-C filtering, which is readily available via the capacitor current, could be sensed and copied with a class AB current mirror (ABCM). The ABCM [15] consists of a class-AB input current conditioner that splits the input bidirectional current into two unidirectional currents ($I_{top}$ and $I_{bot}$, respectively, in Figure 3). These unidirectional current components are subsequently processed by translinear loops to achieve current scaling before their recombination at a high impedance cascode mirror output stage. The ABCM is illustrated in Figure 3.

Figure 4 contrasts the AC response of the time-derivative operation of our design with an ideal differentiator in simulation. The ABCM/capacitor combination works well at low frequencies but deviates significantly from the ideal characteristic at frequencies higher than 5 kHz and exhibits an undesirable peak at around 10 kHz. This results in an unstable drift of the cell voltage outputs across the network. The frequency range for correct operation of the derivative-sensing structure approaches the time constants of bioinspired filtering (< few 10s of Hz). However, to counteract the effect of feeding through a ‘resonant peak’ to neighboring cells which could result in network instability, we apply DC coupling. This is achieved by inserting a grounded capacitor $C_{aux}$ to ground at the point of entry for neighboring currents (see shaded part of Figure 3). In this way, the currents originated from neighbors, both temporal-derivative based and transconductor based would split between entering the summing node and passing through the capacitor to ground.

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The term diffusion is commonly used to describe bi-directional (symmetrical) flow across a medium. Examples in analog networks with symmetrical diffusion can be found in [12, 13], where current flowing from node $V_1$ to node $V_2$ is equally controlled by $V_1$ and $V_2$. E.g. resistive $I = G(V_1 - V_2)$. Here we adopt the term to envision a directional (asymmetrical) flow of information from one node to another, i.e. the current $I_1$ flowing into node $V_1$ from node $V_2$ differs from current $I_2$ flowing from node $V_2$ to $V_1$, e.g. $|I_1| = |gm_2 V_2| \neq |I_2| = |gm_1 V_1|$ and for first temporal-derivative diffusion we have $|I_1| = |A_2 C_2 (d/dt)V_2| \neq |I_2| = |A_1 C_1 (d/dt)V_1|$.

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Figure 3. Class AB current amplifier with current controlled gain/attenuation. Low impedance input stages are employed for current summation and splitting. Two low impedance nodes are employed to decouple (a) local Gm-C filtering (collecting currents originating from the local cell only) and (b) current injection from neighboring cells. The shaded capacitor is for diverting high-frequency signals from neighbors into ground. This ensures network stability (see text). The output stage consists of cascode current mirrors and two translinear loops for gain realization. Multiple outputs (for distribution towards different neighboring cells) can be realized by sensing the gate voltages of the cascode mirrors and replicating the structure.

Figure 4. Simulated frequency response of the ABCM acting as a differentiator by extracting the capacitor current. The simulated response is compared with an ideal differentiator; an undesirable peak near 10 kHz is observed. The inset shows the response of the ‘derivative current’ flowing into the summing node of another ABCM after DC coupling (see Figure 3).

depending on their frequency. At higher frequencies, the impedance of the capacitor $C_{aux}$ becomes much lower than the input impedance of the class-AB summing node (controlled by device sizing and biasing currents) and faster signals are diverted to ground. Whereas for low-frequency signals, the capacitor exhibits high impedance and the signals are injected into the ABCM. The inset of Figure 4 shows a typical AC response of the DC-coupled derivative structure when the current injecting into the ABCM is simulated.

4. EXPERIMENTS AND RESULTS

Based on the architecture and circuit building blocks described in Sections 2 and 3, we have experimented with a fabricated complex two-layered TDCNN chip. A complex TDCNN network with first-order temporal dynamics implements a STTF in the same form as Equation (1) but with complex coefficients $\omega(z_x, z_y), \beta(z_x, z_y)$ [9]. The required dynamics thus correspond to two DEs in the same form as Equation (4) with the respective real and imaginary part of the output.
The STTF complex coefficients are given by $s(x, y, t) = s'(x, y, t) + js'(x, y, t)$, $j^2 = -1$ being the variables on the LHS of the two DEs:

$$\beta_{0,0}^r \frac{d}{dt} s'(x, y, t) = -e(x, y, t) + \sum_{n,m} \alpha_{n,m}^r s'(x-n, y-m, t) - \sum_{n,m} \alpha_{n,m}^i s'(x-n, y-m, t)$$

$$+ \sum_{n,m} \beta_{n,m}^r \frac{d}{dt} s'(x-n, y-m, t) - \sum_{n,m \neq 0,0} \beta_{n,m}^i \frac{d}{dt} s'(x-n, y-m, t)$$

(7)

$$\beta_{0,0}^r \frac{d}{dt} s'(x, y, t) = -\sum_{n,m} \alpha_{n,m}^r s'(x-n, y-m, t) - \sum_{n,m} \alpha_{n,m}^i s'(x-n, y-m, t)$$

$$- \sum_{n,m} \beta_{n,m}^r \frac{d}{dt} s'(x-n, y-m, t) - \sum_{n,m \neq 0,0} \beta_{n,m}^i \frac{d}{dt} s'(x-n, y-m, t)$$

(8)

The STTF complex coefficients are given by $\alpha = \alpha'(z_x, z_y) + j \alpha'(z_x, z_y)$ and $\beta = \beta'(z_x, z_y) + j \beta'(z_x, z_y)$. It should be clear that the treatment presented in Section 2 is equally suitable to implement complex TDCNNs, which can be viewed as two interconnected real TDCNNs. Figure 5 illustrates the architecture of a single cell.

Simulated results of the two layer TDCNN have been reported in [16]. In this paper we present results from the measured prototype: A 5 × 5 complex TDCNN array fabricated in the commercially available AMS 0.35 μm 4M/2P technology. Photoreceptors are not incorporated in this test chip since the sole scope of this first attempt of practical realization of a TDCNN network (with the proposed circuit blocks) was to investigate and confirm its stability and linearity in practical realizations. To facilitate this aim, the input voltage (the real part of the complex input) of each cell is supplied via the individual pins. Each cell in the TDCNN consists of 12 OTAs and 10 ABCMs for local filtering and coupling between cells. The OTAs and ABCMs on the TDCNN chip are biased with currents in the range of few tens of pico-amperes to very few tens of nano-amperes such that all transistors implementing the dynamics are operating in the weak inversion region. This is achieved in practice with current mirrors to scaling down the on-chip biasing currents by a factor of 64, while the off-chip currents are supplied by 6220/6221 Keithley precision current sources. The overall power consumption per cell is around 1.2 μW. Figure 6 is a micrograph of the fabricated prototype. A summary of the measured prototype is presented in Table I. To facilitate testing, additional circuit structures have been incorporated on-chip. This includes, apart from the current scalars mentioned above, an output scanning scheme [17] implemented to observe the 25 complex network outputs (25 × 2 signal lines) one at a time. This reduces the need for excessively large number of packaged pins for our prototype. In the following section, we will be presenting single cell measured responses followed by responses from a set of interacting TDCNN cells.
To gain more insights into the operation of a single TDCNN cell, we first consider Equations (7) and (8) and neglecting the spatially dependent terms:

\[
\beta_{0,0}^e \frac{d}{dt} s^e(x, y, t) = -e(x, y, t) + z_{0,0}^e(x, y, t) - \sigma^e_{0,0} s^e(x, y, t) - \beta_{0,0}^i \frac{d}{dt} s^i(x, y, t)
\] (9)

\[
\beta_{0,0}^i \frac{d}{dt} s^i(x, y, t) = -\sigma^i_{0,0} s^i(x, y, t) - \sigma^e_{0,0} s^e(x, y, t) - \beta_{0,0}^e \frac{d}{dt} s^e(x, y, t)
\] (10)
From Equations (9) and (10) it can be deduced that each single TDCNN cell effectively realizes a complex (polyphase) continuous-time filter. Filters of this kind could be tuned to produce a ‘quasi-bandpass’ characteristic (without exactly-zero DC response) by shifting a low-pass response along the frequency axis [18]. The interested reader can verify that by applying the Laplace transform to Equations (9) and (10) and subsequently derive a transfer function by treating \( s^i(x, y, t) \) as the system’s complex output. For a larger TDCNN array, it is the inter-cell coupling that produces the space–time nonseparable bandpass characteristics [9]. We provide measured results for a single cell to demonstrate its quasi-bandpass behavior in the frequency domain. This can be obtained by minimizing the inter-cell coupling by means of reducing the appropriate off-chip biasing currents to their minimum possible value supported by the Keithley sources. Figures 7 and 8 show the typical frequency response tunings of a single cell with ideal response included for reference. Let us further consider the single cell circuitry shown in Figure 5 and applying KCL to obtain the following dynamics:

\[
C \frac{d}{dt} V_r(t) = \left[ V_{in}(t) - V_r(t) \right] Gm_0 - V_r(t) Gm_1 + C \frac{d}{dt} V_i(t) \tag{11}
\]

\[
C \frac{d}{dt} V_i(t) = -V_i(t) Gm_0 + V_r(t) Gm_1 - C \frac{d}{dt} V_r(t) \tag{12}
\]

Note that (11)–(12) now refers to a specific circuit implementation (Figure 5) of Equations (9)–(10). Solving for \( V_r(t) \) and \( V_i(t) \) in the Laplace domain, we obtain the following input–output
Figure 8. (a) Measured single-cell frequency response while the local $Gm_1$ (see Figure 5) is varied. The tail current value of the input differential pair controlling $Gm_1$ is shown. The input tones are of 150 mVp-p in magnitude and (b) ideal response of the transfer function given in Equations (13) and (14) shows a similar trend as the measured responses when $Gm_1$ is increases while $Gm_0$ is fixed.

Transfer functions:

\[
\frac{V_r(p_t)}{V_{in}(p_t)} = \frac{Gm_0(Gm_0 + Gm_1)}{2C^2 p_t^2 + 2C(Gm_0 - Gm_1)p_t + (Gm_0^2 + Gm_1^2)}
\]  

\[
\frac{V_i(p_t)}{V_{in}(p_t)} = \frac{-Gm_0(Cp_t - Gm_1)}{2C^2 p_t^2 + 2C(Gm_0 - Gm_1)p_t + (Gm_0^2 + Gm_1^2)}
\]

where $p_t$ is the Laplace variable. Equations (13) and (14) indicate that the circuit given in Figure 5 implements pseudo-bandpass two-pole/one zero transfer functions, which overall realizes the aforementioned complex polyphase structure and agrees with the measured frequency response in Figures 7 and 8. Without the temporal-derivative circuitry in Figure 5, Equations (13) and (14) would become

\[
\left[ \begin{array}{c}
V_r(p_t) \\
V_i(p_t)
\end{array} \right]_{noTD} = \frac{Gm_0(Cp_t + Gm_0)}{2C^2 p_t^2 + 2Gm_0Cp_t + (Gm_0^2 + Gm_1^2)}
\]

\[
\left[ \begin{array}{c}
V_r(p_t) \\
V_i(p_t)
\end{array} \right]_{noTD} = \frac{Gm_0Gm_1}{2C^2 p_t^2 + 2Gm_0Cp_t + (Gm_0^2 + Gm_1^2)}
\]

which have a rather different frequency response characteristic compared with Equations (13) and (14), particularly when the imaginary part of the output is a two-pole system without the extra zero.
Figure 9. (a) Measured inter-cell AC response obtained with a Stanford Research SRT785 analog analyzer. All measurements are taken from a single cell where inputs are applied at the same cell, the cell to the left and the cell to the right of the measured cell. Inputs are applied one cell at a time when measurements are taken; these are labeled unambiguously in the figure. Circled lines denote the real part of the output, whereas the triangled lines denote the imaginary part and (b) corresponding simulated ideal inter-cell AC response (in faint lines), an increase in local ABCM current copying results in a shift of the response towards higher frequencies—this matches better with the measured results (see text).

We next provide measured results for a row of three cells interacting according to the TDCNN dynamics described in Section 2. The inter-cell AC response is shown in Figure 9. Note the significant difference between the response originated from the cell on the right to the response originated from the cell on the left, which is not unexpected considering we have different coupling coefficients from left to right and from right to left (i.e. asymmetric diffusion—see Table II for coupling parameters). Such asymmetry is typical and is required to achieve spatiotemporal orientation in the frequency domain: either with a single nonseparable filter as in this case [9], or by combining the response of several space–time separable filters [19]. This confirms the implementation of a space–time nonseparable behavior (i.e. we are not dealing with a cascade of a spatial filter and a temporal filter in which case the inter-cell AC responses would differ at most by a constant gain factor.) With a single cell response exhibiting tunable behavior from the temporal-derivative diffusion circuitry, the inter-cell response follows a similar trend with pseudo-bandpass characteristics.

Measured results of the full array are not available due to practical testing constraints and random offsets present at the OTAs which can cause cell output saturation. Input referred offsets were compensated by applying counter-offsets; however, the default imaginary parts of the inputs are all tied to the ground node. This rules out the possibility of providing cell-specific input-offset cancellation by means of applying appropriate input DC levels (both real and imaginary parts of
implementing a spatiotemporal bandpass filter as reported in [9]. The coupling parameters shown here would give rise to a two-layered TDCNN (given a larger array size).

The stronger signals but also to the fact that some of the OTAs were biased less than optimally. Generally speaking for the inter-cell response is due to an erroneous-increased current gain of the current copier towards the differential pair tail current), we speculate the effect of increased peak frequency result in a reduction of transconductance for OTAs based on a differential pair input (as we are ideal results. Since typical mismatch-induced errors in the form of input referred offsets often results exhibit a frequency shift as well as the amplitude error compared with the simulated results. Finally, we investigate the the effect of increased peak frequency for the inter-cell response is due to an erroneous-increased current gain of the current copier ABCM (see Figure 5) when additional inter-cell coupling is activated compared with the single cell case.

The first column records transconductance coupling parameters. E.g. the first row of the first column indicates that a transconductance value of $80 \times 10^{-12}$ is used to convert the real part of the output voltage into a current that feeds into the capacitor node of the real part of the output voltage at the left neighboring cell. The second column records time-derivative coupling parameters. E.g. the first row of the second column indicates that a scaling factor of $-0.18$ is used when converting the capacitor current at the the real part of each cell’s output into a current that flows into the real part of the output node of the cell to the left. Local coupling parameters between the real $\text{Re}[V] = V_r$ and imaginary parts $\text{Im}[V] = V_i$ of the output at each cell is given in Figure 5. The coupling parameters shown here would give rise to a two-layered TDCNN (given a larger array size) implementing a spatiotemporal bandpass filter as reported in [9].

Table II. Inter-cell coupling parameters.

<table>
<thead>
<tr>
<th>Transconductance type</th>
<th>Time-derivative type</th>
</tr>
</thead>
<tbody>
<tr>
<td>$80 \times 10^{-12} \times \text{Re}[V] = \text{current towards } \text{Re}[V_{\text{left}}]$</td>
<td>$-0.18 \times \text{Re}[V] = \text{current towards } \text{Re}[V_{\text{left}}]$</td>
</tr>
<tr>
<td>$-200 \times 10^{-12} \times \text{Re}[V] = \text{current towards } \text{Re}[V_{\text{right}}]$</td>
<td>$-0.24 \times \text{Re}[V] = \text{current towards } \text{Re}[V_{\text{right}}]$</td>
</tr>
<tr>
<td>$400 \times 10^{-12} \times \text{Re}[V] = \text{current towards } \text{Im}[V_{\text{left}}]$</td>
<td>$0.2 \times \text{Re}[V] = \text{current towards } \text{Im}[V_{\text{left}}]$</td>
</tr>
<tr>
<td>$420 \times 10^{-12} \times \text{Re}[V] = \text{current towards } \text{Im}[V_{\text{right}}]$</td>
<td>$0.27 \times \text{Re}[V] = \text{current towards } \text{Im}[V_{\text{right}}]$</td>
</tr>
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</table>

The coupling parameters shown here would give rise to a two-layered TDCNN (given a larger array size) implementing a spatiotemporal bandpass filter as reported in [9].

Each cell’s input) to bias all the OTAs in the middle of their I-V curves in order to achieve the optimal dynamic range. However, with no direct access to individual imaginary inputs, all results reported here were produced by biasing the real part of the cell inputs at appropriate levels to achieve the best response possible with our setup. When compared with ideal TDCNN response, the measured inter-cell response shows a larger deviation from the ideal characteristic compared with the deviation exhibited by the single cell experimental results (Figures 7 and 8). This is mainly due to the complexity of the circuitry responsible for inter-cell coupling. In particular, many of the inter-cell coupling circuitry are biased at sub-nano amperes levels in order to realize the coupling parameters as detailed in Table II; hence, the inter-cell coupling circuitry is more prone to mismatch errors compared with the circuit blocks used for local filtering at each cell, which are biased with tens of nano amperes. For moderate transistor mismatch, where the mismatch-induced-offsets of each OTAs and current mirror block fall within the operating range of the circuits, the random offsets would be observed as a fixed-pattern noise [20]. For imaging applications, it would result in a fixed offset image superimposed into the output. Note that in Figure 9, the measured results exhibit a frequency shift as well as the amplitude error compared with the simulated ideal results. Since typical mismatch-induced errors in the form of input referred offsets often result in a reduction of transconductance for OTAs based on a differential pair input (as we are operating close to the limits of the useful input voltage range when the output current saturates towards the differential pair tail current), we speculate the effect of increased peak frequency for the inter-cell response is due to an erroneous-increased current gain of the current copier ABCM (see Figure 5) when additional inter-cell coupling is activated compared with the single cell case.

Figure 10 shows the typical time-domain output of a center cell when all three cells are excited with appropriate input signals detailed in the figure legend. Here the measured outputs are shifted to a DC level of zero to ease comparison with simulation results. Finally, we investigate the the linearity of inter-cell coupling. Figures 11 and 12 illustrate the measured distortion levels at the output of a cell when input tones of different magnitudes are applied to the cell itself and its neighbors. The results characterize the linearity of the tested topologies. Generally speaking for input amplitudes higher than 70 mV the distortion level increased. This is attributed not only to the stronger signals but also to the fact that some of the OTAs were biased less than optimally. Since more circuit blocks are involved in the case of inter-cell coupling, biasing ‘errors’ of the input DC levels result in increased nonlinear distortion.
Figure 10. Measured and simulated (faint lines) results of the (a) real part and (b) imaginary part of a center cell output when inputs are applied at the cell and its immediate left and right neighbors. The left cell is exited with an input of 40 Hz/50 mVpk sinusoidal tone; the center cell at 160 Hz/50 mVpk input tone whereas the cell to the right is being presented with a 210 Hz/50 mVpk input tone. Appropriate input offsets are presented at all three cells, respectively, to bias optimally the cells as close to the center of the OTAs’ V-I operating range as possible (see text). The measured waveforms presented here are captured from an oscilloscope (Tektronix TDS3032) and are post processed only for a better presentation.

Figure 11. Inter-cell distortion levels measured at the real part of the output of the center cell in a three cell configuration. Inputs are applied one at a time at: (a) cell on the left; (b) the output-measuring cell at the center; and (c) cell on the right. Circles, triangular and star labeled plots denote inputs at frequencies 110 Hz, 160 Hz and 210 Hz, respectively.

5. DISCUSSION

We have proposed and tested an analog architecture for a recently introduced CNN, which involves the use of time-derivative diffusion across cells (TDCNNs). Despite practical problems mainly caused by circuit offsets, we have collected preliminary single-cell and inter-cell measured results from a 5×5, 12.6 mm², 30 µW prototype array built in the commercially available AMS 0.35 µm CMOS process. However, to further experiment with the TDCNN dynamics, in particular the
Figure 12. Inter-cell distortion levels measured at the imaginary part of the output of the center cell in a three cell configuration. Inputs are applied one at a time at: (a) cell on the left; (b) the output-measuring cell at the center; and (c) cell on the right. Circles, triangular and star labeled plots denote inputs at frequencies 110 Hz, 160 Hz and 210 Hz, respectively.

Characteristics of nonboundary cells, a larger array implementation is required and the present offset problem would need to be resolved. The main cause of the offset problem is due to the use of relatively small transistors with sub-nano ampere biasing currents in our building blocks. This is a direct result of the complexity of each block itself and the large number of blocks required to implement the TDCNN dynamics, forcing us to use smaller transistors to meet the overall allocated chip area. In practice we could trade random offsets for systematic offsets by using simpler circuit blocks (such as regular OTAs without cascode and mirror symmetry). The transconductor blocks used as synapses in Universal CNN machine implementations (CNNUM) [21], which have been reported to exhibit excellent mismatch tolerance given its small transistor count, could also take the place of the differential pair-based transconductor employed here. Overall, for our results to be scaled to larger arrays, we would need to investigate into alternative building blocks that would exhibit good matching behavior under sub-nA biasing currents [22, 23]. Furthermore, advanced read-out schemes (perhaps in the form of on-chip ADCs) would be required for the extraction and digitization of the continuous-time outputs at each pixel [24].

REFERENCES


