A Novel Approach to Character Recognition using Spiking Neural Model

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Abstract - A spiking neural network (SNN) model is used to identify characters in a character set. The network is a two layered structure consisting of integrate-and-fire and active dendrite neurons. There are both excitatory and inhibitory connections in the network. It is found that most of the characters are recognized in a character set consisting of 26 alphabet characters. Spiking Neural Network truly simulates the recognition capability like a human brain biological event. This paper highlights the efficacy of realistic behavior of intelligence in a more realistic way and power to recognize for time related lapsed events is possible only in SNN modeling.[1]

Keywords : Spiking Neural Network (SNN), Artificial Neural Network (ANN), Leaky Integrate & Fire (LIF), Spike Time Dependent Plasticity (STDP).

I. INTRODUCTION

Throughout the past hundred years, researchers have been uncovering an increasingly complex brain structure. The elementary processing units in the brain are the neurons, which are connected to each other in an intricate pattern and can occur in many shapes and sizes. Neuron has four functionally distinct parts, called dendritic tree, soma, axon and synapse. Roughly speaking, signals from other neurons are collected by the dendrites (input device) and are transmitted to the soma (central processing unit). If the total excitation caused by the input is sufficient, i.e., above a threshold, an output signal (action potential, or spike) is emitted and propagated along the axon (output device) and its branches to other neurons. It is in the transition zone between the soma and the axon, the axon hillock, where the essential non-linear processing step occurs. The potential difference between the interior of the cell (soma) and its surroundings is called the membrane potential. This potential is directly affected by the postsynaptic potentials – PSPs generated by the spikes received from presynaptic neurons. If the membrane potential reaches a threshold, an action potential (spike) is triggered and sent out through the axon and its branches to the postsynaptic neurons. If the postsynaptic potential is positive, it is said to be excitatory (EPSP) [18] and if the change is negative, the synapse is inhibitory (IPSP). The process of spike transmission through the axon has an associated delay, called the axonal delay.

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Spiking neural networks (SNNs) fall into the third generation [13] of neural network models, increasing the level of realism in a neural simulation. In addition to neuronal and synaptic state, SNNs also incorporate the concept of time into their operating model. The idea is that neurons in the SNN do not fire at each propagation cycle (as it happens with typical multi-layer perceptron networks), but rather fire only when a membrane potential - an intrinsic quality of the neuron related to its membrane electrical charge - reaches a specific value. [4] [2]

When a neuron fires, it generates a signal which travels to other neurons which, in turn, increase or decrease their potentials in accordance with this signal.

In the context of spiking neural networks, the current activation level (modeled as some differential equation) is normally considered to be the neuron's state, with incoming spikes pushing this value higher, and then either firing or decaying over time. Various coding methods exist for interpreting the outgoing spike train as a real-value number, either relying on the frequency of spikes, or the timing between spikes, to encode information. The idea of...
one spike per neuron to process information was explored by [12].

II. LEAKY INTEGRATE and FIRE


The network architecture consists of a feed forward network of spiking neurons with multiple delayed synaptic terminals (Figure 1.1 a and b). Spiking neurons generate action potentials, or spikes, when the internal neuron state variable, called 'membrane potential', crosses a threshold. The relationship between input spikes and the internal state variable is described by the Spike Response Model (SRM), as introduced by Gerstner (1995). Depending on the choice of suitable spike response functions, one can adapt this model to reflect the dynamics of a large variety of different spiking neurons.

Figure 2(a) shows network connectivity and a single connection composed of multiple delayed synapses. Neurons in layer J receive connections from neurons in layer I. Inset: a single connection between two neurons consists of m delayed synaptic terminals. A synaptic terminal k is associated with a weight $w_{ij}^k$, and delay $d_k$. A spike from neuron i thus generates m delayed spike-response functions, the sum of which generates the membrane-potential in neuron j.

Figure 2 (b) is graph of the learning function $L(\Delta t)$. The parameter $\Delta t$ denotes the time-difference between the onset of a PSP at a synapse and the time of the spike generated in the target neuron.

An action potential is part of the process that occurs during the firing of a neuron. During the action potential, part of the neural membrane opens to allow positively charged ions inside the cell and negatively charged ions out. This process causes a rapid increase in the positive charge of the nerve fiber. When the charge reaches +40 mv, the impulse is propagated down the nerve fiber. This electrical impulse is carried down the nerve through a series of action potentials.

A. Prior to the Action Potential

When a neuron is not sending signals, the inside of the neuron has a negative charge relative to the positive charge outside the cell. Electrically charged chemicals known as ions maintain the balance of positive and negative charges. Calcium contains two positive charges, sodium and potassium contain one positive charge and chloride contains a negative charge.
While at rest, the cell membrane of the neuron allows certain ions to pass through, while preventing or restricting the movement of other ions. In this state, sodium and potassium ions cannot easily pass through the membrane. Potassium ions, however, are able to freely cross the membrane. The negatively ions inside of the cell are unable to cross the barrier. The cell must actively transport ions in order to maintain its polarized state. This mechanism is known as the sodium-ion pump. For every two potassium ions that pass through the membrane, three sodium ions are pumped out.

The resting potential of the neuron refers to the difference between the voltage inside and outside the neuron. The resting potential of the average neuron is around -70 millivolts, indicating that the inside of the cell is 70 millivolts less than the outside of the cell.

B. During the Action Potential

When an impulse is sent out from a cell body, the sodium channels open and the positive sodium cells surge into the cell. Once the cell reaches a certain threshold, an action potential will fire, sending the electrical signal down the axon. Action potentials either happen or they don't; there is no such thing as a "partial" firing of a neuron. This principle is known as the all-or-none law.

After the neuron has fired, there is a refractory period in which another action potential is not possible. During this time, the potassium channels reopen and the sodium channels close, gradually returning the neuron to its resting potential.

[17] The leaky integrate-and-fire (LIF) neuron model is one of the most basic formalisms of the spiking behavior of neurons. It is effectively a simple RC-circuit model (leaky integrator) combined with a delta-function (fire) tacked on when the membrane potential reaches a given threshold followed by a reset and optional refractory period.

\[
\begin{align*}
\frac{dV}{dt} &= \frac{1}{\tau_m} (-V + IR_m), \\
\tau_m &= R_m C_m, \\
I &= \text{input current.}
\end{align*}
\]

where \( V \) is the membrane potential, \( \tau_m \) is the membrane time constant equal to \( R_m C_m \), the equivalent resistance and capacitance of the neural membrane, respectively, and \( I \) is the input current. Adding a refractory period simply turns this into the piecewise equation

\[
\frac{dV}{dt} = \begin{cases} 
\frac{1}{\tau_m} (-V + IR_m) & t > t_{\text{rest}} \\
0 & \text{otherwise}
\end{cases}
\]

where \( t_{\text{ref}} \) is the time at which the neuron's refractory period ends. An example trace of an LIF neuron's membrane potential over time for a constant input is shown below.
III. MODELING WITH SNN

Biological Neural Network (BNN) Toolbox is MATLAB-based software to simulate network of biological realistic neurons, as an abstract model of brain and Central Nervous System. This software enables user to create and simulate various BNN models easily, using built-in library models, and just in a few lines of code. User can also create custom models and add them to the library, using library templates. A set of very descriptive examples are available to give a quick introduction to the toolbox and to reduce the coding time for programmers. In addition this toolbox only covers spiking models of neurons and biologically plausible network components. To simulate firing rate models, there exists very well designed packages, such as Neural Network Toolbox of MATLAB. This toolbox uses powerful MATLAB programming language. MATLAB is a popular computation platform with highly specialized and powerful toolboxes for most scientific and engineering fields. This toolbox is created and developed for modeling brain and CNS and is provided to other users as an open source free software under GNU GPL3. The main goal of this software is to provide users a set of integrated tools to create models of biological neural networks and simulate them easily, without the need of extensive coding. Users can create and simulate a huge network of spiking neurons in less than 10 lines of code (or even in one line, if they give all arguments to the main function) using predefined library functions. It is also possible to create and add new models to the library easily, using template library items provided for this reason. Since programming in MATLAB is now very popular, users also would have the benefits of other toolboxes to extend their code and models easily.

IV. RESULTS

For initial testing, the network was trained using twenty six alphabets ('A', 'B', 'C', and till 'Z'). There were 35 input neurons and 26 output neurons for this case. The binary pattern of characters is as shown in figure.

Figure shows the soma potentials of all the 1st and 3rd neuron after training on presentation of a single character. Similar observations were made with rest of the characters.
All neurons and their spikes are as shown in figure.

Plot of Sum Squared Error during the process of ANN based recognition is as shown.

Following Table Summarises the accuracies and Errors involved during the process of recognition.

<table>
<thead>
<tr>
<th>Total Number of Time instants for Recognition of Characters</th>
<th>% of Correctly Recognised Characters over 30 microseconds using ANN</th>
<th>% of Correctly Recognised Characters over 30 microseconds using SNN</th>
<th>% of Correctly Recognised NOISY Characters over 30 microseconds using ANN</th>
<th>% of Correctly Recognised NOISY Characters over 30 microseconds using SNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>1696</td>
<td>98.18</td>
<td>100</td>
<td>91.23</td>
<td>98.23</td>
</tr>
<tr>
<td>1750</td>
<td>97.25</td>
<td>100</td>
<td>85.19</td>
<td>96.87</td>
</tr>
<tr>
<td>2030</td>
<td>96.12</td>
<td>99.23</td>
<td>82.54</td>
<td>95.23</td>
</tr>
<tr>
<td>1580</td>
<td>99.12</td>
<td>100</td>
<td>93.23</td>
<td>99.57</td>
</tr>
</tbody>
</table>

Figures 5, 6, 7, 8, 9 and 10 show the output of all the twenty six Spiking Neurons when the character 'C' is presented as input after training using ANN and SNN. We can see that only SNN has accurate and quick capability due to integration of past memory (inputs).

V FUTURE SCOPE

In this paper accuracy of recognition of character A to Z is more in case of Spiking Neural Network Model. There is a scope of recognition of numeric...
VI. CONCLUSION
From the results obtained we can conclude that accuracy of recognition is more in case of spiking neural network model as compared to Artificial Neural Network. A two layered spiking neural network was used to identify characters in a character set. [5] [15] [18] [19] [20] [21][22] STDP was used to train the network. The network was trained until no significant weight change was observed. Most of the characters were recognized when the network was trained using a character set of 26 characters. The network was successfully trained with characters of increased resolutions. The network was able to recognize characters after addition of random noise pixels. Evolution of the weights during training shows that each output neuron adjusts the value towards the desired output.

REFERENCES