Self-organization of neural maps using a modulated BCM rule within a multimodal architecture

Mathieu Lefort, Yann Boniface, Bernard Girau

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Abstract Human beings interact with the environment through different modalities, i.e. perceptions and actions. Different perceptions as view, audition or proprioception for example, are picked up by different spatially separated sensors. They are processed in the cortex by dedicated brain areas, which are self-organized, so that spatially close neurons are sensitive to close stimuli. However, the processings of these perceptive flows are not isolated. On the contrary, they are constantly interacting, as illustrated by the McGurk effect. When the phonetic stimulus /ba/ is presented simultaneously with a lip movement corresponding to a /ga/, people perceive a /da/, which does not correspond to any of the stimuli. Merging several stimuli into one multimodal perception reduces the ambiguities and the noise of each perception. This is an essential mechanism of the cortex to interact with the environment. The aim of this article is to propose a model for the assembling of modalities, inspired by the biological properties of the cortex. We have modified the Bienenstock Cooper Munro (BCM) rule to include it in a model that consists of interacting maps of multilayer cortical columns. Each map is able to self-organize thanks to a continuous decentralized and local learning modulated by a high level signal. By assembling different maps corresponding to different modalities, our model creates a multimodal context which is used as a modulating signal and thus it influences the self-organization of each map.

1 Introduction

The cortex is divided into several areas, each one having a specific function. Some of them are dedicated to compute a perceptive flow as visual areas V1 to V5. Each area is made up of multilayer cortical columns. Thanks to this generic structure, areas are

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able to process other functions, depending on the type of inputs they receive, as it can be seen in perceptive cortical areas of disabled people.

An object is defined by a set of perceptions and affordances. This term, defined in Gibson's theory [7], means the possible interactions between an object and a living being. Examples of affordances of a tree are "lie down" or "climb on" for a human or "perch on" for a bird. In order to perceive an object, the cortex has to compute this set of modalities as a single multimodal stimulus.

Although perceptions from an object reach the cortex through different sensors, the cortex merges them in areas named associative maps to form a unified representation. Associating perceptions and actions to make a unique multimodal stimulus is an essential mechanism to interact with the environment. This makes it possible to recall one perception from another one. For example, an adult is able to identify an object he only touches among a set of previously seen objects.

Perceptual flows are not only associated in the cortex but they interact with each other. These influences are easily detectable. For example, when someone is watching a ventriloquist show, his ears perceive a sound coming from the ventriloquist and his eyes see the lip movements of the puppet. Visual perception influences the auditory one that appears to come from the puppet. Bonath *and al.* [4] have shown that, during the ventriloquist illusion, activity in the auditory area first matches the real sound perception and secondly, after the associative feedback, activity raises in the zone that corresponds to the perceived sound location.

Moreover, perceptive merging is useful to increase our perception threshold. Goldring *and al.* [9] show that the reaction time to a monomodal stimulus (visual or auditory) is longer than to the multimodal one. The gain may be the consequence of the reduction of noise in multimodal stimuli due to an increase of information quantity.

The context of our study is the design of a multimap, multimodal and modular architecture to process perception/action tasks. The aim is not to model the cortex but to be inspired by its properties such as the genericity of its architecture, the self-organization and plasticity of perceptive areas, the merging of perceptions and their reciprocal influences to form a unified view of the environment. This paradigm raises the question of how to associate different modalities, especially how to obtain the self-organization of a perceptive map in a multimodal context thanks to a continuous learning? To answer this question, we propose a model of perceptive neural map which self-organizes thanks to a continuous decentralized and local learning modulated by a high level signal. By assembling several perceptive maps around an associative one, we create a multimodal context which is used as a modulating signal to influence the self-organization of each map.

We will first explain more precisely the objectives of our study and then describe the association architecture named Bijama [11], on which our study is based. In the third section, we will describe the Bienenstock Cooper Munro (BCM) rule that we introduce in the Bijama model to solve some of its problems. In section 4, we modify the BCM rule by modulating it with a multimodal high level signal. Section 5 shows results that confirm the validity of our model.

2 Objectives

Our goal is to develop a multimap and multimodal architecture inspired by the properties of the cortex to perform perception/action tasks or missing modality recall (see figure 1). The system consists of neural maps which may be modality maps processing all kinds of perceptions or actions, or associative maps linking several modality maps. Each map has a 2D architecture and intra and extra map connections, which all are generic. Each modality map self-organizes in the multimodal context thanks to a continuous decentralized and local learning.

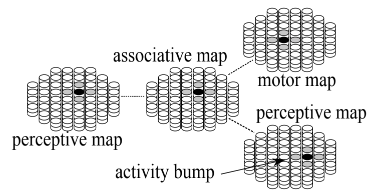


Fig. 1 Example of use of the multimap architecture.

The design of this architecture raises a lot of problems. The first one is how to obtain the self-organization of a map with a continuous decentralized and local learning, especially in a multimodal context. For example, the self-organizing map model proposed by Kohonen [10] works with a centralized learning and a decreasing learning distance. The second main problem is how to associate modality maps to influence perceptions and to provide a recall mechanism.

This article focuses on the first point and it answers by modulating the BCM rule by a multimodal high level signal. This modification is introduced within the Bijama model (see section 3) which provides a solution to the second question.

3 Bijama architecture

3.1 General description

In [11], Ménard and Frezza-Buet propose Bijama: a multimap and multilayer model for multimodal processing. Two types of maps are available: perceptive and associative. Both are round maps made up of generic multilayer cortical columns. To compute its output, each layer of a cortical column has access to the previous layer output and to the upper layer outputs of the columns it is connected to. Perceptive maps self-organize thanks to a continuous decentralized local learning of input weights. Perceptive maps are reciprocally connected with strips to an unique associative map which represents the unified multimodal context. These strip connections influence the sensory perceptions and continuously learn modalities correspondences.

We first describe the role of each layer of a cortical column in a perceptive and associative map in the two next sections respectively. Then, we present how maps are interconnected and the learning of the system. We conclude by an analysis of the inherent problems of the multimodal association and of the limitations of this model.

3.2 Perceptive map

A cortical column of a perceptive map is made up of four layers (see figure 2 (A)). The first one (at the bottom) is a perceptive layer based on Kohonen's model, its value depending on the difference between its input, corresponding to a perception, and its weights. The next layer is a cortical layer integrating multimodal constraints. Its output is the value of the strip connection to the associative map, i.e. the weighted sum of the outputs of the cortical columns that lie in the connection (see subsection 3.4 for precisions on inter map connectivity). The third layer merges the two previous ones to influence the perception by the multimodal context. This is done by the product of the cortical layer activity, plus a leaking term, with the perceptive activity. The leaking term is useful when multimodal context is not yet consistent. Finally, the upper layer takes the previous layer as input and it computes a competition between the different cortical columns of the same map. In this upper layer, all cortical columns are connected with a difference of gaussian shape. It is based on Amari's equation of continuous neural field theory (CNFT) [1], providing an activity bump in the map as output.

3.3 Associative map

An associative cortical column has a various number of layers depending on how many perceptive maps are connected to it (see figure 2 (B)). Each one of the first layers, named cortical layers, reflect the activity in a strip of the corresponding perceptive map by a weighted sum of the outputs of the cortical columns (see subsection 3.4 for precisions on inter map connectivity). The next layer integrates all the perceptive information by multiplying the values of the previous layers plus a leaking term. The leaking term, as in the perceptive cortical column, is useful when the different perceptions are inconsistent. The upper layer is the same as in a perceptive cortical column, taking the previous layer as input and providing a competitive activity bump, that represents the multimodal context, as map output.

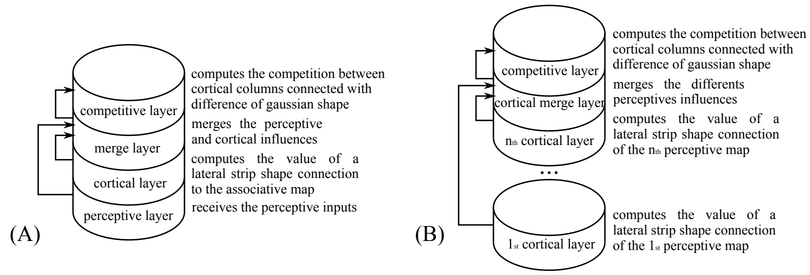


Fig. 2 Generic structure of a cortical column in (A) a perceptive map, (B) an associative map.

3.4 Connectivity

Perceptive maps are reciprocally connected to an associative map as described in figure 3. These connections have strip shapes, inspired by the cortical column model of Burnod [5].

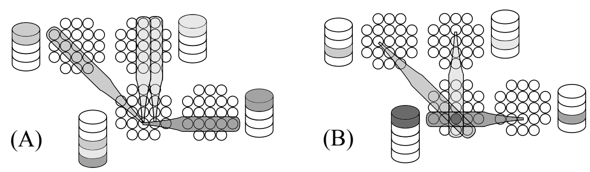
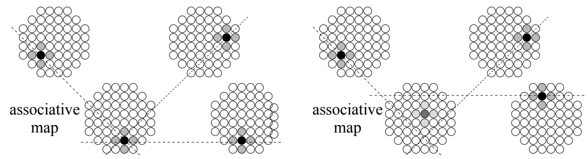


Fig. 3 The different perceptive maps are reciprocally connected to an unique associative map with a strip connectivity topographically organized. (A) The associative map is connected to all perceptive maps. The first layers (in grays) of an associative cortical column are each connected to a different perceptive map with a strip connectivity depicted in corresponding gray. (B) Each perceptive map is connected to the associative map using the same strip connectivity. See subsection 3.2 (resp. 3.3) for precisions on the perceptive (resp. associative) cortical column architecture.

Strip connectivity introduces constraints in the multimodal integration. Indeed, if the perceptive activity bumps are not wholly consistent, meaning that they are not located in strips that cross in a single point (see figure 4 (B)), activity in the associative map remains low and is badly located. In this case, the relaxation of the strips constraints, through the dedicated layer in each cortical column, leads the perceptive bumps to move until they reach an equilibrium point (see figure 4 (A)).

3.5 Learning

Learning in the Bijama model is continuous and decentralized. This allows the system to adapt to any change of its environment. Learning terms are modulated by the



(A) consistent activity bumps (B) inconsistent activity bumps

Fig. 4 (A) The activity in the associative map is high if the different perceptions in the perceptive maps are consistent, i.e. the activities are located in strips with an unique intersection point. (B) In other cases, integrating the perceptions provides a badly located and low level activity bump.

upper activity of the column, so that only the active columns can learn. There are two parallel learning processes: one for the self-organization of the perceptive maps and one for the correspondence between perceptions.

The first learning process occurs on the input weights of the perceptive layer in the perceptive cortical columns. This layer is Kohonen-like [10] but the difference is that the learning is decentralized. The distance function to the maximum activity is replaced by the activity bump of the upper layer. Technically speaking, input weights are modified towards the input value by adding the difference between the weight and the input, modulated by the upper activity and a learning rate (see equation 1).

$$\Delta w = \alpha A^*(w - i) \tag{1}$$

with w the input weights, α the constant learning rate, A^* the activity of the output layer of the column and i the perceptive input.

The second learning process is performed on the lateral weights of the strips that connect the maps. The use of Widrow and Hoff's rule [14] makes the strips learn presences and not values. The activity in the strip, i.e. the weighted sum of the output activities of the cortical columns that lie in the strip, will be high only when an activity bump is present in the strip at some learned positions. Moreover, the number of such learned positions is not limited, so that a single cortical layer may be active (high activity) for multiple distant perceptions. This allows the system to learn multiple correspondences for a single perception, like for example a red box and a blue one. Technically speaking, the cortical activity moves towards the upper activity of the column with equation (2). This learning is modulated by the upper activity plus a leaking term preventing weights from saturation.

$$\Delta w_{ij} = \alpha(A_i^* + \beta)(A_i^* - A_i^c)A_j^* \tag{2}$$

with w_{ij} the weight from a column i to a distant column j in the strip, α the learning rate, A_i^* the output activity of the column i, β a leaking term and A_i^c the activity of the cortical layer of column i.

3.6 Analysis

We tested Ménard and Frezza Buet's model in several multimodal contexts and we observed a non convergence of the perceptive layers in perceptive maps. The model as to be parametrized as a whole because an isolated map is not able to self-organize. This lack of convergence may be explained by inappropriate parameters but some other reasons have been pointed out.

Firstly, the learning process that is used in the perceptive layer replaces the centralized winner-take-all with decreasing neighborhood that is used in Kohonen's maps by the bump activity of the upper layer of cortical columns with a constant width. Moreover, with a constant learning rate due to a continuous learning, a constant width neighborhood may cause instability.

Secondly, when a new example is presented, the system has to move from an equilibrium point to another by relaxing strips constraints. This takes time especially because of the spatial and temporal inertia of the competitive activity bump. This results in an inconsistent internal state of the system. As the activity bump drives the perceptive learning, inconsistent bumps cause unlearning and lead to instability.

We consider that these two points have a common cause which is the important perceptive learning dependency on the activity bump location. As it drives completely the learning process, the incoherence of the bumps is transfered to the self-organization. We propose to reduce this dependency by using a perceptive learning that can self-organize more independently, the activity bump only influencing this learning. This idea is consistent with Wallace's observations [13] that show that the neuron ability to integrate multisensory information and so the dependency to multisensory merging, grows with age.

We focus on the problem of a too important perceptive self-organization dependency on the activity bump. We suggest to change the learning rule to have a self-organization not driven but only influenced by the activity bump. We choose the BCM learning rule which has the property to self-organize a neural map when used with lateral connections. We adapt this rule to our multimodal model by introducing a modulation feedback from the activity bump.

4 BCM rule

4.1 Biological inspiration

Hebbian learning is based on the correlation between the pre-synaptic and the post-synaptic neural activities. Moreover when the pre-synaptic activities do not succeed in activating the post-synaptic neuron above a certain threshold, weights decrease (LTD for long term depression), whereas long term potentiation (LTP) occurs when the post-synaptic neuron activity is above the threshold. Bear [2] shows that this LTD/LTP threshold is sliding in the opposite direction of the previous activity history of the neuron, meaning that if LTP recently occurred, the threshold increases to favour LTD (see figure 5). The Bienenstock Cooper Munro (BCM) rule (see [3]) is based on this biological fact that has the property of self regulating weights contrary to the hebbian rule.

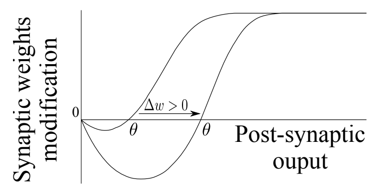


Fig. 5 LTP/LTD threshold θ is sliding depending on the recent neuron activity. If LTP recently occurred ($\Delta w > 0$), LTD is favored by the increase of θ (adapted from Bear [2]).

4.2 Equations

The output activity u of a neuron is equal to the weighted sum of its input x. The θ value of sliding LTP/LTD threshold is equal to the expectation of u^2 on a τ temporal window:

$$u = w.x \quad \text{and} \quad \theta = E_\tau[u^2]$$

The modification of weights is defined by:

$$\Delta w = \eta * x * \phi(u,\theta) \quad \text{and} \quad \phi(u,\theta) = u*(u-\theta) \tag{3}$$

with η the learning rate and $\phi(u,\theta)$ a function that defines the proportion of LTP and LTD as an approximation of the biological observations (figure 5).

4.3 Properties

The first interesting property is that the modification rule of the weights (equation 3) leads the neuron to develop a selectivity to a specific input. Neuron weights have converged when $\Delta w = 0$, which corresponds to $u = 0$ or $u = \theta$. In the case of independent noisy input vectors, the only stable weight vectors contain only one non zero value (see Cooper *and al.* [6] for more precisions).

The second property is the plasticity of the BCM learning rule. Equation 3 uses a constant learning rate and its stabilization is reached when the neuron is selective to one input. If the input distribution changes, corresponding to an environmental change, neural weights are no more stable and they develop another selectivity.

4.4 Self-organization

Autonomous selectivity and plasticity are two sought properties for our system, but the BCM rule only considers an independent neuron. As we want to use the BCM rule for self-organization we may introduce lateral connectivity between neurons. In their book, Cooper *and al.* present an adaptation of their rule to obtain a self-organization of a neural map. It consists in the addition of a lateral connectivity influence to the output. The lateral connectivity used is a difference of gaussians. It adds excitation to close neurons to favour the learning of close inputs, by raising their output u above θ. Similarly, inhibited neurons learn dissimilar inputs.

5 Modification of the BCM rule

5.1 Principle

We propose to use the BCM rule as the learning rule of the perceptive layer of a cortical column (see section 3.2). The activity bump of the upper layer still has to be introduced as an influence upon the self-organization of the perceptive layer. This activity bump results from the relaxation and the competition between local perception and multimodal context. Girod and Alexandre [8] showed that it is possible to influence the selectivity of a neuron using the BCM rule by modulating its output. We propose to add a modulation to the BCM rule, depending on the activity of the upper layer. The idea is to favour the LTP (respectively the LTD), by increasing u above θ, when the competitive activity is positive (respectively negative).

We choose to use a multiplicative modulation mechanism. When testing the self-organization with additive lateral connectivity (see section 4.4), we have noticed some problems due to a possible negative output and the modification of the equilibrium points which prevents from high modulation. Moreover, multiplicative modulation occurs in the cortex, especially for coordinate transformation (see for example Salinas and Thier [12]). By the strip constraints, we create a multimodal common coordinates in which each modality, initially perceived in its own coordinates, is able to self-organize in a spatially consistent way with respect to other modalities.

5.2 Equation

We introduce a multiplicative modulation feedback within the BCM learning rule by means of a bump activity-dependent term. The equation is the following:

$$u = w.x * mod_{\alpha,\beta}(A^*) \quad \text{and} \quad mod_{\alpha,\beta}(A^*) = \frac{\alpha}{1 + (\alpha - 1) * e^{-\beta * A^*}} \tag{4}$$

with A^* the activity of the upper layer and α, β the parameters of the sigmoid. The used modulating term is a sigmoid (figure 6) which is limited by 0, to avoid negative outputs, and $mod_{\alpha,\beta}(A^*) > 1$ for $A^* > 0$. As a consequence, when there is an activity bump, the value of the output u increases because of the modulating term. It may then overcome θ and thus learn the current perception (LTP).

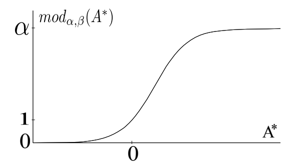


Fig. 6 Modulating term $mod_{\alpha,\beta}(A^*)$ of the BCM's rule.

6 Experiments

6.1 Protocol

The model of perceptive map we propose is adapted from the one developed by Ménard and Frezza-Buet (see section 3) using our modified BCM rule as the learning rule for the perceptive layer (equation 4). We first test our modified BCM rule in an isolated perceptive map. This validates our approach and allows to separate the parameter space. Secondly, we put our map in a multimodal context with the Bijama assembling architecture (see section 3.4) to validate the self-organization in a multimodal context.

The inputs used for the tests are float values within a finite range, that are coded by a population of neurons. This may represent the orientation coding of a bar in the visual cortex. Technically speaking, the output function of each neuron of the population is a gaussian centered at a fixed preferred input. The preferred inputs are homogeneously distributed on the input interval, so that the output shape of the population is also a gaussian (see figure 7). This output gaussian shape has to be large enough to ensure the spatial continuity of the self-organization of the map.

6.2 Results

We first test our map model in an isolated context. To do this, we use the population coded output (see section 6.1) as the input of the perceptive layer. As learning rule of the perceptive layer, we compare our modified rule with the usual BCM rule to see the influence of the modulating feedback on the map organization. For the version

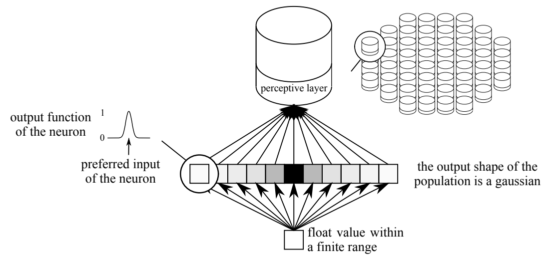


Fig. 7 Inputs used to test our map model are successive random floats limited in an interval and coded by a population of neurons. Each neuron of the population has a gaussian centered an a fixed preferred input as output function. The preferred inputs are homogeneously distributed on the input interval.

with feedback, as the map is isolated, we directly connect the perceptive layer as input of the competitive layer.

Comparing the results of the discriminated input by the perceptive layer of each column of the map, we clearly see, as expected, a self-organization of the map using our modulated BCM rule (see figure 8). This validates our modification of the BCM rule and provides a model of self-organizing map using a local, continuous and decentralized learning. Moreover, the upcoming use of this map within a multisensory context does not require any modification of its existing parametrization.

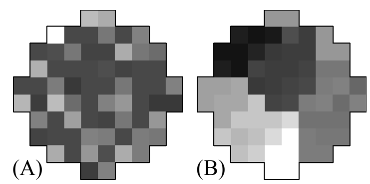


Fig. 8 Representation in gray scale of the discriminated input by the perceptive layer of each column of the map using (A) the usual BCM rule, (B) the modified BCM rule.

To test our map model in a multimodal context, we use the inter map strip connectivity around an associative map as proposed in the Bijama architecture (see section 3). We use three perceptive maps which receive a population coded input as previously. By simplicity, the three inputs are identical. We compare the self-organization of a map within and out of the multimodal context using the same common parameters and receiving the same input flow (see figure 9).

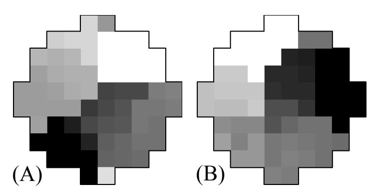


Fig. 9 Representation in gray scale of the discriminated input by the perceptive layer of each column of a map in (A) an isolated context, (B) a multimodal context.

We observe that the multimodal context biased the self-organization of the perceptive map by constraining the localization of the activity bumps of the system so that bumps will be spatially consistent as in figure 4 (A).

7 Conclusion

We modify the BCM learning rule with the introduction of a high level feedback modulation signal. This multiplicative modulation favours or unfavours the increase of the neuron output over the LTD/LTP sliding threshold. Using this modified rule as perceptive learning rule in the multilayer cortical columns of the multimap architecture proposed in Bijama, we obtain a self-organization of the perceptive maps with a continuous decentralized and local learning. Using the Bijama strip connectivity as assembling paradigm around an associative map, we obtain a self-organization influenced by the multimodal context. This architecture may enable to learn modalities associations and recall missing perceptions.

References

1. Shun-Ichi Amari. Dynamics of pattern formation in lateral-inhibition type neural fields. *Biol-Cyb*, 27:77–87, 1977.
2. M. F. Bear. Mechanism for a sliding synaptic modification threshold. *Neuron*, 15(1):1–4, Jul 1995.
3. EL Bienenstock, LN Cooper, and PW Munro. Theory for the development of neuron selectivity: orientation specificity and binocular interaction in visual cortex. *J. Neurosci.*, 2(1):32–48, 1982.
4. Bjoern Bonath, Toemme Noesselt, Antigona Martinez, Jyoti Mishra, Kati Schwiecker, Hans-Jochen Heinze, and Steven A. Hillyard. Neural basis of the ventriloquist illusion. *Current Biology*, 17(19):1697 – 1703, 2007.
5. Y. Burnod. *An adaptive neural network: the cerebral cortex*. Masson ed., Paris, France, 1990.
6. Leon N. Cooper, Nathan Intrator, Brian S. Blais, and Harel Z. Shouval. *Theory of Cortical Plasticity*. World Scientific, Singapore, 2004.
7. J. J. Gibson. The theory of affordances. In R. Shaw and J. Bransford, editors, *Perceiving, acting, and knowing: Toward an ecological psychology*, pages 67–82. 1977.
8. T. Girod and F. Alexandre. Effects of a modulatory feedback upon the bcm learning rule. In *CNS*, 2009.
9. Jenny E. Goldring, Michael C. Dorris, Brian D. Corneil, Peter A. Ballantyne, and Douglas R. Munoz. Combined eye-head gaze shifts to visual and auditory targets in humans. *Experimental Brain Research*, 111:68–78, September 1996.
10. T. Kohonen. Self-organization and associative memory. 24:145–147, January 1985.
11. Olivier Ménard and Hervé Frezza-Buet. Model of multi-modal cortical processing: coherent learning in self-organizing modules. *Neural Netw.*, 18(5-6):646–655, 2005.
12. E. Salinas and P. Thier. Gain modulation: a major computational principle of the central nervous system. *Neuron*, 27(1):15–21, Jul 2000.
13. M. T. Wallace. The development of multisensory processes. *Cognitive Processing*, 5:69–83, June 2004.
14. Bernard Widrow and Marcian E. Hoff. Adaptive switching circuits. pages 123–134, 1988.