

History-Dependent Neurons and Identification of Temporal Sequences

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April 23, 2007

Remark to the referees and program committee: the results here are extremely recent, and so the paper is not as polished for style as we would normally wish. Nonetheless, we think this result is potentially quite important and so we are sending it off as it is because we would very much like to present it initially at BISFAI. Of course, we expect to have a more polished version before the meeting. If accepted, the senior author will present it.

Abstract

We describe a new kind of abstract artificial neuron, called here *MM-neurons*, based on the relatively recent discovery that refractory periods and other constants in biological neurons are not constants but are history dependent. We then show that, in principle, such neurons can be used for temporal detection and classification; and that in a natural way it leads to the transfer of rate codes to temporal ones.

We examine this in the most simple situations (McCullough Pitts with history dependent refractory periods) where we see that surprisingly the system forms clusters of periodic input, and these clusters are surprisingly robust to the architecture of the network. We also indicate future directions of research where on the one hand this phenomenon can be combined with the "usual" discriminatory ability of standard neural networks, and on the other hand can be combined with more temporal networks (like pulsed neurons).

1 Introduction

In 1943, McCullough and Pitts [7] abstracted the properties of a neuron and created a model of an artificial neuron and began the study of its properties. This continued and the use of what is called "artificial neural networks" is now a well developed subject, both theoretically and practically in applications of machine learning [2].

Nonetheless, this neuron is essentially a static device in the sense that there is no integration of signals over time. As a result, the development of the application of artificial neural networks has focused on static pattern recognition, identification and clustering. The temporal dimension is much less developed, with many of the applications, essentially being a form of transforming a temporal signal into a spatial one, with all the limitations that imposes. (Most other techniques in machine learning also have this limitation.)

This is significant, because actual neurons do in fact integrate their input over time, and there is much research in the neuroscience community about the various constants involved in this. From the mathematical viewpoint, an abstraction of the limited "integrate and fire" neuron was pursued by Maass [4] and his colleagues; these neurons are called "pulsed artificial neurons". These neurons are endowed with the ability to integrate input signals over time as well as a "leak" and so forth. However, importantly, the constants of these networks are *fixed*, a condition which corresponds to the classical view of real biological neurons.

However, recent work now shows that these parameters are *not* fixed, but in fact are history-dependent in what seems to be a complex fashion [6], [9], [10]. That is, the changes are not linear with respect to recent firing rate inputs, in fact they are not even monotonic.

This non-monotonicity was investigated theoretically in [5] and was shown that it could arise from inter-actions between chemical reactions that affect the *rates* of other reactions.

In this paper, we pursue this further and define a class of abstract "neurons" that when firing affect the rates of other neurons. These rates can be related to different parameters of neurons; for example in "integrate and fire" [] neurons they could affect the leak rate and so on, while in Hodgkin-Huxley neurons [3] they could affect the rate of flow of various ions. This idea has some ideas in common with [1].

We choose to call such neurons MM neurons because of [5]. In this paper, we give a full definition of these neurons in the simplest case of an MM neuron of the McCullough Pitts type, and show some of the temporal properties of the neuron. In particular, we show: a network of such neurons will converge to a cyclic signal if the input is cyclic. The period and other parameters of the resultant signal is not necessarily monotone in the input. Moreover, simple signals can give rise to complex cyclic signals thus giving a form of conversion to "temporal code" from a simple rate code. In addition, there are natural attractors of signals thus indicating that the conversion is a robust operation.

2 What is a Neuron?

A "real" biological neuron is a complex object and any description of it necessarily contains simplifications. However, it is known that neurons communicate via chemical and electrical connections over synapses that lie between the axon of one neuron and the dendrite of another. The fundamental process that trig-

gers synaptic transmission is the action potential, a propagating electrical signal that is generated by exploiting the electrically excitable membrane of the neuron. However, there are many properties of the membrane such as ion channels [8], the neuron, the media the neuron lies in, and the axon which controls the production and propagation of the action potential. There are also further complexities. For example, different neurons have different anatomical properties. Thus, if one is trying to isolate the specific chemical, electrical and biological properties which are relevant to the brain's computational function; it is not so evident at what level and which items to abstract.

The brain has on the order of 10^{11} neurons arranged in different architectural connectivity.

2.1 McCullough-Pitts Neuron

This model of the neuron is the underlying basis of most of what is currently called "artificial neural networks". Here McCullough-Pitts abstracted what was thought at the time (1943) to be the properties of the neuron that was important for transfer of information and computation in the brain.

Here the neuron has state on/off; it has many weighted inputs. Its output is 1 if the linear combination of inputs passes a threshold; otherwise zero. See figure 1.

The main point is that (i) given the architecture of the neuron, its function is determined solely by the weights and (ii) the output function is not a linear function of the inputs.

Note that the neuron works in "lock-step", i.e. all inputs are calculated at the same time, and given fixed weights the neuron has no "memory"; i.e. at each time step everything is calculated afresh.

2.2 Integrate and Fire Neuron

Here the neuron has the following parts:

Note that since this, in fact, integrated over time, the activation level is given by a differential equation. However, the spike itself is "outside" the differential equation; once the activation passes a threshold, a spike is generated and the neuron is reset.

2.3 Pulsed Neurons

This neuron is described in detail, for example, in [4]. The main point is that this neuron is a realization of the integrate and fire neuron and so had temporal rates in the model. However, these rates are fixed.

2.4 Hodgkin-Huxley

This is the most famous of the models of a neuron resulting from the famous 1952 Nobel prize work [3]. In this model there is an interaction of various differential

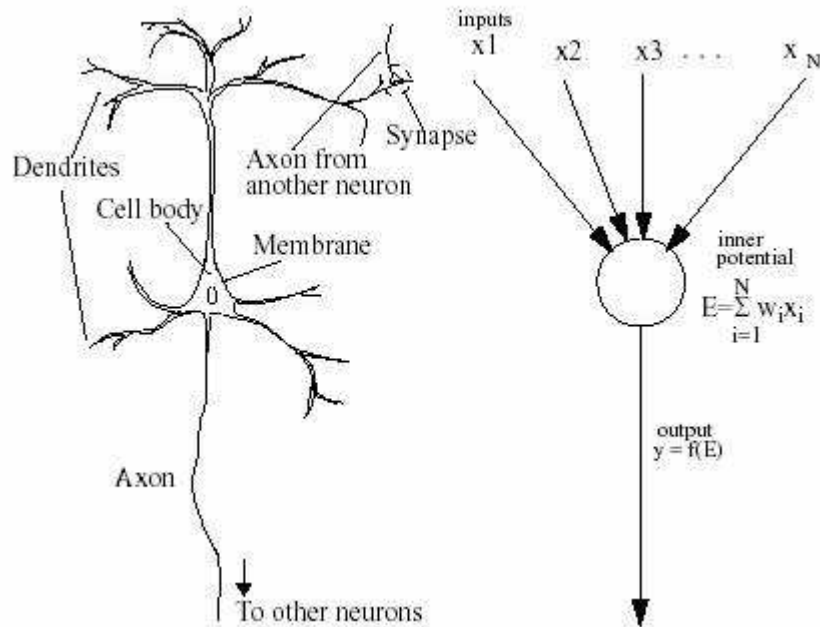


Figure 1: McCullough-Pitts Neuron

equations relating to various temporal constants of the neuron (such as various ion flows). Again, this model assumes fixed rate rates for the equations.

Note that these models are more and more complex, and of course from the NN perspective this leads to questions about the representability and learning methods appropriate in each case.

However, our main point is that, even in the H-H model, all the temporal parameters are *fixed*; and as a result the neuron's own temporal behavior does not change over time. (Nonetheless various temporal properties can be nonetheless be computed in these models; e.g. the shape of the activation function in the HH model; and so on.)

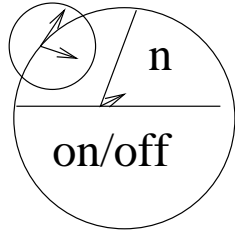
2.5 The MM (History Dependent) Neuron

Actually this is a class of such models, as each of the above ones can be adapted to this concept. That is, each of the fixed parameters of the model can in principle be thought to vary based on the affect of action potentials being received to the neuron.

We describe here the simplest such model, an adaptation of the McCullough Pitts model.

Each neuron has besides its inputs, state and output, a refractory period parameter (n) and a count down parameter (m) where $0 \leq m < n$.

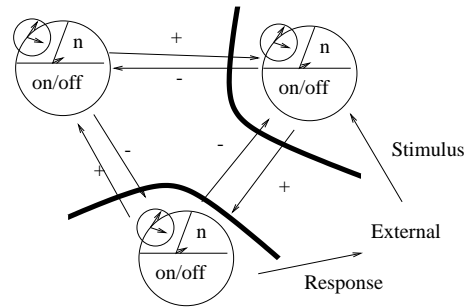
Each neuron has inputs and outputs and each input is either "catalytic"



A reaction is determined by its state (on/off); its waiting time (n) and the time remaining on the waiting time. ⁱ

(i.e. shortens the refractory period) or "impedic"¹ (i.e. lengthens the refractory period).

Thus a simple network of three nodes looks like the following



A "triad" of reactions; external stimulus may affect one or more of the reactions; response is read from the state of one of the reactions. Reactions affect each other either with impedance (-) or catalyzation (+).

The basic functionality of the neuron is described below in the updating subsection and table.

2.5.1 Input/Output

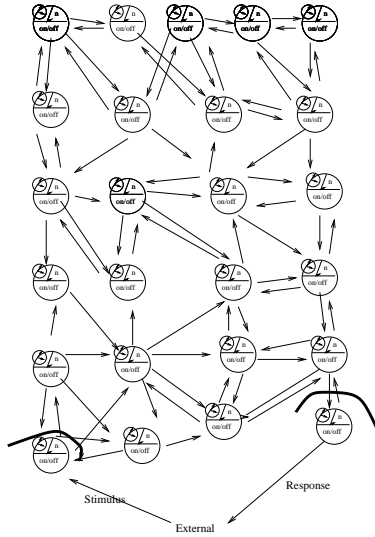
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To analyze this, we arbitrarily chose a specific neuron to be the "input" i.e. receiving an external value, we chose the "output" to be one "far" from the input in the connection graph of the network. (If the network was completely connected, it was chosen arbitrarily.)

2.5.2 Internal Connections

In general, the MM-neurons can be connected in an arbitrary fashion.

¹This word is derived from "impedance", but is not in most dictionaries.



We found that the best results were obtained in networks that are highly connected. Therefore, in this preliminary study we used completely connected bi-directional graphs. Half of all outputs were impedic and half were catalytic; to be simple we chose the number of neurons to be odd (hence an equal number of impedic and catalytic connections to *each* neuron.²

We also did some experimentation with different architectures and different input architecture (in particular with the input "broadcast" to all neurons.

Note that in this paper, we do not examine the affect of "weights" on the output; each connection is either simply impedic or catalytic and the thresholds are all zero. We expect that combining these two mechanisms will be very interesting and hope to do this in a future work.

2.5.3 Updating

Each neurons next state is deterministic determined by its state, its waiting value, m , and the state of its inputs. In brief, it updates its state to "1" only if m is at zero, and in this case, also changes its n value to either $n + 1$, $n - 1$ or n depending on whether or not the number of impedic connections exceeds, is smaller than, or is equal to, the number of catalytic connections. In this case m is reset to new value of n . Thus a network can be thought of as a complex cellular automata. A full set of the rules in the case of a triad automata is presented in Table 1.

The temporal properties is emergent in the rate of output firing.

²The reason for this "balance" was to keep nodes from either shutting down as n gets very large, or becoming a simple one-step delay as it was reduced to zero.

Stimulus		Event			Consequence		
External	Internal	State (q)	Wait (n)	Remain (m)	State (q)	Wait (n)	Remain (m)
Any	Any	1/0	n	$m \neq 0$	0	n	$m - 1$
Yes	No	1/0	n	0	1	n	n
Any	+ only	1/0	n	0	1	$n + 1$	$n + 1$
Any	- only	1/0	n	0	1	$n - 1$	$n - 1$
Any	+ & -	1/0	n	0	1	n	n

Table 1: Rules of change for standard triad

3 Results

For this paper, we ran four different network architectures – with 3, 5, 7, 9 internal neurons; under the assumption that all neurons are connected to all other neurons with half of all connections being catalytic and half impedic. Moreover, this was done locally, so that each neuron was "balanced" both on the input and on the output. Each network was tested with all possible periodic inputs of length up to 8, as well as some random inputs. The input signal went to an arbitrary (but specific) neuron and the output was read from a different neuron. The results were not sensitive to the choice of these neurons.

3 neurons in 8 bit sequence			
Item	ISI Patterns	period	number
1	1,7,8,8,1,7	32	20
2	1,5,2	8	81
3	5,1,2,5,1,2,5,3,5,3	32	53
4	4,4,1,3,1,3	16	30
5	3,1,4	8	30
6	1,3,2	6	27
7	2,4,3,2,5,3,2,4,4,1,2,2,4,3,1,3,3,1,2,1,2,3,4,3	64	12
8	4,1,2,2,5,3,1,2,1,2,3,4,3,2,4,3,2,4	48	1
9	1,3,3,1,2,1,2,3,4,3,2,4,3,2,4,3,2,4,3,2,4,4,1,2,2,4,3	72	1

Table 2: 8 bit Periodic Inputs to a 3 Neuron Network

Outputs to periodic Input

The results of these experiments show that in all cases, periodic input results in periodic output. However, the periods are not the same; nor (as was already shown in [5]) is the relationship monotonic. (Hence, in particular, a fortiori, the relationship is clearly non-linear.)

Here we wish to focus on another interesting result; the total number of outputs is very limited compared to the number of inputs. For sequences of period 8, there are 255 (non-zero) such inputs and the number of output sequences is 9 for 3 units, 7 for 5, 6 for 7 and 8 for 9 (including sequences that passed to the zero sequence). Furthermore, and remarkably, the sequences to which they converge are remarkably similar. In detail, 5 of 7 output sequences of 5 units

5 neurons 8 bit sequence			
Item	ISI Patterns	period	number
1	1,7,8,8,1,7	32	20
2	1,5,2	8	81
3	1,1,2,1,1,2,1,4,3,5,3	24	38
4	4,4,1,3,1,3	16	30
5	3,1,4	8	45
6	1,3,2	6	27
7	2,3,3,1,3,3,1,2,1,2,3,4,3,1,1,2,1,1,2,1	40	14

Table 3: 8 bit Periodic Inputs to a 5 Neuron Network

7 neurons 8 bit sequence			
Item	ISI Patterns	period	number
1	1,7,8,8,1,7	32	31
2	1,5,2	8	81
3	4,4,1,3,1,3	16	68
4	3,1,4	8	45
5	1,5,5,5,1,5,5,1,4	32	3
6	1,3,2	6	27

Table 4: 8 bit Periodic Input to a 7 Neuron Network

9 neurons 8 bit sequence			
Item	ISI Patterns	period	number
1	1,7,8,8,1,7	32	27
2	1,5,2	8	81
3	4,4,1,3,1,3	16	27
4	3,1,4	8	28
5	11,12, 1,11, 1, 2, 1, 2, 1, 2, 3, 1	48	6
6	1,3,2	6	27
7	15,16, 1, 2, 1, 1, 2, 9, 1,15, 1, 2, 1, 1, 2, 1, 1, 7,16, 1,15, 1, 2, 1, 1, 2, 9, 1	128	2

Table 5: 8 bit Periodic Input to a 9 neuron network

3 neurons 7 bit sequence			
Item	ISI Patterns	period	number
18	28	7,7,1,6,1,6	1
53	7	2,1,4	2
16	28	3,4,3,4,1,2,4,1,2,4	3
9	28	2,2,5,4,3,2,5,4,1	4
26	7	3,3,1	5
4	28	3,2,4,3,2,5,3,2,4	6
1	6	2,1,3	7

Table 6: 7 bit Periodic Input to a 3 neuron network

5 neurons 7 bit sequence			
Item	ISI Patterns	period	number
18	28	7,7,1,6,1,6	1
53	7	2,1,4	2
4	56	6,7,1,6,1,6,1,6,7,1,2,1,2,2,6,1	3
39	7	3,1,3	4
3	56	6,1,6,1,6,7,7,1,6,1,6,2,5,1	5
9	21	3,4,3,1,1,2,1,1,2,1,2	6
1	6	2,1,3	7

Table 7: 7 bit Periodic Input to a 5 neuron network

3 neurons 9 bit sequence			
Item	ISI Patterns	period	number
22	36	8,9,9,1,8,1	1
98	9	6,2,1	2
64	9	5,3,1	3
68	9	4,4,1	4
16	36	3,5,4,5,4,5,1,3,5,1	5
14	36	6,3,6,1,2,6,1,2,6,3	6
144	9	4,3,2	7
10	36	5,4,2,7,5,1,3,2,7	8
18	36	4,5,4,2,4,1,2,2,4,3,1,4	9
49	12	2,3,3,1,2,1	10
8	6	2,1,3	11

Table 8: 9 bit Periodic Input to a 3 neuron network

Item	ISI Patterns	5 neurons 9 bit sequence	number
28	36	8,9,9,1,8,1	1
98	9	6,2,1	2
38	18	6,3,1,1,2,1,1,3	3
40	9	4,4,1	4
66	27	2,1,1,3,4,5,4,1,1,2,1,1,1	5
7	36	5,1,7,1,4,1,4,1,7,1,4	6
64	9	5,3,1	7
124	12	2,1,2,3,3,1	8
2	72	5,2,4,2,5,5,1,5,2,5,5,2,4,2,5,5,1,5,1,6	9
9	81	7,2,5,6,2,5,2,5,2,5,2,4,2,5,2,5,2,5,6,2,5	10
9	36	2,1,1,2,1,2,4,3,1,3,3,1,3,4,3,1,1	11
8	144	2,1,4,2,6,7,7,7,1,6,1,7,7,7,1,6,1,6,8,7,1,6,1,6,7,8,7,1,1,5,1,2,4	12
6	9	3,2,4	13
2	27	6,1,7,6,1,6	14
8	6	2,1,3	15
1	72	7,9,1,8,1,8,9,1,8,1,8,1,8,2	16
1	72	5,2,2,9,1,4,2,2,9,1,4,2,2,9,5,2,2,9	17

Table 9: 9 bit Periodic Input to a 5 neuron network

are the same as in the 3 units, and in fact appear in the 7 unit output and the 9 unit output as well. The "exceptional" sequences are in fact rather long ones.

The full table of these results appears in tables 2 through table 9.

One can look at the output as being a cluster of input sequence. If one compares the clusters produced by 3 units, 5, 7 and 9 one sees the property that the clusters are consistent, in the sense that most clusters stay together from one set-up to another; while the combinations are of a simple kind of either one cluster splitting into two or two clusters combining into one.

For example, all the 30 members of sequence number 4 in 3 units went to the identical output sequence in 5 units; and all the additional 15 sequences that went to this classification came from the sequence number 3 i.e. this was a *union* of two clusters formed in the 3 unit output.

To further investigate this, we also look at the clusters formed by different period sequences (i.e. different periods of input on the same architectural arrangements.)

In the experiments run so far, there are no intersections in the output sequences for two sequences of different period when the periods are relatively prime.

We also checked what happens when an input sequence switches from one periodic input to another. For example, given the sequence 0000001**00000001**000000001 (i.e. sufficient repetitions of the first sequence (period 7) followed by sufficient repetitions of the second (period 8) followed by sufficient repetitions of the third (period 9) followed by sufficient repetitions of the first; we found that the out-

put did converge to each of the expected ones. Moreover, the transient periods before converging was not longer than from the usual initial conditions; i.e. they system was quite able to handle shifting periodic signals.

4 Discussion

1. We note that the network reacts fairly fast, in the sense that the transient period is typically about 60 -70 repetitions of the periodic input and seems independent of the starting position. This also means that the network can quickly switch from one stage to another, should the input sequence change and we have observed this in tests.

2. There are relatively few clusters.

3. Moreover, the sequences that passed to these systems were remarkably coherent between the models. Many such clusters remained identical between models; others "split" or "joined" between models. Thus the temporal code of the cluster robustly indicates certain sequences.

4. It is tempting to look for the uniform properties that unite the elements picked out by the clusters. However, eight length sequences are too short to do this analysis, and this will wait for future experiments. One possible hypothesis is that the clusters relate the elements of similar entropy. We did see that the same signal (of ISI [2 1 3]) occurred in all nets from the input of 1*; although for some periodic inputs there were other inputs that went to the same cluster.

4. Note that, by looking at simple "rate" codes; i.e. sequences of simple one beat per sequence, and looking across the length of input, we see that there is a transformation into a temporal code. This was briefly discussed in [5].

Future work:

1. It seems likely that a combination of the temporal detection ability of these neurons together with the static spatial properties of standard McCullough-Pitts neurons can be used to very good effect.

2. These same ideas can be applied to other neurons; in particular we are interested in their effect on networks of pulsed neurons.

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