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Circuit implementation of digitally programmable transconductance amplifier in analog simulation of reaction-diffusion neural model

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ABSTRACT

This paper is concerned with circuit implementation in reaction-diffusion neuron model. Firstly, in order to realize easily, one obtains the equivalent form by discretization of this neuron model. In the frame of discrete model, every parameter can be represented by the basic circuit component. Then the digital programmable transconductance amplifier (DPTA) is designed to realize the digitally function in circuit. In addition, the DPTA is applied to realize two activation functions and the simulation results are verified in Multisim.

1. Introduction

Nowadays, many kinds of neural network models are very common in our daily life and they are used in engineering and science widely [1–4,26–29]. In the last few decades, various neural network models have been widely investigated and successfully applied to many kinds of research areas, such as image analysis, signal processing, pattern recognition, cryptography, associative memory, optimization, and model identification. Generally speaking, these models are described by ordinary differential equations where the neurons are well simulated. However, it is worth noting that the ordinary differential equation models ignore the spatial evolution at the level of neuron assemblies and cannot account for diffusion and reaction of neurons in biological systems. With the purposes that the good approximation of the spatiotemporal actions and interactions of actual neurons can be obtained, it is necessary to introduce the reaction-diffusion terms in neural network models. In [1], Chen et al. proposed a trainable reaction diffusion model for effective image restoration by extending conventional nonlinear reaction diffusion models and many applications have been investigated such as associative memory in [2], image processing in [3] and topology optimization in [4].

The synchronization and adaptive control in reaction–diffusion networks have been investigated deeply in some literature [5–11]. In [5], Wang et al. derived some sufficient conditions ensuring the passivity and global exponential stability by utilizing the Lyapunov functional method combined with the inequality techniques. In [6], Li et al. established the global exponential stability of the neural networks with its estimated exponential convergence rate by using the Lyapunov function method and M-matrix theory. In [7], Zhang and Xiao proved that the one-leg θ-method preserves stability and dissipativity of the underlying equations. In [8], Qiu considered the problems of global exponential stability and exponential convergence rate for impulsive neural networks with time-varying delays and reaction–diffusion terms. Moreover, others analysis methods are proposed on this such as impulsive control [9], hybrid coupling [10] and uncertain parameters [11].

Inspired by the sophisticated functionality of human brains where hundreds of billions of neurons interconnected process information in parallel, artificial neural networks (ANNs) rise in artificial intelligence since the 1980 s. ANNs are a family of models which are used to estimate and approximate functions that depend on a large number of generally unknown inputs [12–15]. ANNs are usually proposed as system of interconnected “neurons”. These “neurons” exchange message with each other. With the chase of high order information processing, the circuitry implementation of neural-network model is more important. As shown in [12], Zhang et al. proposed an ANN modeling approach to analyze noise figure of the entire circuit for the first time. In the proposed technique, the effects of input and output matching networks on the circuit's noise figure are analyzed respectively. In [13], Adhikari et al. proposed a Memristor-based circuit architecture for multilayer neural networks Memristor-based circuit architecture for multilayer neural networks. In [14], Wang et al. combined several circuit units to realize some neuron-network models. Results showed that the phenomenon such as hyperchaos, limit cycles, homoclinic orbits of the designed circuits are closely similar to the results of numerical experiments successfully. In addition, as a classical and developed branch of ANNs, cell neural networks (CNNs) are effective in many applications. In [15], some impressive applications

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of cellular neural networks to such areas as huge processing and pattern recognition have been demonstrated. In [16], Martinez et.al. proposed a new CNN architecture conceived for hardware implementation of complex ML-CNNs on programmable devices.

Come up with this idea of CNNs, a reaction-diffusion neural network is proposed to estimate the reaction-diffusion equations' dynamic properties in this paper. It is necessary to consider that reaction-diffusion equations the discretization in time may affect the reliability of the simulation results. Therefore a digital programmable value in circuit is brought and realized. In order to control the discrete parameters in the simulation of RD-PDE, it requires varying the value of the resistor$R$. There are some people have contributed to this field. In [17], Sargeni et. al proposed the analog amplifier in each cell to realize a new CNN. This circuit share in time in order to generate the all current contributions required to feed the neighbourhood and the cell. In [18], a digital-to-transconductance converter was presented for use with digitally programmable Nauta structure operational amplifiers. In this paper, the reaction-diffusion neural network is established according to the reaction-diffusion equation. And the key component digitally programmable transconductance amplifier (DPTA) is designed to realize the changeable resistor with digitally programmable bits. With the circuit simulation, the digitally programmable characteristic is certified. Firstly, the classical OTA scheme is used to obtain the differential current by combining them with corresponding switches to obtain total current. Then a couple of differential circuit is connected to it in each group. The circuit simulation is described and the implementation is supported by Multisim simulation results. Considering the universality of the circuit model, its application in complex dynamical behavior of neural networks in circuit implementation is also taken into consideration.

The remainder sections is organized as follow. In Section 2, the macro-structure of the reaction-diffusion neural network is proposed and some theoretical demonstrations are listed to simulate the net and single neuron respectively. In Section 3, the circuit implementation of DPTA in detail is explicated. In Section 4, two another active functions $N(v)$ and $g(x)$ are realized by utilizing the proposed circuit in Section 3. Finally, Section 4 concludes this paper.

1.1. The reaction-diffusion neural network to RD-PDE's solution and single unit model

In [9], Wang et al. proposed a single reaction-diffusion neural network with Dirichlet boundary condition by the following partial differential equations (PDEs):

$$\frac{\partial w(x,t)}{\partial t} = d_i \Delta w_i(x,t) - a_i w_i(x,t) + J_i + \sum_{j=1}^{n} b_{ij} f_j(w_j(x,t)) \tag{1}$$

where $i = 1, 2, \ldots, n$, $x = (x_1, x_2, \ldots, x_q)^T \in \Omega$, $w_i(x,t) \in R$ is the state of ith neuron at time t and in space x, $\Delta = \sum_{k=1}^{q} \frac{\partial^2}{\partial x_k^2}$ is the Laplace diffusion operator on Ω, $d_i > 0$ evaluates the transmission diffusion coefficient along the ith neuron, $f_j(\cdot)$ represents the activation function of jth the neuron, $a_i > 0$ indicates the rate with which the jth neuron will reset its potential to the resting state when disconnected from the networks and external inputs in space x_i, b_{ij} shows the strength of the jth neuron on the ith neuron, and J_i is a constant external input. In this paper, a simplifying 1-D reaction-diffusion equation from Eq. (1) without b_{ij} and J_i is obtained to realize the circuit implementation.

For the reaction-diffusion characteristic can be performed circuit, the Laplace diffusion operator and the activation function of neurons are kept. Based on the Eq. (1), the constant part and summation part are omitted to realize the circuit. The equation is shown as follow:

$$\frac{\partial w(x,t)}{\partial t} = d\frac{\partial w(x,t)^2}{\partial x^2} + bf(w(x,t)) \tag{2}$$

with initial condition

Table 1
The solution of different rates of b/d.

Region	Mainly circumstance	The form of regime solution
$b/d > > 1$	Reaction	Two values
$b/d < < 1$	Diffusion	Only trivial solution

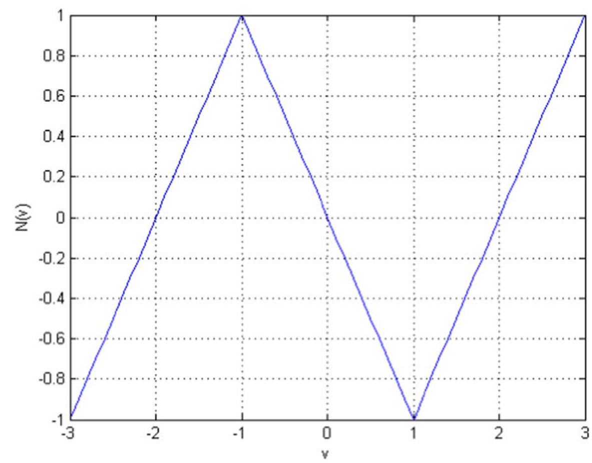


Fig. 1. Nonlinear function $N(v)$.

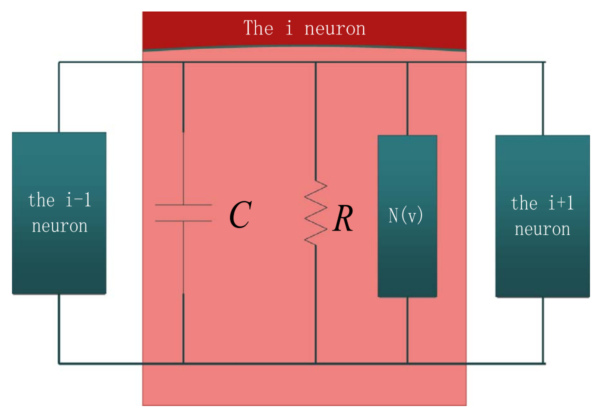


Fig. 2. The single neuron in reaction-diffusion neuron network according to Eq. (8).

$$W(X,0) = W_0(x) \qquad 0 \le x \le l \tag{3}$$

and with one of the following boundary conditions

$$W(0,t) = W(l,t) = 0 \qquad \textit{Dirichlet} \tag{4}$$

$$\left.\frac{dW}{dx}\right|_{x=0} = \left.\frac{dW}{dx}\right|_{x=l} = 0 \qquad \textit{Neumann} \tag{5}$$

$$W(0,t) = W(l,t) \qquad \textit{Circulant} \tag{6}$$

In Eq. (2), the relationship between reaction and diffusion is depicted by the rate of b/d when b/d belong to different regions. For arbitrary value of $b/db/d$, there is a regime solution. Specific circumstances are described in Table 1.

It is noted that only the specific frequencies can have stable solution, so the behaviors in the equation is richness. Moreover, the performance of the equation will be rather richer if the Neumann and/or Circulant conditions are considered. And the function $f(.)$ is piecewise with a part of negative slope.

To realize the unit in circuit, a physical model is designed corresponding to Eq. (2). One which can be depicted in each neuron is obtained as follow [18]

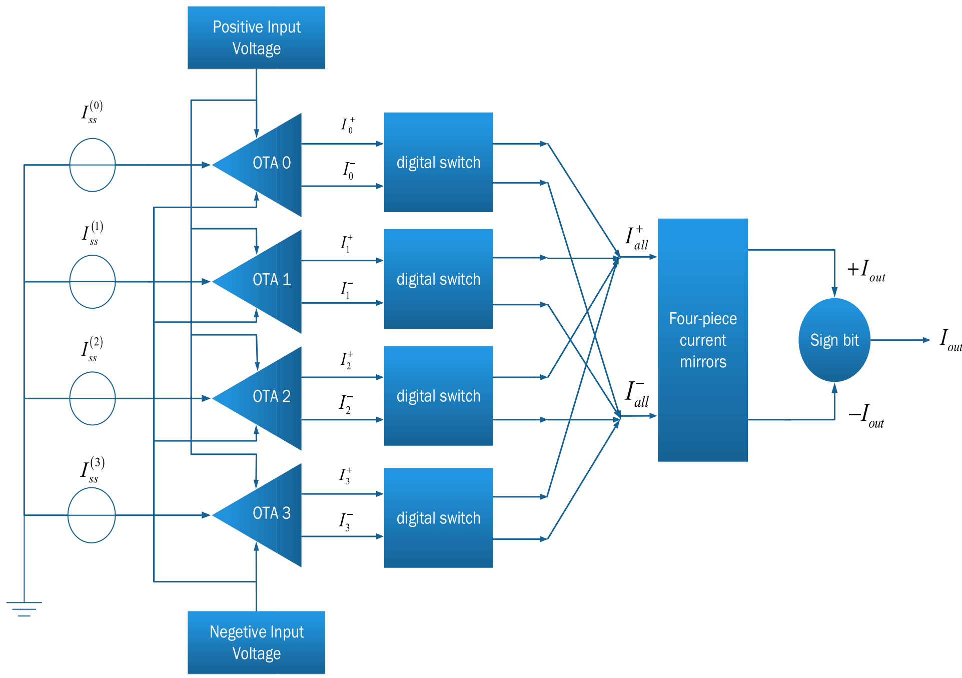


Fig. 3. Basic architecture of proposed multiplier.

$$C\frac{dv_i}{dt} = -\frac{v_i}{R} - N(v_i) + f_i \tag{7}$$

and

$$f_i = -\left\{\lambda\left[C\frac{dv_{i-1}}{dt} + N(v_{i-1})\right] - \frac{1}{2}\frac{v_{i-1}}{R}\right\} - \left\{\lambda\left[C\frac{dv_{i+1}}{dt} + N(v_{i+1})\right] - \frac{1}{2}\frac{v_{i+1}}{R}\right\} \tag{8}$$

where the function $N(v)$ is nonlinear in Fig. 1

The parameter λ can be expressed as

$$\lambda = \frac{\beta}{6(1-\beta/3)} \tag{9}$$

As seen in Eq. (7), there are four parameters in the circuit C, R, I_g and V_g. To depicted each neuron model in the circuit, the value of C, I_g and V_g are fixed with technical constraints and let the value of R vary with the law:

$$R = \frac{\alpha}{\delta}\frac{1}{2(M-1)^2}\frac{V_g}{I_g}\left(1-\frac{\beta}{3}\right) \tag{10}$$

M is the number of the units in the net. The model simulating single neuron in reaction-diffusion neuron network is designed as follow:

Obviously, in order to control the parameters of the simulation of reaction diffusion equations, it requires to vary the parameters R. So in the neuron design the parameter must be digitally selectable. In order to satisfy the former requirement, an active resistor has been implemented inside each neuron in the next section. A 5-bit DPTA has been used to implement the resistor. In this way, the user can be allowed to select the necessary parameter values. For particular set of equation parameters an external passive resistor should be connected in parallel to the active resistor.

2. Circuit implementation of DPTA

The single neuron well suited to solve the RD-PDE equations described in the former section has been designed. In this section, an artificial circuit is designed to make the proposed DPTA come true. We realize the circuit based on the classical OTA (Operational Transconductance Amplifier) scheme, the sketch map [19] is shown in Fig. 3. In terms of Fig. 3, we design the schematic diagram in Fig. 4.

As shown in Fig. 3, the sketch map consists OTAs, digital switches and current mirrors, OTAs are used to product I_i^+ and I_i^-. In the meantime, they are changeable by setting different pairs of parameters. Then the digitally programmable characteristics depend on n switches. We obtain discrete transconductance by setting different electrical levels on switches to decide which are picked on. And the current mirrors can realize the subtraction between the I_{all}^+ and I_{all}^-. The P-MOS are used to construct all circuit parts, since that P-MOS can amplify the current through it and could be used as switches. Its output characteristics are shown in Fig. 5.

The transconductance parameter β_p of the P-MOS can be expressed by the following equation [20]:

$$\beta_p = \frac{W\mu_p C_{ox}}{L} \tag{11}$$

The parameter annotation is given in Table 2.

β_p is the same for the two transistors of every differential pairs. The differential current $I_0 = I_0^+ - I_0^-$ can be achieved approximately by the following equation:

$$I_0 = I_{ss}\sqrt{\frac{\beta_p}{2I_{ss}}}V_{in} \quad with \quad |V_{in}| < \sqrt{\frac{2I_{ss}}{\beta_p}} \tag{12}$$

The proposed analog multiplier with digital selectable bits is shown in Fig. 4, for n=5, sign included. The currents I_i^+ and I_i^- are designed to satisfy the following laws

$$I_i^+ = 2^i I_0^+ \qquad I_i^- = 2^i I_0^- \tag{13}$$

to realize Eq. (12), we design the rate of W/L in current generators and differential pairs simultaneously and the rate of W/L satisfies the following equation [21]:

$$\frac{W^{(i)}}{L^{(i)}} = 2^i\frac{W^{(0)}}{L^{(0)}} \tag{14}$$

Therefore, the single OTA combined with switch is designed in Fig. 6. The results are verified in Multisim. In Fig. 7, the rate of W/L control characteristic is performed, for the rate of W/L in Fig. 7(b) is designed two times than (b). In Fig. 8, the positive and negative slopes

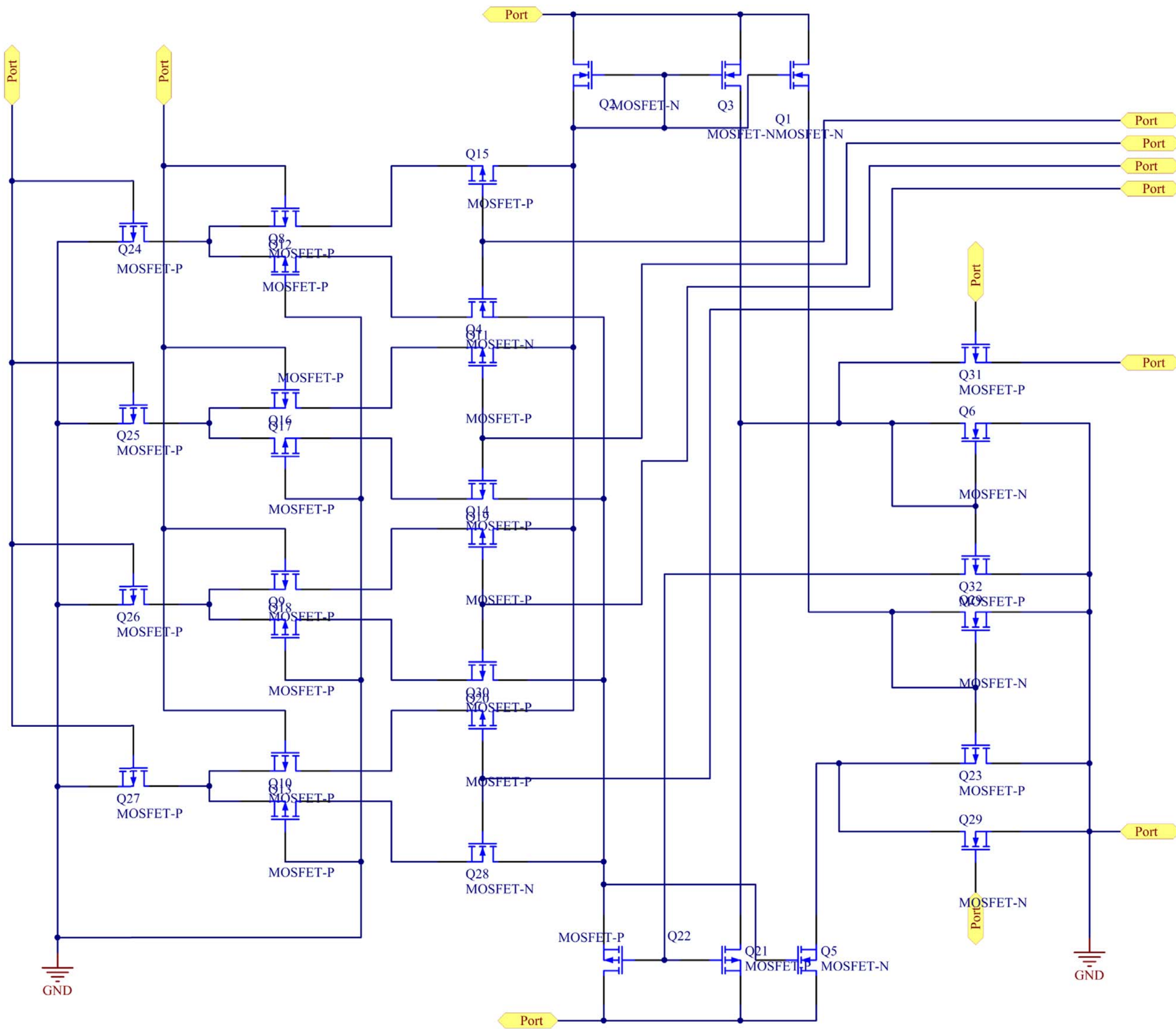


Fig. 4. Digitally Programmable Transconductance Amplifier (DPTA).

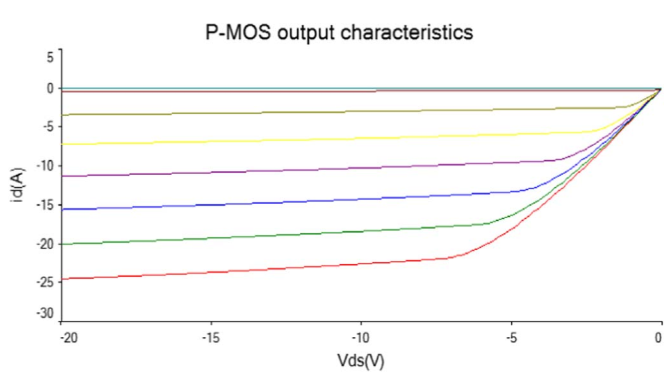


Fig. 5. P-MOS output characteristics.

Table 2
Parameters annotation.

Parameters	Meaning
W	Channel length
μ_p	Hole mobility
C_{ox}	Unit-area capacitance
L	Channel width

are obtained respectively by changing the direction of current mirrors to verify the changeable direction characteristic.

In the amplifier, the digitally programmable characteristic is realized by current mirrors as switches. The switches are connected to corresponding bits. Then the four differential currents are added and we can obtain positive and negative output currents by two pairs of current mirrors as follow [22]:

$$\pm I_{out} = [\sum b_i I_i^+ - \sum b_i I_i^-] = \sum b_i I_0^{(i)} \tag{15}$$

In Fig. 4, we design the digital selectable circuit which can select the positive or the negative output current through the sign bit. Let set $I_{ss}^{(i)} = 2^i I_{ss}^{(0)}$ and using Eqs. (11), (12), (14), we obtain

$$I_0^{(i)} = V_{in} I_{ss}^{(0)} 2^i \sqrt{\frac{1}{2\alpha}} \tag{16}$$

Then the output currents of the OPAs is given as follow with circuit simulation in Multisim (Fig. 9)

$$\pm I_{out} = \pm I_{ss}^{(0)} \sqrt{\frac{1}{2\alpha}} [\sum b_i 2^i] V_{in} \tag{17}$$

We can obtain a digitally programmable transconductance parameter as follow:

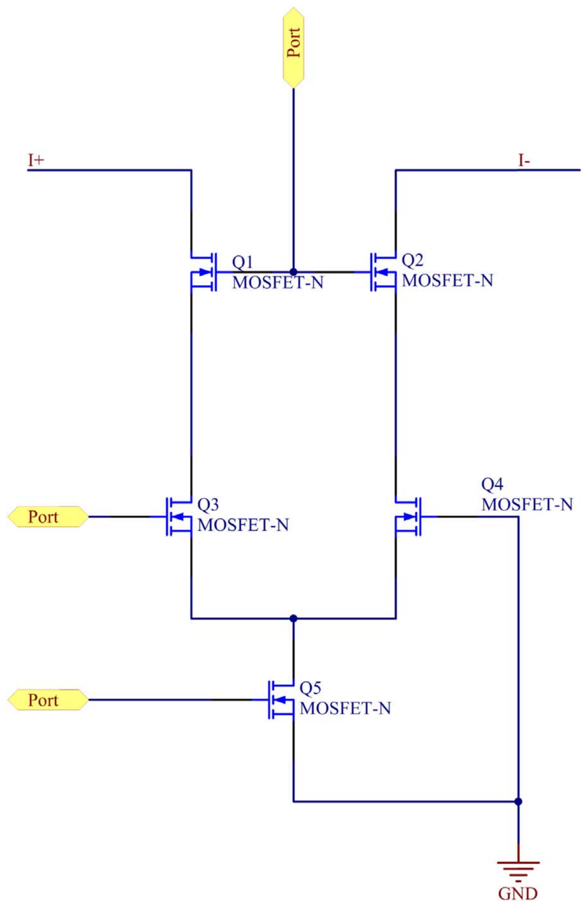


Fig. 6. Single group of OPA combined with bit switch.

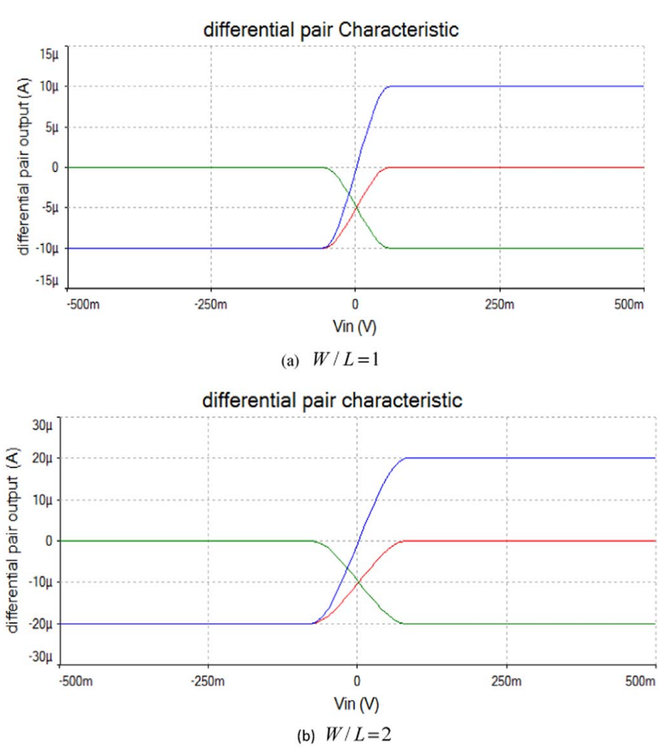


Fig. 7. Differential pair currents with different rate of W/L. (a) $W/L = 1$. (b) $W/L = 2$.

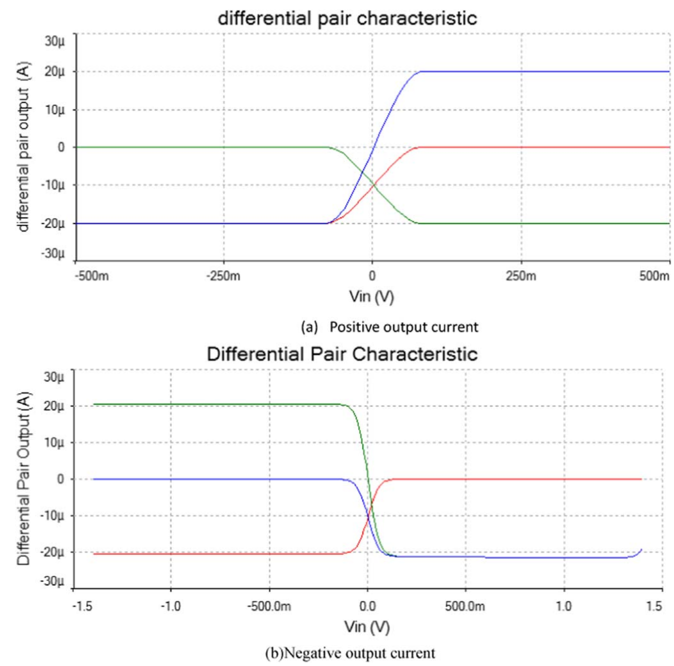


Fig. 8. Different slopes of the output currents with opposite directions of current mirrors. (a) Positive output current. (b) Negative output current.

$$g_m = g_0 k \tag{18}$$

in which

$$k = \sum_i b_i 2^i \tag{19}$$

$$g_0 = I_{ss}^{(0)} \sqrt{\frac{1}{2\alpha}} \tag{20}$$

If we use four bits to represent integer k, we can select 15 different values of g_m. The choice of parameter α is related to the peak-to-peak input and the minimum of transconductance requirement. As an example, for a linear region $\alpha = I_{ss}^{(i)}/\beta^{(i)}$, we set $\alpha = 0.005V^2$ and $V_{in} < 0.1V$, when $|V_{in}| > \sqrt{2\alpha}$, each OTA gives its saturation current corresponding to its current source $I_{ss}^{(i)}$. The total saturation current I_{outsat} is

$$I_{outsat} = [\sum b_i 2^i] I_{ss}^{(0)} \tag{21}$$

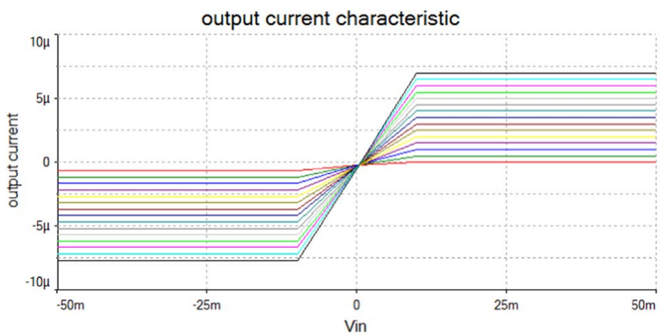
Due to the cut-off characteristics when $V_{gs} < V_t$, we put a voltage level on its g-source to control the working condition of P-MOS to realize the switches. The sign of output current is selected by the sign bit. With the current mirrors and two sets of outside differential circuit, we realize the positive and negative differential currents and the DC sweep simulation result of the DPTA is tested in Multisim (Fig. 10). Furthermore, the layout of schematic diagram in Altium Designer is shown in Fig. 11.

3. Application

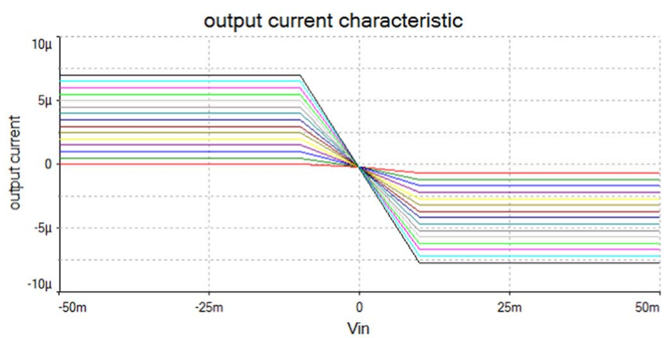
In this section, we realize two non-linear functions by designing circuits which are based on OTA and differential circuit respectively.

3.1. Circuit implementation of an common activation function

As proposed in Section 2, we propose a reaction-diffusion Eq. (2). The reaction-diffusion neuron network that simulates the equation is composed of elementary neurons shown in Fig. 2. The neuron can be described as Eq. (7), in which the active function $N(v)$ is in Fig. 2. We realize the nonlinear function $N(v)$ by connecting together three unity-gain OTAs (Fig. 12). The three OTAs present the part of the nonlinear function respectively by setting the different input voltage V_g.



(a)The positive output current for different digital values



(b)The negative output current for different digital values

Fig. 9. Output current by different output template. (a) The positive output current for different digital values. (b) The negative output current for different digital values.

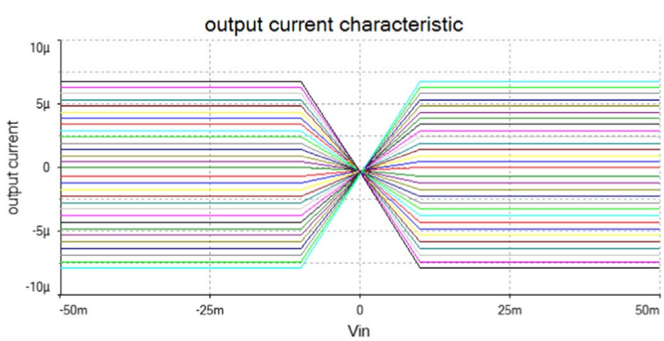


Fig. 10. Electrical simulation (Multisim) of proposed DPTA: Output current against input voltage for different digital values.

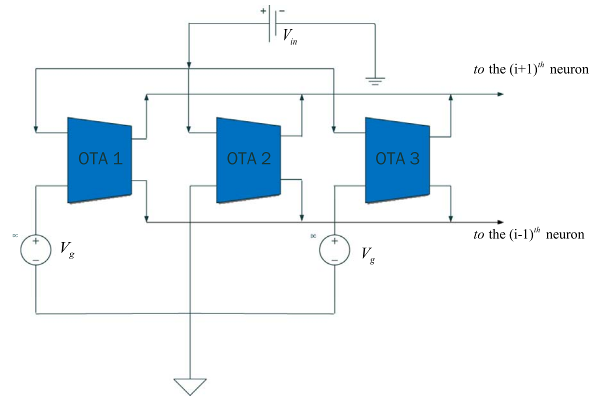


Fig. 12. Scheme of the circuit for the non-linear element $N(v)$.

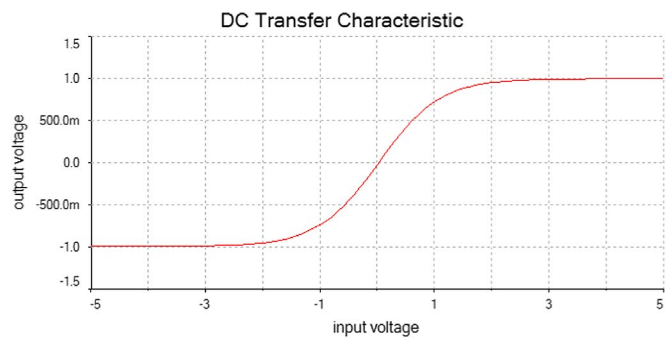


Fig. 13. DC sweep result for the activation function $g(x)$.

3.2. Circuit implementation activation function $g(x)$

One of the most attractive properties of ANNs is the possibility to apply their behavior to the changing characteristics of the modeled system. In [23], five different well-known activation functions in ANNs such as Bipolar sigmoid, Uni-polar sigmoid, Tanh, Conic Section, and Radial Bases Function are uesd to compare their performances. The differential circuit proposed in this paper also can be used to implement a Uni-polar sigmoid activation function $g(x)$. The function is given as follows:

$$g(x) = \frac{1}{1 + e^{-x}} \tag{22}$$

The function has an advantage over the other equations in neural networks trained by back-propagation algorithms. Because it is easy to

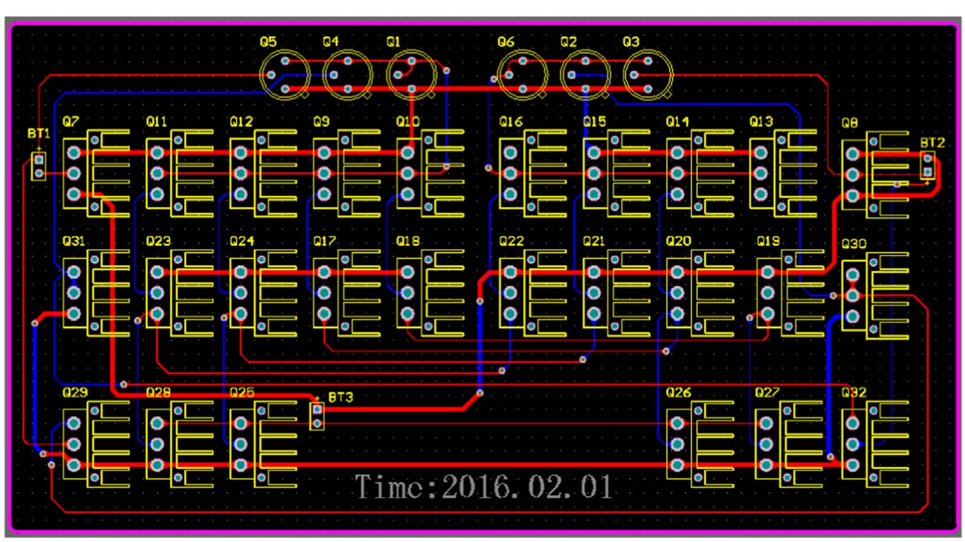


Fig. 11. The layout of schematic diagram in Altium designer.

distinguish, and this can minimize the computation capacity for training. The term means 'S-shaped', and logistic form the sigmoid maps the interval (−∞, ∞) onto (0, 1) as seen in Fig. 13. As the DPTA's characteristic is shown in Figs. (7–9), the 'S-shaped' characteristic can be realized in single differential circuit. In Fig. 10, the whole circuit of DPTA also can realize the circuit for more complex and flexible circumstance.

4. Conclusion

In this study, we have structured a reaction-diffusion neuron network simulating the reaction-diffusion equation and realized the changeable resisitor in its single neuron circuit implementation. We design the schematic based on theory from parts to overall. With the simulation results in Multisim, the facticity is verified and the layout in Aultim Designer is also given. Different from others, in this paper, the digitally programmable amplifier is implemented in analog circuit compared to the literature [24] realizing the function in digital module and in [25], where the function is realized on electronically programmable conductance. Moreover, the circuit is brought in reaction-diffusion neural network aiming to implement the reaction-diffusion equation characteristics with mathematical proofs. Finally, two basic circuit OPAs and differential pairs are applied into implementation. In the future, neurons will be connected with each other to a reaction-diffusion neuron network. In addition that, the different size transconductance characteristic in Nauta arthitecture had been explored in theory in [18]. As a circuit component designed in panel, the realization is also in hope.

Acknowledgements

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