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International Symposium on Aviation Psychology - 2019

International Symposium on Aviation Psychology

5-7-2019

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TEMPORARY MEMORY NEURON FOR THE LEAKY INTEGRATE AND FIRE NEURON MODEL

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Low-level terrain-following systems require the ability to rapidly and accurately respond to the environment to prevent inadvertent actions. Catastrophic and fatal results could occur if missed cues or latency issues in data processing are encountered. Spiking neural networks (SNNs) have the computational ability to continuously process spike trains from rapid sensory input. However, most models of SNNs do not retain information from the spike train of a previous time step because the membrane potential is rapidly reset to a resting potential after activation. A novel approach is presented, allowing the spike train of a previous time step to be 'remembered.' Results are presented showing rapid onset of a membrane potential that exceeds the threshold and spikes in the presence of the same continuous spike train without the latency of increasing the membrane potential from its resting state.

Piloted operations for both man and unmanned aircraft grow in complexity, which can overtax a pilot's cognitive ability. One area where this is especially true is with low altitude operations. This type of operation is often necessary for mission success, thereby giving the pilot a significant advantage by avoiding adversarial engagement. The number of visual cues a pilot must quickly process in order to avoid controlled flight into terrain (CFIT) coupled with parallel communications and weapons tasks can quickly saturate cognitive ability, severely degrading a pilot's situation awareness (SA). This degradation in SA can negatively affect mission performance and result in unnecessary loss of life and assets.

Terrain-following systems aid pilots with low altitude navigation. However, the latency with which these systems need to operate must be as small as possible allowing for high accuracy in terrain scanning. These systems should also be of low Size, Weight, and Power (SWaP) for easy integration as a subsystem to an overall SWaP-constrained aircraft system. Third generation neural networks, also known as SNNs, are modeled after the neurons of the brain. Much research has been done on the modeling of neuron function of the brain. Some models are considered more biologically plausible, while others are considered more biologically inspired, such as the Leaky Integrate-and-Fire (LIF) model, as they aim to borrow only certain advantageous neuron cell characteristics for easy practical implementation Hazan et al. (2018).

This paper proposes a novel neuron model, termed a temporary memory neuron (TMN), based on the LIF model with a tunable "memory" parameter which is correlated to a limited presynaptic spike time frame. This neuron, with its temporary memory capability, integrates into a SNN architecture and reduces the latency required to identify a previously learned spike train. This reduction in latency allows the terrain-following system to more rapidly provide the pilot with critical time-of-flight information necessary for mission success.

I. RELATED WORK

Different techniques have been explored that develop dynamic spike firing rates. The work by Triesch (2005) develops a mathematical model of a neuron that provides plasticity that could be intrinsic to the neuron. This model provides for an adjustment to the firing rate to approximate an exponential regime. While this method is novel, and provides a method for plasticity within the neuron (not just the synapse), it does not provide for a memory or temporary memory capability based on a sequential spike train that could decrease latency in the system. Other similar approaches have been explored as in Stemmler et al. (1999). In order to reduce latency, some have approached this concept by optimizing the parameters of the neuron model, to include the thresholds, based on the specific task to be solved. Diehl et al. (2015) developed an approach to optimize the accuracy or latency by adjusting the threshold levels until the appropriate values were obtained. It was found that to optimize one, the other was sacrificed on a spike-by-spike basis. Other intrinsic plasticity based neuron parameters, e.g. thresholds, have been developed as part of the neural models as in Pozo et al. (2010). However, these all have thresholds that are increased to prevent a specific neuron from overshadowing the response pattern. The development of the dynamic thresholds of the previous works do not produce a offset membrane potential allowing for an associated temporary memory function based on the previous input spikes. In contrast, the novel neuron model of this paper produces a temporary memory function based on an offset membrane potential.

II. BACKGROUND

The spikes that are received by the postsynaptic neuron affect the membrane potential of the soma. As the membrane potential is increased, it will eventually surpass a threshold that causes the soma to send a spike down its axon to be delivered to other neurons. Once the spike occurs the membrane potential enters a refractory period during which it remains unaffected by any presynaptic spikes. After the refractory period, the membrane potential is reset to its original resting value after which new presynaptic spikes will again influence the membrane potential Gerstner et al. (2002).

The synapse resistance, or lack thereof, governs the amount that the presynaptic action potential effects the postsynaptic membrane potential. This process is translated into the artificial neural network (ANN) as the input weights of the ANN. The ability to adjust these weights is considered the synaptic plasticity. Less common, and less accounted for, is the intrinsic plasticity of a neuron that common neuron models do not take into account, i.e. the threshold values Hao et al. (2018).

A. Leakey Integrate-and –Fire Model

The LIF neuron model is one of the most common neuron models used in spiking neural networks. This model is represented with a capacitor in parallel with a resistor and driven by a current, where a time constant $\tau_m = RC$ is introduced. The leaky integrate and fire model expresses spikes based on a firing time $t^{(f)}$. The LIF neuron builds up its membrane potential between spikes and will eventually reach the threshold if enough input spikes are received that overpower the leak function of this neuron, a refractory period is observed immediately following the induced postsynaptic spike. The refractory period is a finite amount of time in which incoming spikes are not allowed to have any influence on the membrane potential.

B. Spike Response Model

The Spike Response model (SRM) is a generalization of the leaky integrate and fire model, where the generalization is in the form of dependence on the last time a spike occurred Gerstner et al. (2002). The SRM evaluates the membrane potential by integrating over the past for a specific current time t. The state of a neuron is determined with respect to the membrane potential. This model defines a resting state u_{rest}, a spike response, as presynaptic spikes are encountered, ϵ, the form of the action potential η, and synaptic weights ω_{ij} Gerstner et al., (2002). The zeroth order of the SRM (SRM_0), is a simplistic "zero order" version of the SRM. Therefore, independent of the presynaptic neuron and the last firing time of the postsynaptic neuron $\widehat{t_\iota}$, the postsynaptic potential is developed with each presynaptic spike weighted by the synaptic efficacy ω_{ij}. This model is mathematically represented by Gerstner et al., (2002):

$$u_i(t) = \eta(t - t_i) + \sum_j \omega_{ij} \sum_{t_j^{(f)}} \epsilon_{ij}\left(t - t_j^{(f)}\right) + u_{rest}, \tag{1}$$

where, $u_i(t)$ is the membrane potential, $\eta(t - t_i)$ is the action potential based on the time from the previous postsynaptic spike, ω_{ij} is the synaptic efficacy, $\epsilon_{ij}\left(t - t_j^{(f)}\right)$ is the postsynaptic potential based on the presynaptic spikes, and u_{rest} is the resting membrane potential.

III. TEMPORARY MEMORY NEURON MODEL

The desire to develop a neuron-level capability to decrease latency for previously discovered spike trains is paramount to real-time detection and classification missions. The intrinsic speed of the cognitive neuromorphic architecture developed for SNNs will determine the baseline processing speed of the SNNs. However, this baseline still produces latency when a neuron requires multiple spikes (multiple number of events i.e. computational cycles) to reach a threshold and emit a spike. Assuming that a specific spike train indicates an event of interest, most neuron models require multiple spike trains between postsynaptic spikes. This representation of a neuron model introduces latency between postsynaptic spikes.

While the novel approach presented in this paper is not suggesting that it is representative of a biological neuron, it is building on the capabilities of the biological neuron models to provide an advanced capability. This concept utilizes computational models of spiking neurons and synapses implementing the biologically inspired LIF model and more specifically the SRM model; adding a tunable memory component as in Dayan et al.(2001), and Gerstner et al., (2002). The LIF neuron integrates the input spikes modulated by the inter-connecting synaptic weights, leading to a change in its membrane potential. The SRM_0, equation 1, is a generalized LIF model where the model parameters are based on the last output spike Gerstner et al.(2002). The temporal dynamics of the TMN neuron are formulated in equations 2 and 3,

$$u_i(t) = \eta(t - \hat{t}_i) + \sum_j \omega_{ij} \sum_{t_j^{(f)}} \epsilon_{ij}\left(t - t_j^{(f)}\right) + u_{rest} + \zeta_i(t), \tag{2}$$

where $u_i(t)$ is the membrane potential of neuron i at time t, and $\eta(t - \hat{t}_i)$ is the model 'form' of the spike at some time t after the last spike of neuron i, $(\hat{t}_i)$, $\sum_j \omega_{ij}$ is the synaptic efficacy (the sum of the synaptic weights of the presynaptic neurons j exciting the postsynaptic neuron i), $\sum_{t_j^{(f)}} \epsilon_{ij}\left(t - t_j^{(f)}\right)$ is the sum of the postsynaptic potential ϵ_{ij} based on the current time and its relation to the presynaptic spikes of presynaptic neurons j at time f, and the membrane resting potential of neuron i, u_{rest}. The TMN neuron builds on the basic equation of the SRM_0 model with the addition of $\zeta_i(t)$, the neuron memory of neuron i defined at time t as shown in equation 2 and developed in equation 3. The memory addition to the SRM_0 model is:

$$\zeta_i(t) = -\left[-\frac{1}{1 + e^{-[t-(t_i+\tau_d)+\tau_{off}]}} + 1\right]\left(-\left[u_{rest} - \left(v - v_{offset}\right)\right]\right), \tag{3}$$

where τ_d and τ_{off} are time constants that set the point in time after neuron i spikes allowing the membrane potential will be allowed to decrease back to its resting state, v is the neuron threshold and v_{offset} is the desired level below the threshold value where the membrane potential will be temporarily set. The TMN allows for a neuron to spike more readily upon receiving a spike once it has produced a postsynaptic spike. This concept, built into an ensemble of neurons, will provide a quicker response to an already known spike train, preventing the latency between postsynaptic spikes.

IV. RESULTS

The TMN neuron simulated with a constant current input at set intervals. Various parameters were changed in the TMN neuron to illustrate the capability for this neuron to reduce latency upon receiving additional spikes. This simulation provides constant current input between 1000-1200ms (200ms period), 2000-2300ms (300ms period), 2800-3200ms (400ms period), and 4200-4250ms (50ms period) to observe the response of the TMN for the different time periods. For the simulation illustrated in this work, the membrane rest potential is set to -70mV, the membrane reset potential is set to -75mV, the membrane threshold is set to -55mV and the refractory constant is set to 10ms. The temporary memory part of this neuron has the v_{offset} set to 7mV the τ_d (governs the time until the membrane potential is allowed to decay to its rest state assuming no other spikes have occurred) is set to 20mS and the τ_{off} (governs the rate of the decay back to the rest potential) is set to 200ms.

Figure 1(a) illustrates the TMN with an input current set to a magnitude of 10A. It is noted that with the varying time periods of, 200ms, 300ms, 400ms, 50ms, respectively, the number of spikes produced within the time periods would be fewer without the temporary memory. The initial spikes of each time period required significant more ramp up time as compared to subsequent spikes. It is also noted form figure 1(a) that the temporary memory is maintained for a specific time period, afterward decaying back to its resting state in the absence of a spike (e.g. the 100ms and 200ms time periods).

In contrast, figure 1(b) shows the effect of the temporary memory where an additional current was inserted at 139ms to 145ms allowing a post synaptic spike to occur where otherwise no spike would have occurred. This action reset the temporary memory values allowing for a new spike train to be recognized within the specified time frame.

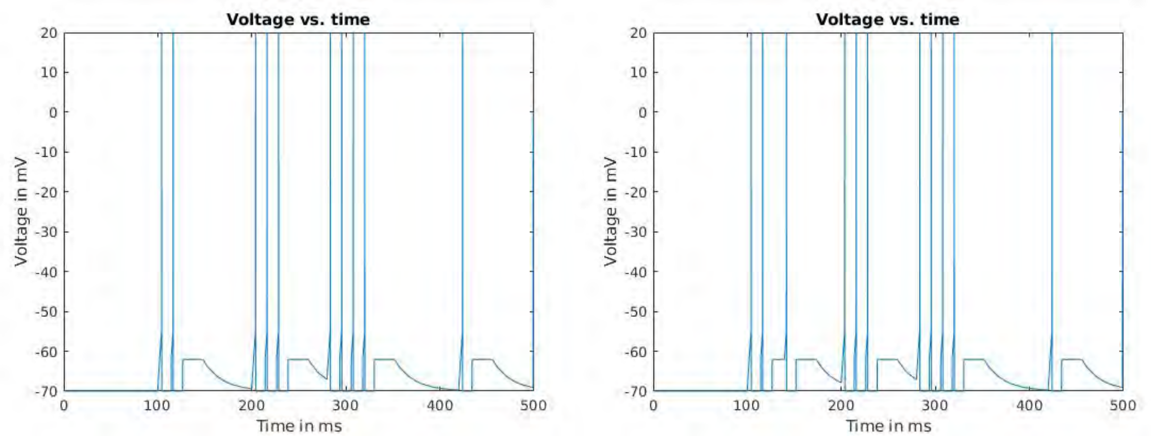

Figure 1. (a) Spike Response of a TMN neuron with 4 time periods (200ms, 300ms, 400ms, and 50ms) illustrating the temporary memory capability to produce subsequent spikes in a set time period, (b) illustrating the temporary memory capability to produce subsequent spikes in a set time period with an additional 6ms time period for starting at 139ms.

V. CONCLUSIONS

A novel neuron model based on the LIF neuron with a tunable temporary memory parameter is proposed. This tunable parameter allows for the temporary 'remembrance' of specific spike train inputs. After a prescribed time period previously learned spike trains are ‘forgotten' allowing for future spike trains to be learned. This dynamic capability can be integrated into a third generation ANN system allowing for reduced latency in the recognition of specific inputs. An application where this concept could be of benefit is that of low altitude, high speed, terrain scanning systems. These systems require both low latency and low SWaP which third generation artificial neural networks show promise to deliver. Enabling a reliable terrain scanning navigation aid will help reduce cognitive overload and improve SA for pilots. Future work with this concept is underway where the optimal intrinsic neuron plasticity parameters such as sub-threshold voltage and temporary memory duration will be explored, modeling human sensory memory and working memory.

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