Hierarchical Neural Network Model with Intrinsic Timing

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Abstract

In order to overcome some of the challenges that current, conventional computing faces, a large set of research is being performed into unconventional computing platforms, most often inspired by discoveries in neuroscience. This tends to result in Artificial Neural Networks, which are commonly an oversimplified version of their biological equivalent, where various aspects are being ignored, e.g. the aspect of time. This tends to prevent these networks from handling temporal sequences directly in the time domain. Hence, this research studies how the intrinsic timing of a neuron cell can be used to design a hierarchical neural network with feedback. The network is based on a simple Leaky Integrate and Fire RC-model for each neuron where the intrinsic timing is determined by the capacitor discharge. The results show that the model is able to differentiate between temporally different stimuli. Moreover, feedback allows the model to put lower level cells in a predictive state. Finally, the hierarchical model allows for higher-level cells to remain stable for a longer period and therefore allow for a better combination of sequential information at lower levels.

Keywords: Artificial Neural Network, Intrinsic Timing, Leaky-Integrate and Fire, RC Neuron Modelling

Introduction

Many aspects of the human body that are controlled by the brain require some aspect of timing [1]. However, timing within the brain itself is not well understood to date [2], but is of capital importance in controlling the signalling between neurons, which is key in neural functioning [3]. Many scientists believe that timing in the brain lies within the neurons themselves [4] whereby the spikes not only carry information but would also provide the necessary triggers for the brain's "clocking mechanism".

Additionally, in modelling the human brain Artificial Neural Networks (ANN) are currently used most regularly, but they often only handle spatial comparison, and do not allow for direct temporal comparisons [5]. This is due to the fact that cells within the ANN would trigger based on the number of active inputs at a certain discrete time step, without considering when these inputs occurred in time. This problem becomes increasingly more challenging in a hierarchical model where feedback from a higher level would need to interact with the input to the lower level and that with the correct timing. The use of correct timing is important to identify which neuron will fire next, based on the learnt information and/or to ensure a sustained activity in order to allow temporally close events to be associated together.

Background

One of the most important experiments in understanding the functions of the brain was performed by Hubel and Wiesel [6]. The experiment observed the reaction of a cat's brain towards certain visual stimulus. While the experiments revealed that the group of neurons being probed were active when a specific stimulus was present, they also indicated that the rate of spiking was related to how close the detected stimuli was to the diagonal white light that these neurons reacted to. The observation was a strong indication that the signalling between neuron relies on time.

The neuron is the main "computational block" that makes up the brain. It is a complex system with electrical as well as chemical reactions and is the main system that drives a human's function [7]. Considering the complexity of each neuron, understanding the functioning of the brain as such is quite complicated, let alone replicating it artificially. While the brain inspires ANNs, they do not achieve the same as the brain itself. Quite a few models these days are based on a rather simplistic model of the neuron, which builds upon a simplistic sigmoid transfer function. One major shortcoming of this model lies in the lack of dynamism in time that the brain is known to exhibit. As a consequence, these ANNs are not able to handle sequences in time directly. This has given rise to more and more complex architectures that attempt to bring the ability to ANNs to handle sequential processing.

Frameworks such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) have shown ability to process sequential data [8, 9]. To achieve this, layers of the network evolve at each time step and depend on the previous state of that layer. While this method has allowed the use of RNN and CNN in problems such as speech processing they are known to scale up badly, requiring enormous amounts of computing resources. The reason for this is that since ANNs are made of simplistic neuron models, in order to handle complex tasks, a more complex architecture is needed.

Spiking Neural Network (SNN) is another type of neural network that tends to be based upon a more realistic model of the neuron. One of the major differences between SNN and ANN is the introduction of time information at each neuron level. This is based on a believe that precise relative timing is important in controlling information encoding and signalling between the neuron.

The relative timing concept stands in contrast to the timing used in conventional computing which is built around a centralised configuration. There is however no evidence that the brain would use such a centralised clocking system and most recent studies infer the use of a more distributed timing system that is intrinsic to the neurons themselves akin to the concept used in the SNN model. Two schools of thought support this theory of intrinsic timing. Firstly, neuronal populations synchronise themselves with dedicated spike trains as discussed in [4]. Secondly, some researchers think that timing in the brain arises from non-dedicated neurons involved in processing of information itself [10]. The implication of the latter is that processing at neuron level is not only probabilistic spatially but also temporally.

Hence to develop a model with intrinsic timing, there is a need to look at neuron models that provide an intrinsic timing within each neuron. Therefore, one of the models that is interesting in this context is the Leaky Integrate and Fire (LIF) model [11], as first proposed by Louis Lapique [12], who modelled the neuron as a Leaky RC circuit. In this context, the constant discharge of the capacitor, which follows an inverse exponential law, acts as an indication of elapsed time.

Modelling the System

A. Model Specifications

The aim of this model is to provide a platform to test a relative timing approach that is intrinsic to the neuron. To implement the neuron network LTSpice was used because it provides a way to model and test the network in terms of electronic components as proposed in Lapique's paper [12]. Additionally, LTSpice allows for a pseudo-parallel execution of the various components within the circuit. The ability to have a network with multiple neural cells running simultaneously is of significant importance and would have been more complicated to achieve when a low level programming language was chosen.

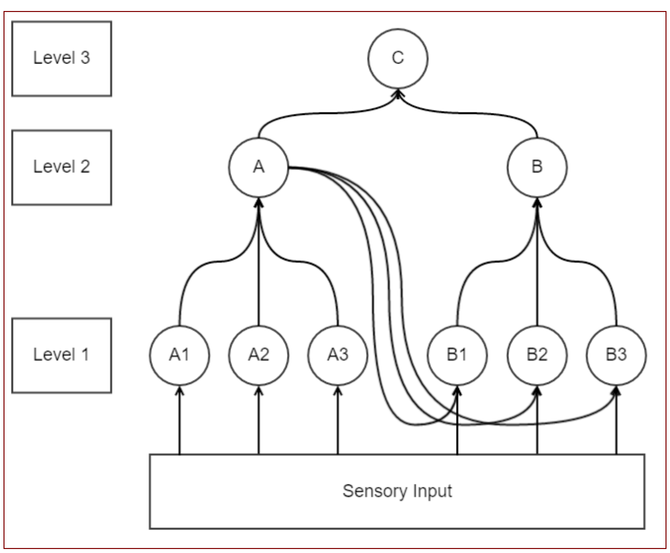


Figure 1: Model Block Diagram

Figure 1 shows the three level hierarchical network model that was designed to test the intrinsic neuron-timing model. Each cell is implemented as an identical LIF cell and sparsely connected to the other cells. Sensory input is provided using 6 pulse generators, which are driven independently to test the various aspects of this network. Within the system learning takes place based on establishment of connection, therefore A1, A2 and A3 fires before B1, B2 and B3. Hence, cell A can be associated with cells B1, B2 and B3 so that when A fires due to lower level cells, it can put cells B1, B2 and B3 in a state that allows them to fire earlier in time.

B. LIF Neuron Model

The first step in this project was the development of a LIF neuron model using an RC circuit. Figure 2 shows the various sub block of this circuit.

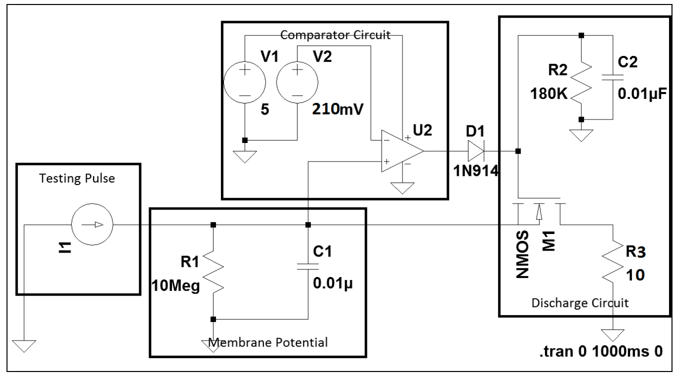


Figure 2: Neuron RC Circuit

An input current pulse charges capacitor C1 to voltage V_0. Following this spike, the initial potential across the capacitor decays exponentially. The relationship between time t is given by Equation 1 and is indicated by the instantaneous voltage V_m across the capacitor.

$$t = RC \cdot \ln \frac{V_0}{V_m} \tag{1}$$

Subsequent spikes accumulate and increase the capacitor Voltage. When the voltage exceeds the threshold set by V2, which is 210 mV in this case, op-amp U2 triggers MOSFET M1 and the capacitor discharges across R3. The rate of discharge of the capacitor is determined by the value of R3||R1. To keep the discharge channel open long enough for the capacitor to discharge completely, another RC circuit consisting of R2 and C2 is used. The value of R2 and C2 are selected so that their RC constant is 5 times the RC constant of R1 and C1. As long as the discharge channel remains open, stimulus would not cause the membrane potential to increase. The period where the channel is open therefore acts as a refractory period.

C. Connectivity between the Neurons

A further step is needed to use the RC neuron model to implement the hierarchical network shown in Figure 1. Considering cell A in the network, there are multiple inputs to the cell and multiple outputs branching out from the cell. Multiple outputs imply that the output current spike would be divided and with an increasing number of outputs, the current would divide equally across each of the paths and therefore become insignificant. To maintain the simplicity of the network it is therefore important to ensure that the spike along any connection is of a similar level. To achieve this a Voltage Controlled Voltage Source (VCCS) was used at the output (Axon) of a cell. Considering that the membrane potential capacitor is a charge device also implies that it is important to maintain the amount of charge contributed by each spike and arriving at a neuron is similar. This was also achieved by the use of a Voltage Controlled Current Source at the input end (Dendrite).

Consequently, the complete unit cell of the network becomes the one shown in Figure 3. In order to ensure a constant voltage peak value across the VCCS, diode D3 is added.

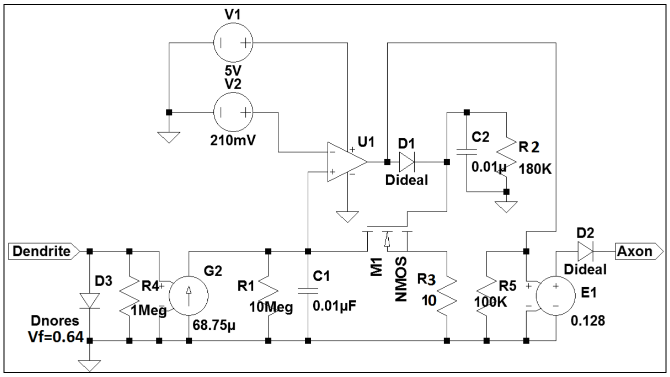
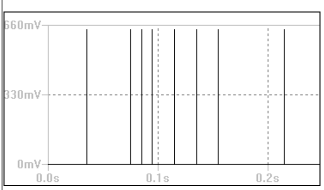
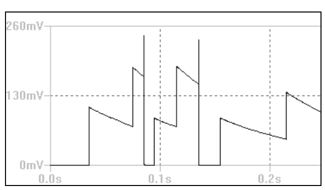


Figure 3: Neuron Cell

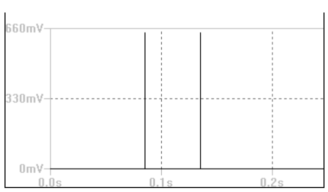
In order to establish the response of this cell to input, Figure 4(a) shows a set of inputs, to which Figure 4(b) shows the evolution of the membrane potential, with the axon output shown in Figure 4(c). As can be noticed, the membrane potential decreases constantly as soon as it is above zero, giving an indication of the elapsed time. Hence, an output spike depends on the temporality of the input spikes as well as on a set threshold.



(a) Input Spikes



(b) Membrane Potential



(c) Output Spike

Figure 4: Neuron Cell Characteristic

This threshold, along with the rate of the input spikes determines the firing rate of a neuron cell. A higher set threshold implies either a larger number and/or faster succession of spikes to make the particular neuron fire.

Subsequently the neuron cell implemented was encapsulated into a higher level two terminal component. The terminals were the axon and the dendrite. The design of the neuron allowed multiple connections to the dendritic end and also allowed multiple fan-out from the axon.

Results and Discussion

The implemented network is tested for its ability to produce decisions in terms of spikes produced across the network. The first test was performed to evaluate how the network is influenced when the period of the given pattern changes. Another test was performed to demonstrate how the network handles prediction via the formation of stable representation.

A. Discrimination of Temporally Different Sequences

Having established how the membrane potential brings an element of time intrinsic to each neuron, there is a need to see how different blocks use this intrinsic time to interact with each other. The time elapsed between input spikes is important as it determines the state of any particular cell at any particular point in time.

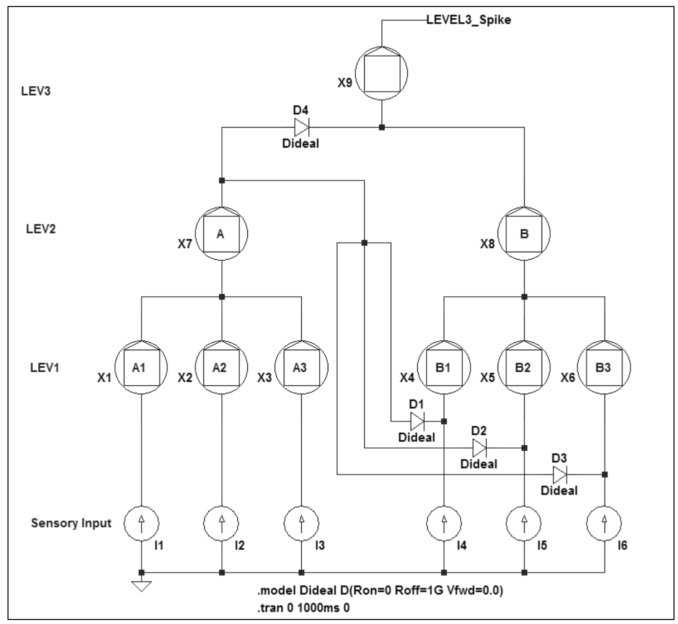


Figure 5: The Hierarchical Neural Network

To test the network, 6 independent current pulse sources are instantiated to ensure that the combination of all these source forms results in a certain stimulus. The first test consisted of observing how the firing pattern of the network changed with a variation in the time gap between the input pulse trains. Table 1 shows the spiking pattern of Level 3 Cell C and Level 2 Cells A and B spiking 3 times each.

Sensory Input Period Variation (ms)	Number of Spikes at A	Number of Spikes at B	Number of Spikes at C
0	3	3	2
+2	3	2	1
+4	2	3	2
+6	2	2	2
+8	2	3	1
+10	2	2	1
+12	2	1	0

Table 1: Spike Pattern with a decrease in input spike frequency

The results in Table 1 indicate that the network responds to a variation in sensory input frequency. There is even a limited immunity to the variation of the input time based on the range of values for the variation of the period. As can be deduced from Hubel and Wiesel's cat experiment [6], the rate variation tested here would be akin to a reduced spiking rate noticeable when the external visual stimulus was not close to what the group of probed neurons reacted to. This corresponds with the fact that at a higher level within the hierarchy a decrease of firing can be noticed when the stimulus rate at the sensory/input level decreases.

B. Prediction and Stable Representation

The use of hierarchy requires one to consider two additional items within the context of timing. As discussed in [13] and [14], prediction is the brain's way to become more efficient. It also allows e.g. for attention shifting where it allows a person to shift their focus to something that is not usual. Prediction obviously takes place before the actual event, and in this network that is incorporated through feedback. This is due to the fact that through feedback a higher level cell can predict the normal order of how cells would fire in certain situations, which then feeds the lower level cells to ensure they fire earlier in time. Spikes being fed back to a lower level cell result in that cell having an increased membrane potential which allows them to fire earlier in time. In the context of the tested network this led to lower level cells firing 20 milliseconds earlier when compared to the absence of feedback.

A second timing related aspect of hierarchical structures lies in stable representation, which covers the aspect of stability of the system over time. Within a hierarchical context the use of stability over time is more important for higher level cells which requires these levels to trigger less quickly in comparison to lower level cells. This is achieved by giving the higher levels a higher membrane potential, which in its turn then also determines how far in time new stimuli will get linked with the precedent active neuron.

Conclusion and Future Work

In this paper, a neural model with inherent timing is proposed where time is distributed throughout the network and is not centralised. The network can also deal with feedback and has a certain tolerance towards time variance on the input. From this model, one can derive that there is no need for centrally controlled timing or to incorporate time-stamps within the signals, but that the use of a distributed model where each cell has its own timing and cooperates with the other cells to achieve an overall aim is perfectly achievable.

The use of LTSpice for the simulation allowed for rapid modelling of the system without requiring detailed low level developments, although it limits the ability to learn the system with actual data, for which a low level coding model will be developed next.

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