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The Neuroid: A Novel and Simplified Neuron-Model

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Abstract— **In this paper we introduce a novel computational neuron-model, the Neuroid, which is based on three basic operations that are carried out by nerve cells to process the incoming information, such as comparison, and frequency pulse modulation-demodulation. The model was implemented using LabVIEW 10.0, in order to assign to each of these operations, an execution block (Virtual Instrument). The results of its implementation showed a very similar behavior to that exhibited by real neurons. Furthermore, due to its simplicity and low computational requirements, it is expected that the Neuroid can be used to create several software models of biological neural systems, either for research or teaching purposes.**

I. Introduction

In order to mimic the information processing capacity exhibited by the nervous system, numerous efforts have been made to emulate the behavior of its functional units, the neurons. A first approach was introduced by Lapicque in 1907 [1], who modeled the neuron as a RC-circuit, basing on the capacitive and resistive properties of the cell membrane. The integrate-and-fire model proposed by Lapicque, has proven to be useful in the study of both, the synaptic integration in single neurons and simulations of large neural networks, even though the underlying mechanism responsible for the generation of action potential was unknown. Several decades later, McCulloch and Pitts focused on the "all or none" character of nervous activity [2], and developed a discrete and oversimplified version of the neuron, so it was possible to conceive the neural networks as computing machines. From this pioneering work, these "digital neurons" have evolved to analog signal processors, taking into account the electrophysiological characteristics of living membranes, as Hodgkin and Huxley did, by proposing a new model that explained the dynamics of the voltage-dependent membrane conductances responsible for action potential generation [3].

Many advances have also been made in the field of semiconductors, emphasizing the fact that the principles that govern the conductivity of both, the cell membrane and the silicon devices, are very similar. This led to the design and implementation of several neural models based on analog integrated circuits that have the characteristics of nerve cells, by using standard CMOS processes [4]-[7], including some models able to emulate spike frequency adaptation, refractory period and threshold voltage modulation [8], and others based on mathematical models of oscillating biological neurons [9]. There are also hardware-modular implementations, as the analog model proposed by Koch and Brunner [10], who used a combination of resistors, switches and JFET input operational amplifiers to produce specific discrete units, through which, it was possible to model the structural and functional features of real neurons.

In order to reproduce spiking and bursting patterns exhibited by some types of nerve cells, other neuron-models like the one presented by Izhikevich [11] have been developed. This model combines the computational efficiency of the Lapicque's integrate-and-fire model, with the accurate biological dynamic of the Hodgkin and Huxley model, as a result of a two-dimensional reduction of the biophysical approach. It could be said that almost all of these neuron-models are based on certain electrical properties of the cell membrane. In this paper, we propose a new computational neuron-model based on simple operations, which emphasizes the functional rather the physiological character of nerve cells.

II. Conceiving the Neuron-Model

The neuron is the functional unit of the nervous system (i.e., the smallest structure that can carry out all of the functions of the entire system). Neurons, as muscle cells, are characterized by their ability to generate and propagate electrical signals. These electrical signals can be classified in two basic types: *graded potentials* and *action potentials* [12]. Graded potentials are depolarizations or hyperpolarizatons whose amplitude is directly proportional to the strength of some triggering event (a mechanical, thermal or chemical stimulus), traveling through neurons until they reach the region known as the trigger zone. If graded potentials reaching the trigger zone depolarize the membrane to a minimum level known as the threshold voltage, an action potential is initiated. If the depolarization does not reach threshold, no action potential is begun, and the graded potential simply dies out.

Action potentials are large, uniform depolarizations that can travel rapidly for long distances through the neuron. They are changes in membrane potential that occur when some voltage-gated ion channels open, altering membrane permeability to Na^+ and K^+, and they differ from graded potentials in several ways: (1) all action potentials can be considered as "all or none" events, and (2) they do not diminish in strength as they travel along the neuron. But, if this is so, then how does the neuron transmit information about the strength and duration of the stimulus that started the action potential? One possible explanation lies in the frequency of action potential propagation [12]. It means that, for certain range of intensities, if the stimulus increases in strength, the number of action potentials fired per unit time increases. Likewise, the amount of neurotransmitter released at the axon terminal is directly proportional to the total

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number of action potentials that arrive per unit time, as illustrated in Fig. 1.

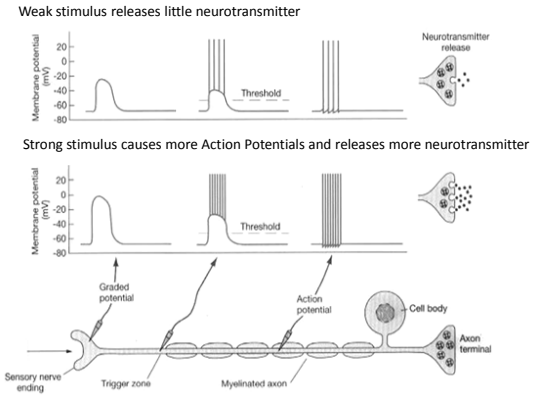

Figure 1. The influence of stimulus intensity on firing frequency (Modified from [12])

From a functional perspective, the phenomenon described above looks like a pulse frequency modulation-demodulation process, only if the stimulus is strong enough to overcome the activation threshold. Thus, the first operation involved in neuronal activity is a comparison, as McCulloch and Pitts established in their neuron-model [2], whereby it is possible to conceive a first block similar to a comparator, such that if the incoming analog signal exceeds the threshold value, it will pass through the block. On the contrary, if the incoming signal is not strong enough to overcome the threshold, then the outcome will be zero. As the next step, if the relationship between the amplitude of the incoming signal and the firing frequency is assumed as proportional, the second block can be conceived as a pulse frequency modulator, whose outcome is an impulse train with a frequency that varies proportionally to the input's amplitude. A mathematical approach is proposed as follows: Let $s(t)$ the resulting depolarization that reaches the trigger zone, then, the output of the pulse frequency modulator block, $y(t)$, is given by

$$y(t) = \begin{cases} 0, & s(t) \le umbr \\ \sum_{n=1}^{\infty} \delta\left(t - \frac{n\beta T}{s(t)-umbr}\right), & s(t) > umbr, \end{cases} \quad (1)$$

where T is the time interval to elapse between one pulse and the following, *umbr* is the activation threshold, and β is proportionality constant. For consistence, $s(t)$, β and *umbr*, are dimensionless. As observed, the condition $s(t) > umbr$ excludes the division by zero. A third block able to demodulate the impulse train was required. Finally, from this functional approach, we constructed a novel neuron-model, the Neuroid, which preserves the functional essence of the cell. We thought that as *android* is to man, *neuroid* is to neuron.

III. Implementation

From (1), each of the stages described previously, was translated into algorithmic terms, and rewritten as an independent block or Virtual Instrument (VI) in LabVIEW 10.0 [13] (running on Acer Aspire One). The algorithms are described as follows:

A. Comparator

A first algorithm was implemented using a counter variable called *count1*, whose value would increases at each cycle, as long as $s(t) > umbr$, and only until $count1 > \beta/(s(t) - umbr)$. In that case, *count1* would be restarted and begin to increase again if $s(t)$ overcomes *umbr*:

If $s(t) \ge umbr$, then

  If $count1 > \beta/(s(t) - umbr)$, then

    $count1 = 0$;

  Else

    $count1 = count1 + 1$;

Else

  $count1 = 0$;

B. Pulse Frequency Modulator (PFM)

To generate the impulse train, a second algorithm would extract the value of *count1*, keeping the result at 0, until $count1 = 1$, in which case the result would change to 1, only at that instant. For any other value of *count1*, the result of this algorithm would remain at 0:

If $count1 = 1$, then

  $y(t) = 1$;

Else

  $y(t) = 0$.

C. Pulse Frequency Demodulator (PFD)

Finally, to demodulate the impulse train, a third algorithm was implemented using a second counter variable called *count2*, whose value would increases as long as the outcome from the previous algorithm ($y(t)$) remains at zero. When that outcome changes to 1, which could be interpreted as the rising phase of the action potential, the resulting signal would be obtained from the reciprocal of the value reached by the second counter, and immediately, the counter would be restarted. The cycle would repeat until detecting the next impulse. The final outcome would be multiplied by a regeneration constant, K_r, which would yield a signal similar to $s(t)$, called *nt_out*. To prevent this signal to be extended indefinitely, once the stimulus is removed ($s(t) = 0$), *nt_out* would be 0, as soon as *count2* reaches a maximum value, called *maxcount*.

If *input* = 1, then

  $nt\_out = K_r/count2$;

  $count2 = 0$;

Else

  $count2 = count1 + 1$;

If $count2 > maxcount$, then

  $nt\_out = 0$.

After being translated into LabView 10.0, the 3 blocks were connected in cascade to assemble the Neuroid, whose functional scheme, as well as its configuration parameters, are shown in Fig 2.

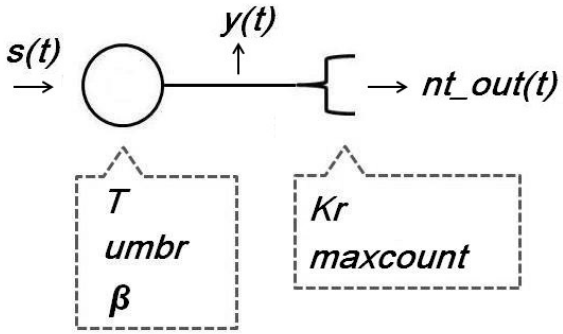

Figure 2. The Neuroid, functional scheme and parametters

IV. Evaluating the Neuroid

In order to evaluate the performance of a single Neuroid, another VI with similar characteristics to wave generators, was implemented. This block was able to generate three different kinds of periodical signals (square, triangular and sinusoidal), so that it was possible to adjust the amplitude (values between 0 and 1), duration and delay (values in ms), for each waveform. A testing interface with 3 display windows up to 1000 ms, which is shown in Fig. 3, was created to observe the incoming signal (1), the signal from the axon (2), and the signal representing the amount of neurotransmitter that would be released (3). For illustrative purposes, the values of *umbr* and *T* were set arbitrarily at 0.1 and 2, respectively, so the performance of the Neuroid was evaluated, given 3 different values for β (1.25, 2.5 and 5). By applying a series of rectangular pulses whose amplitude was incremented in 0.1 steps, from 0 to 1, we obtained 3 different intensity-frequency relations. The value of K_r was adjusted to obtain the maximum output value for the maximum input value. The value of *maxcount* was adjusted taking into account both, the similarities between the input and output signals, and the minimum firing frequency reached by the Neuroid.

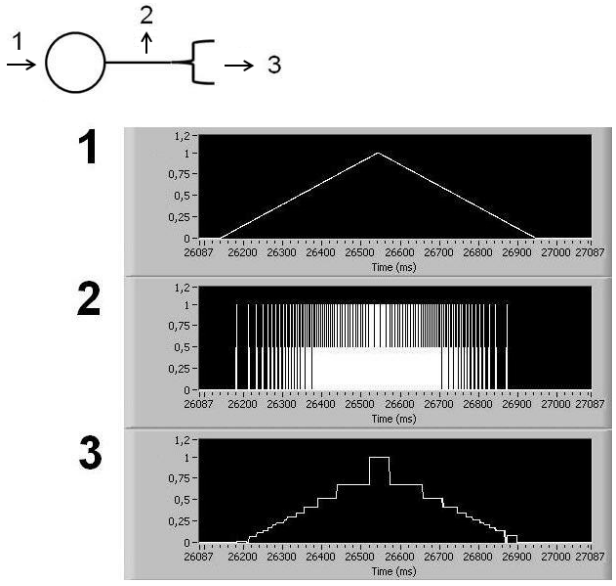

Figure 3. Evaluation of a single Neuroid.

V. Neuroid Networks and the Synaptic Coupling

To evaluate the performance of the Neuroid as basic functional unit of a neural network, some topologies derived from Koch and Brunner [10] were used. An additional VI was implemented, in order to connect 2 or more Neuroids and, at the same time, emulate the excitatory and inhibitory influences exerted by neural (synaptic) coupling. This was accomplished following the McCulloch and Pitts model [2], but omitting the step of comparison, and obtaining, an analogical real-valued output. A testing interface with display windows up to 1000 ms was created in order to observe, not only the input and output signals, but also the impulse train that would be transmitted along the axon, as shown in Fig 4. Each network consisted of 3 identical Neuroids, all of them with *umbr* = 0.1, $T = 2$, $\beta = 1.25$, $K_r = 2.1$ and *maxcount* = 24. Synaptic couplings were implemented in both topologies to combine excitatory and inhibitory influences (where the synaptic weights W_1 and W_2, according to [2], were set at 1 for excitatory, and at -1 for inhibitory, respectively).

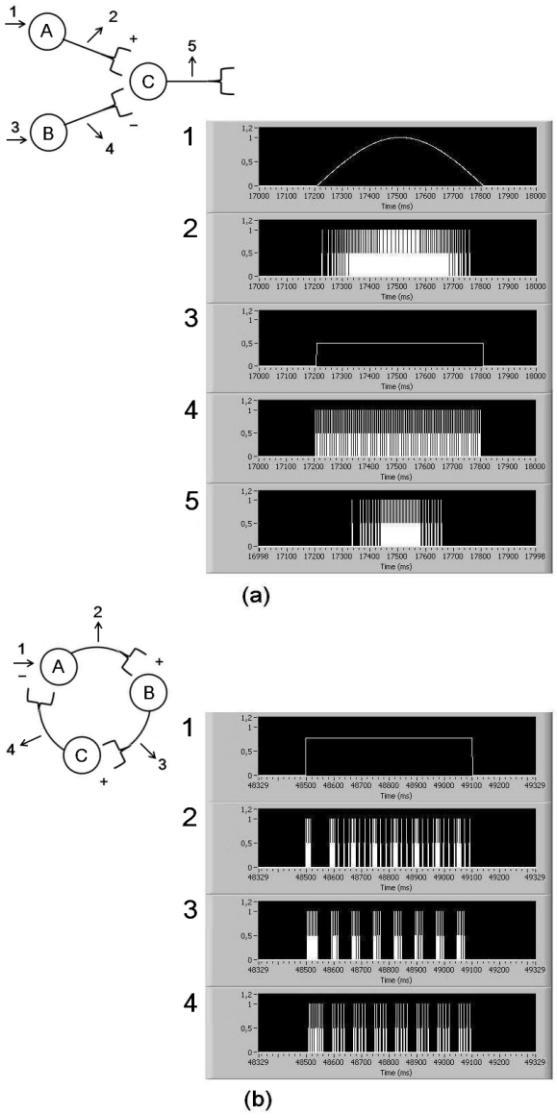

Figure 4. A couple of Three-Neuroid Networks.

VI. Discussion and Conclusions

As illustrated in Fig 4(a), activity was observed in the axon of the Neuroid C (5), only when the excitatory influence, which was modulated as a sinusoidal wave for the Neuroid A (1 and 2), exceeded the inhibitory influence exerted by the constant firing rate of the Neuroid B (3 and 4). For the closed loop network depicted in Fig 4(b), burst patterns were observed in the axons of Neuroids B (3) and C (4), as a result of applying a constant amplitude signal $s(t) = 0.7$ (1) to the Neuroid A. These patterns were quite similar to those obtained by Koch and Brunner [10], and Izhikevich [11], suggesting that our functional approach would be able to mimic the behavior of some physiological neural networks, with a well known and relatively easy to implement architecture.

All parameters were chosen arbitrarily to provide, regardless of the sensory modality, a qualitative description of the changes in the incoming signal (i.e. the stimulus), once it reaches sufficient intensity to overcome the activation threshold, and then be transmitted as an impulse train, to finally be demodulated into an analog signal. We think that it could be very useful for teaching purposes. However, these values may also be the result of a well studied physiological process, such as the membrane potential, for which already exist several biophysically accurate models (like the one proposed by Hodgkin and Huxley). These models could also be implemented in LabVIEW, in order to get a more physiologic Neuroid, and for instance, more realistic. Furthermore, although it is known that there are differences between sensory neurons in regard to their activation thresholds [12], little is known about their intensity-frequency, assumed to be proportional in this work. Few studies show frequency-intensity curves for certain types of neurons, and even fewer are able to establish if the relationship between stimulation intensity and the number of action potentials emitted per unit of time, is linear, quadratic, logarithmic or exponential. This could be the object of study for future research, which would allow, not only to expand the knowledge we have about the neurobiological phenomenon, but also to get better approaches in the field of the neural modeling.

Here, we conceived, designed and implemented a novel neuron-model from a functional approach. Despite of its simplicity, it has some features worth highlighting. First, its modular design, simplicity, and low computational requirements, allow the connection of a large number of Neuroids, in order to study the behavior of certain physiological neural networks, whose outcomes are given by both, excitatory and inhibitory interactions (e.g. the Gate Control System, introduced by Melzack and Wall in 1965 [14]). Second, the model is *parameterizable*, it means that is possible to change the values of the Neuroid's parameters, such as β, *umbr* (the activation threshold), and also, to add delay blocks for emulating the behavior of different types of nerve cells (e.g., mechanoreceptors, nociceptors, corticals, etc.). Third, through its implementation in LabVIEW, it is feasible to dynamically modify the values of the parameters described above, which allows modeling some neurophysiological phenomena, such as long-term potentiation (LTP) and peripheral sensitization, both involved in pain processes. We don't know if the Neuroid belongs to one of the levels described by Herz et al. [15]. On the other hand, it is worth remembering that every model, whether simplified, biophysically accurate, or functional, represents a different approach to understanding a particular problem, and will be the specific aspects of that problem what will lead us to choose the best approach.

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