



# Unsupervised learnable neuron model with nonlinear interaction on dendrites



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## ABSTRACT

Recent researches have provided strong circumstantial support to dendrites playing a key and possibly essential role in computations. In this paper, we propose an unsupervised learnable neuron model by including the nonlinear interactions between excitation and inhibition on dendrites. The model neuron self-adjusts its synaptic parameters, so that the synapse to dendrite, according to a generalized delta-rule-like algorithm. The model is used to simulate directionally selective cells by the unsupervised learning algorithm. In the simulations, we initialize the interaction and dendrite of the neuron randomly and use the generalized delta-rule-like unsupervised learning algorithm to learn the two-dimensional multi-directional selectivity problem without an external teacher's signals. Simulation results show that the directionally selective cells can be formed by unsupervised learning, acquiring the required number of dendritic branches, and if needed, enhanced and if not, eliminated. Further, the results show whether a synapse exists; if it exists, where and what type (excitatory or inhibitory) of synapse it is. This leads us to believe that the proposed neuron model may be considerably more powerful on computations than the McCulloch–Pitts model because theoretically a single neuron or a single layer of such neurons is capable of solving any complex problem. These may also lead to a completely new technique for analyzing the mechanisms and principles of neurons, dendrites, and synapses.

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## 1. Introduction

The human brain, built of about  $10^{11}$  neurons and  $10^{15}$  interconnections, is of staggering complexity. The fundamental structure of a neuron consists of a cell body, an axon, and a dendrite. Neurons have different functions depending on the branch patterns of their dendrites, i.e., the function changes with differences in these structures (Cajal, 1909). The first model of a neuron was proposed by McCulloch and Pitts in 1943 and has been widely used as a basic unit for modern researches on neural networks (McCulloch & Pitts, 1943). However, this model has been criticized as being oversimplified from the viewpoint of the properties of real neurons and the computation that they perform because only one nonlinear term (thresholding on cell body) is included in the model and the nonlinear mechanisms of dendrites are not considered (London & Häusser, 2005). Meanwhile, recent researches have provided

strong circumstantial support for dendrites playing a key role in the overall computation performed by the neuron (Agmon-Snir, Carr, & Rinzel, 1998; Anderson, Binzegger, Kahana, Martin, & Segev, 1999; Euler, Detwiler, & Denk, 2002; Magee, 2000; Single & Borst, 1998; Stuart, Spruston, & Häusser, 2008). Based on these experimental findings, Larkum, Zhu, and Sakmann (2001), and Rhodes and Llinás (2001) modeled apical dendrites as a compartment distinct from the somatic compartment, and were successful in reproducing the diverse range of neuronal firing patterns (Kepecs, Wang, & Lisman, 2002; Mainen & Sejnowski, 1996). After the experimental observation of localized regenerative spikes in the fine distal dendrites (Schiller, Major, Koester, & Schiller, 2000; Schiller, Schiller, Stuart, & Sakmann, 1997; Wei et al., 2001). Poirazi, Brannon, and Mel (2003a, 2003b) proposed a simplified two-layer neural network model where individual dendritic subunits perform a sigmoidal thresholding nonlinear operation on their inputs. This model provided a useful abstraction on the spatial integrative function of a pyramidal cell (Wang & Liu, 2010).

However, they all are bound to require the addressing of the relevant synaptic input to the relevant locality in the dendrites

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(Koch, Poggio, & Torre, 1983; Koch, Poggio, Torre, & Casey, 1982). Recently, many algorithms for learning such nonlinear processing have been proposed. Instead of using a weighted sum, Durbin and Rumelhart used a weighted product as a computational unit for feedforward learning networks of the backpropagation type (Durbin & Rumelhart, 1989). Other models of a nonlinear neuron and algorithm for learning, such as the sigma-pi unit in which the output activation is calculated as the weighted sum of the products of independent sets, or clusters of input values (Mel, 1990; Rumelhart & McClelland, 1986), and the cluster in which each input has a synaptic weight (the term “cluster” is used to refer to inputs that can affect the activation received by a particular synapse) (Spratling & Hayes, 2000), have also been proposed. However, they could not solve the 3-bit parity problem. Furthermore, these models used “weights” to represent the degree of clustering between synapses. Thus, all sense of locality was lost, and these models could not represent local interactions within a fixed dendritic tree. In this sense, they are not biologically plausible models of nonlinear dendritic processing (Spratling & Hayes, 2000).

Koch, Poggio, and Torre found that in the dendrites of a retinal nerve cell, if an activated inhibitory synapse is closer than an excitatory synapse to the cell body, the excitatory synapse will be intercepted. They suggested that the interaction between synapses and the action at the turning point of a branch be considered in terms of logical operations (Koch et al., 1983, 1982). Several experimental examples such as direction selectivity in retinal ganglion cells (Taylor, He, Levick, & Vaney, 2000) and coincidence detection in the auditory system (Segev, 1998) have provided strong circumstantial support to Koch’s model. Recent theoretical and experimental studies using the neuron simulation environment also suggested that such an inhibitory effect be located in a single dendritic branch (Liu, 2004) and dendritic computation results from the interaction of excitatory and inhibitory synaptic inputs (Fortier & Bray, 2013). However, for a specific given task, particularly a complex task, it is usually very difficult for Koch’s model to identify what type of synapse (excitatory or inhibitory) is needed, where the synapse should be located, which branch of the dendrite is needed, and which one is not needed (Destexhe & Marder, 2004). Koch pointed out that we need a learning algorithm based on the plasticity in dendrites to answer these questions and understand how the conductance of a neuron’s cell body and dendritic membrane develops in time (Koch, 1997). Fortunately, a wide variety of plasticity mechanisms have been identified in pyramidal neurons (Artola, Brocher, & Singer, 1990; Bi & Poo, 1998; Dringenberg, Hamze, Wilson, Speechley, & Kuo, 2007; Gu, 2003; Losonczy, Makara, & Magee, 2008; Makara, Losonczy, Wen, & Magee, 2009; Markram, Lübke, Frotscher, & Sakmann, 1997; Ngezahayo, Schachner, & Artola, 2000; Reynolds & Wickens, 2002; Sjöström, Rancz, Roth, & Häusser, 2008; Sjöström, Turrigiano, & Nelson, 2001). Meanwhile, Holtmaat and Svoboda showed experimental evidence to support structural synaptic plasticity and learning (Holtmaat & Svoboda, 2009). In particular, recent experimental evidence suggested that back-propagating action potentials can provide a feedback signal to the input layers and may be involved in the process of synaptic plasticity (Larkum, Zhu, & Sakmann, 1999; Stuart & Häusser, 2001).

In our previous papers (Tang, Kuratu, Tamura, Ishizuka, & Tanno, 2000; Tang, Tamura, Okihiro, & Tanno, 2000), we proposed a neuron model with interaction among synapses with dendrites and successfully trained the model to learn the directionally selective problem and the depth rotation problem (Sekiya, Aoyama, Tamura, & Tang, 2001; Sekiya, Wang, Aoyama, & Tang, 2001; Sekiya, Zhu, Aoyama, & Tang, 2000; Takeuchi, 2010; Tamura, Tang, & Ishii, 2002; Tamura, Tang, Okihiro, & Tanno, 1999). However, the trainings were all performed by the supervised learning of a mechanism that compares the desired and the actual outputs and feeds back the processed corrections. Such a supervised training mechanism is biologically implausible; it is difficult to conceive such a

training mechanism in the brain. Recently, Legenstein and Maass provided mathematical proof that these plasticity mechanisms induced a competition between dendritic branches, and such dendritic competition enabled a single neuron to acquire nonlinear computational capabilities, such as the capability to bind multiple input features in a self-organized manner (Legenstein & Maass, 2011). However, even having used nonlinear branches, the model could not solve such non-linearly separated problems as a simple exclusive OR (XOR) function. Spratling and Hayes presented a model of an initially standard linear node that uses unsupervised learning to find clusters of inputs within which inactivity at one synapse can occlude the activity at the other synapses. However, because they used “weights” to represent the degree of clustering between synapses, all sense of locality was lost, and this model failed to include local interactions within a fixed dendritic tree. In this sense, it is not a biologically plausible model of nonlinear dendritic processing (Spratling & Hayes, 2000). In this paper, we assume that neurons learning to compute what they compute and develop an unsupervised learnable neuron model with interaction among synapses of a dendrite. The unsupervised learning algorithm for a single layer of such neurons requires no teaching signal for the output, and hence, there are no comparisons with the predetermined ideal responses. The training set consists solely of input vectors, and the desired output patterns are obtained from the input patterns. We show how such an unsupervised rule enables the neurons to decide their synaptic connections and delete the unnecessary synaptic connections and dendritic branches. We also show that such an unsupervised learning algorithm can be used to learn two-dimensional eight-directionally selective problems.

## 2. Model and learning

### 2.1. Model

From measurements made using histological materials, Koch, Poggio, and Torre found that the interactions between excitation and inhibition can be strongly nonlinear, and shunting inhibition can specifically veto an excitatory input if it is located on the direct path to the soma (Koch et al., 1983, 1982). Fig. 1 shows a model that implements the idea. Here, if the inhibitory interaction is described as an AND NOT gate, the operation implemented in Fig. 1 could be read as

$$u = \bar{x}_1 \cdot x_2 \quad (1)$$

where  $x_2$  denotes an excitatory input and  $x_1$  represents an inhibitory input. Each input is either logical 0 or 1. Thus, the signal to the cell body (soma) becomes  $u = 1$  when and only when  $x_1 = 0$  and  $x_2 = 1$ .

Fig. 2(a) shows an idealized dendrite of a  $\gamma$  cell, receiving excitatory and inhibitory synapses distributed from the tip to the soma. As shown in Fig. 2(a), most  $\gamma$  cells have a small cell body and dendrites that usually have only one branch (Koch et al., 1982). Koch, Poggio, and Torre showed that a given excitatory input would be effectively vetoed by the inhibitory inputs on the direct path to the soma whereas the remaining inputs essentially remain unaffected by all other more distal inhibitory synapses (Destexhe & Marder, 2004; Koch et al., 1983). Thus, the operation implemented in Fig. 2(a) can be read as

$$u = \bar{x}_1 \cdot x_2 + \bar{x}_1 \cdot \bar{x}_3 \cdot x_4, \quad (2)$$

and Fig. 2(a) can also be represented by Fig. 2(b).

Compared with a  $\gamma$  cell, the dendrite of a  $\delta$  cell has considerably more branches (Koch et al., 1982). A  $\delta$  cell is shown in Fig. 3(a). The operation implemented can be expressed as follows:

$$u = \bar{x}_7 \cdot x_8 + \bar{x}_5 \cdot x_6 + \bar{x}_1 \cdot x_2 + \bar{x}_1 \cdot \bar{x}_3 \cdot x_4 \quad (3)$$

and thus, Fig. 3(a) can also be re-drawn as Fig. 3(b).

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