# Motion & Velocity Detection From A Compartmental Spiking Neuron Model

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*Abstract*—Processing of visual motion begins early on in the retina, but remains poorly modeled by computational neuroscience. Breakthroughs in our understanding seem possible given the large volume of experimental data on said subject. Advances as such could impact many fields like autonomous robots which need to understand spatial relationships as they navigate unfamiliar terrain. This work modestly tries to take a step towards understanding motion computation in the retina by expanding an exponential integrate and fire neuron model to include two dendritic compartments. Despite its simplicity it replicates findings from motion selective neurons in mouse retina, and could further be implemented on neuromorphic hardware.

*Index Terms*—spiking neural networks, compartmental neuron modeling, motion detection, retina

## I. INTRODUCTION

Deep neural networks (DNNs) have driven this last 10 years of the latest AI summer [9]. These types of networks use most of the same abstractions as those of the PDP group in the 1980s. Minor modifications include using the RuLU activation function and the modern advent of massively parallel graphics cards (GPGPUs). Neither of these ideas are inherently new as ReLU goes back to at least Fukushima in 1968 where he originally used the term "analog threshold units" instead [5] [1].

Deep convolutional neural networks (CNNs) from Jim Dicarlo's lab called CorNet have been shown to resemble neural recording data from real monkey's ventral visual pathway [10]. The same has not been done for the dorsal pathway. It remains a more difficult problem. Some of this difficulty probably arises from some simplifying modeling assumptions of DNNs. Time is often only implicit in DNNs through layering and average firing rates (i.e. the output value of the activation function). The dorsal visual stream deals more with motion data (e.g. optic flow) than the ventral stream is thought to, which itself deals with classification. Another potential modeling improvement could come from explicitly modeling the retina and lateral geniculate nucleus (LGN). Motion is being processed in the eye in multiple parallel pathways yet we do not even have it in our deeper layers of the cortex yet.

[1]Chapter 10 of Rosenblatt's 1962 book [13] included transfer functions that each have components of ReLU as used today (e.g. thresholding, non-linearity, and monotonically increasing functions). It would not surprise me to find ReLU in that text upon further investigation.



Fig. 1. A micrograph of a mouse retinal wholemount highlighting a class of RGCs whose asymmetric dendritic arbors correlate with its ability to detect upward motion in the visual image plane. Image from [8]

The LGN is known to do processing as well and have more complicated temporal receptive fields than earlier on in the pathway at the retina. CNNs often lack recurrence at all. It is no wonder that they cannot capture motion data. By definition it seems to require some recurrence, at least in terms of stateful information being inside the network between two subsequent image inputs.

The assumption that we can model neurons as point neurons which convey all information in their firing rates is an old one. Much motivation for the latter came from [2] in the 1920s. They found that hanging heavier weights from a muscle led to faster firing rates from neurons inside the muscles. This is where rate coding originated from, the idea that information in nervous systems are communicated in the form of average firing rates. This is surely one form of information in biological neural networks (BNNs), but several other temporal codes are known to be used nowadays [6], [14].

It is from this background that the motivation of this work stems. Many practitioners of DNNs are happy to build upon poor, old assumptions about neural computation. It is this authors opinion that some of these deep and fundamental assumptions should be further challenged and improved. This work constitutes a modest step towards that ambitious goal.

This work models a spiking neuron with two simply linked dendritic compartments. With this model I try to replicate some physiological findings from [8], where a class of retinal ganglion cells (RGCs) were discovered whose asymmetric dendritic arbors led to upwards motion detection. RGCs of the same class with symmetric dendrites could detect motion, but lacked any selectivity for specific directions. This is a great example of the need to model dendrites to capture motion information, even as early on in processing as the retina. The timing and location of inputs along the dendrites determine the magnitude of the response at the soma [1], even for passive dendrites.

## II. METHODS

An exponential leaky integrate and fire neuron model was chosen to expand upon. For details on the equations see [4]. It was extended to include two compartments, each of which had no firing dynamics. The dendrites had the same default membrane conductance parameter value as the soma ($G\_L$ = 1e-8 Siemens). They were linked to other compartments by the same resistance value of 500 M$\Omega$ [2].

When the dendritic compartments were sufficiently depolarized, the leak conductance parameter ($G\_L$) was instantly reduced to half its default value (1e-8 -¿ 5e-9). This membrane voltage threshold for dendrite #1 & #2 was 7mv and 0mv, respectively. Every timestep the membrane was hyper-polarized below these values, $G\_L$ was increased 2e-11 Siemens until it reached the original value. (see blue traces in Fig. 4 and Fig. 5)

This paper's model can be seen as a modified version of the classic Reichardt detector (see Fig. 2), where the typical axonal delay is on a shared dendrite instead. See the discussion section for suggested computation advantages of such a system.

If feature detecting neuron 'B' fired up to 50ms before 'A' then it had an inhibitory effect on 'A' such that its synaptic efficacy was halved. See the results and discussion sections for further details.

Each simulated timestep was 0.1 millisecond (ms). There were 4000 timesteps for a total simulation time of 400ms. The leak/resting potential ($E\_L$) was set at -70mV, the threshold for spiking (Vth) was 50mV, and the reset potential (Vreset) post-spike was set to -80mV.

Current flowed bidirectionally down the dendrites and soma proportional to their voltage difference and inversely proportional to the resistor's strength coupling them. This is typical of many neurons, in contrast to what is usually taught or assumed in early studies of neuro-electrophysiology (e.g. [11]). This is

[2]Does this seem high? Hmm, maybe should have played with this more :)
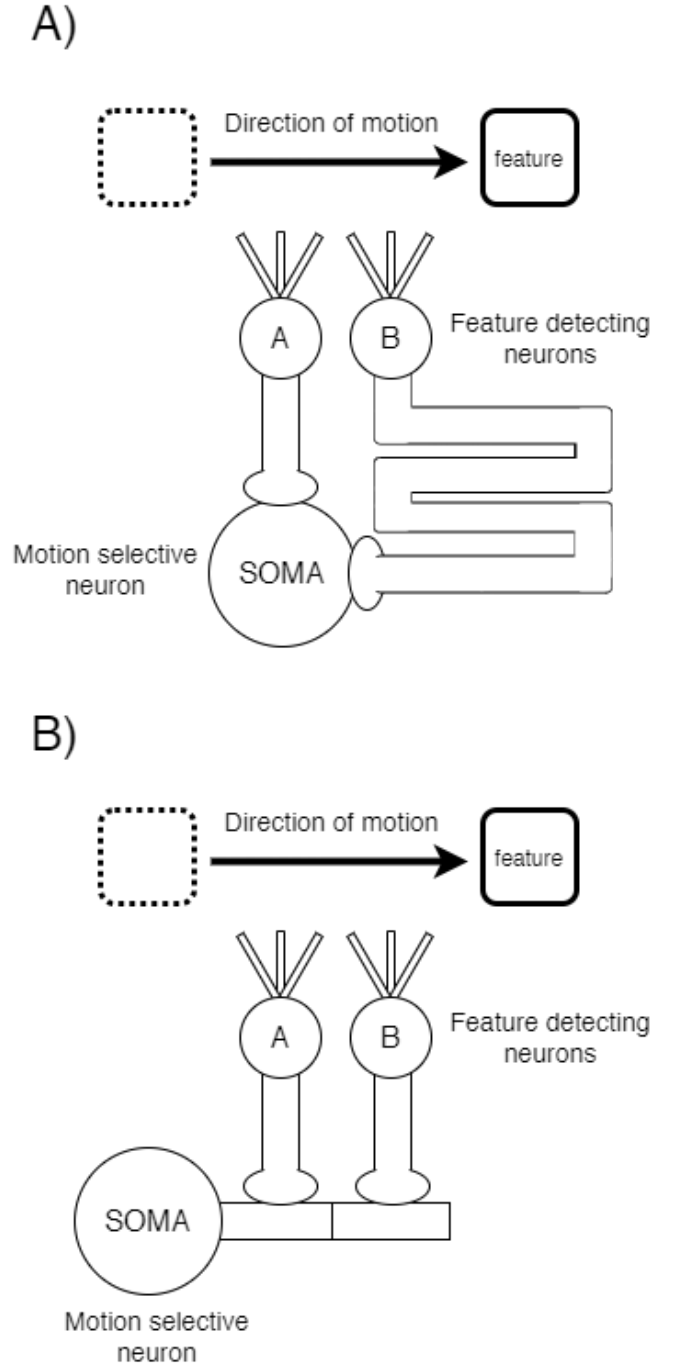


Fig. 2. A) Half of a Reichardt detector. The feature selective neurons 'A' and 'B' detect a feature (here it is a simple square) as it moves across the visual input. The axonal delay of neuron 'A' ensures that the two signals arrive at the third neuron at approximately the same time so their magnitudes can be integrated together and elicit a larger response. B) The proposed modified Reichardt detector from this work. Note that the axonal delay is now replaced by a shared dendrite. This sharing is more like the full Reichardt detector with two symmetric units as shown in A).

another potentially poorly modeled temporal aspect of BNNs. Stateful information is bouncing around inside the neuronal processes that affect later computations. Contemporary DNNs wholly fail to capture these dynamics.

For further details (e.g. hyperparameter values) please see the publicly available code using this link.

## III. RESULTS

The modified Reichardt detector model with shared dendritic delays replicated the findings from [8] where asymmetric dendritic arbors were used to detect motion that originally signaled at the soma and traveled outwards distally along the dendrites.

These results were had from conceptually including voltage sensitive channels in the dendritic compartments that acted to decrease potassium leak when they were depolarized beyond roughly 0mV. These channels were very fast to close and much slower to reopen.

The initial results did not include any inhibition. In this case the motion neuron was still responsive to motion, but was equally activate by either cardinal direction of movement (see Fig. 3 and Fig. 5). With temporally asymmetric inhibition (implemented not by inhibitory neuron modeling, but by a simple *if* block in the code) the motion model lowered its firing rate for one way of motion and increased it for the other direction (see Fig. 4). In other words, the neuronal form of the inhibition of 'B' upon 'A' is unspecified, but a violation of Dale's principle could lead to several possible solutions involving a fast-spiking inhibitory interneuron(s). More fully specifying the mechanism of temporal input selectivity is a future direction of this work.

It cannot be determined from this experimental what the detected velocity would have been. The feature's size and the separation between 'A' and 'B' on the receptive field of the retina could span many different values. The takeaway is that a range of velocities elicits lowered firing rates, and the near symmetric range about 0 produces increased firing rates. Outside either of these ranges produces middling responses.

The difference in firing rates across 'B' time delays is small, but could potentially be made larger given further hyperparameter tuning (e.g. the resistance coupling compartments) and by including more conductances in the dendrites (e.g. Na+, K+, Ca++, NMDA). Speeding up the travel time of PSPs when the leak is reduced might have helped improve sensory contrast as well.

## IV. DISCUSSION

This work shows that modeling dendrites has important computational significance for motion detection. It was able to create a motion and speed selective cell using a standard exponential-leaky integrate and fire neuron model.

Sharing a transmission line (i.e. the dendrites) could make the signal arrive at the soma quicker and stronger. Subsequently that could lead to higher sensory contrast enhancement. Active dendritic conductances (e.g. NMDA spikes) could increase the contrast as well.
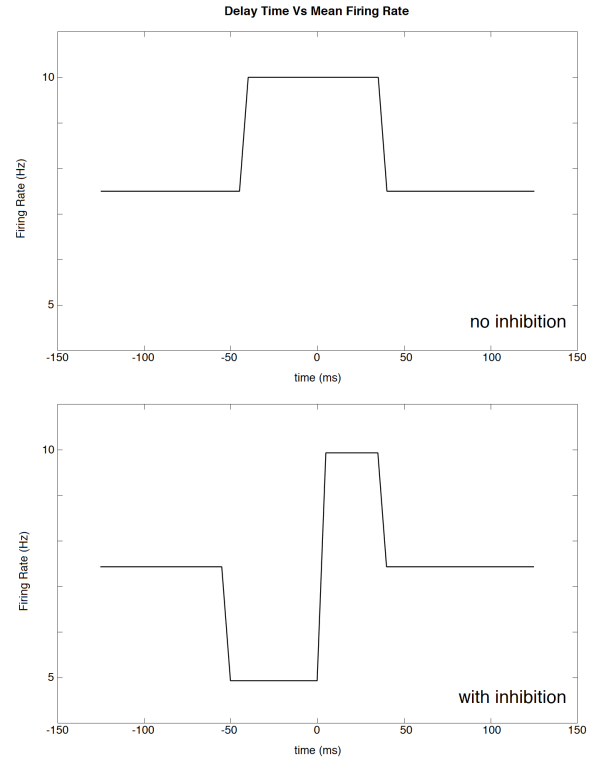


Fig. 3. How long before or after feature detecting neuron 'B' fires relative to neuron 'A' versus mean firing rate of the downstream motion detecting neuron. The top figure shows how no inhibition causes the motion neuron to be equally responsive to opposing directions of motion. However, if 'B' firing first inhibits the synapse from 'A', then the motion neuron has a decreased firing rate for one direction of motion, causing it to be directionally tuned.

This work is similar to she work from Elisabetta Chicca's lab, where they made the spiking elementary motion detector (sEMD) [12]. EMD is another name given to the Reichardt detector. In their design the multiplication of the detector is carried out by a facilitatory synapse on the other one. This ensures specificity to the temporal order of 'A' and 'B' arriving at the motion selective neuron. This same lab has implemented their sEMD on neuromorphic hardware with mixed results. It would be interesting to do the same for this paper's model as it is a simple extension to the LIF model which is the de facto spiking model, and thus most neuromorphic chips will probably support it. These chips have the advantage of using very little energy, but the disadvantage of competing with much more mature Von Neumann CMOS technologies.

There are acetylcholine (ACh) receptors and synapses in the retina. At least some ACh receptors act a multiplier by closing typically open potassium channels in the membrane. This mechanism could be an implementation of the reduced signal attenuation through reduced leak conductance used in my model.

Incorporating more and more detail that has been previously abstracted away, or simply not known about at the time the abstractions were originally made, will prove useful for addressing the modern shortcoming of artificial neural networks.
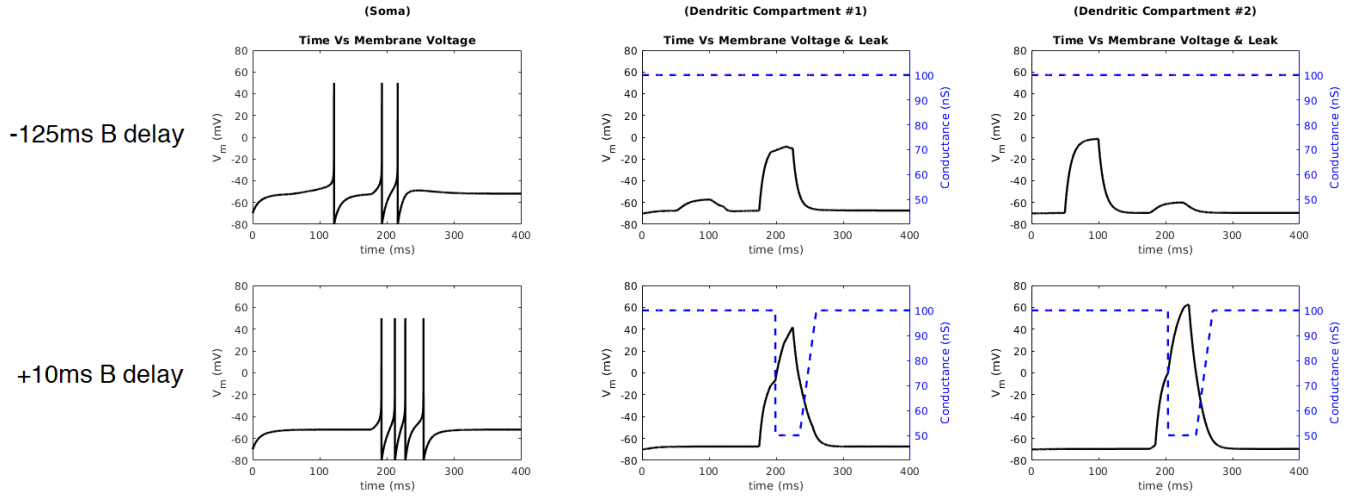
Fig. 4. *Top row*: When 'B' detects the feature before 'A' by 125ms 3 spikes occur at the soma. The first spike is rather isolated in time. *Bottom row*: When 'B' is detected just after 'A' by 10ms the signals are integrated to produce 4 spikes in a much stronger grouped burst of activity. This summation is further aided by the decreased leaking in the dendritic compartments upon sufficient depolarization. More current flows to the soma under these conditions.
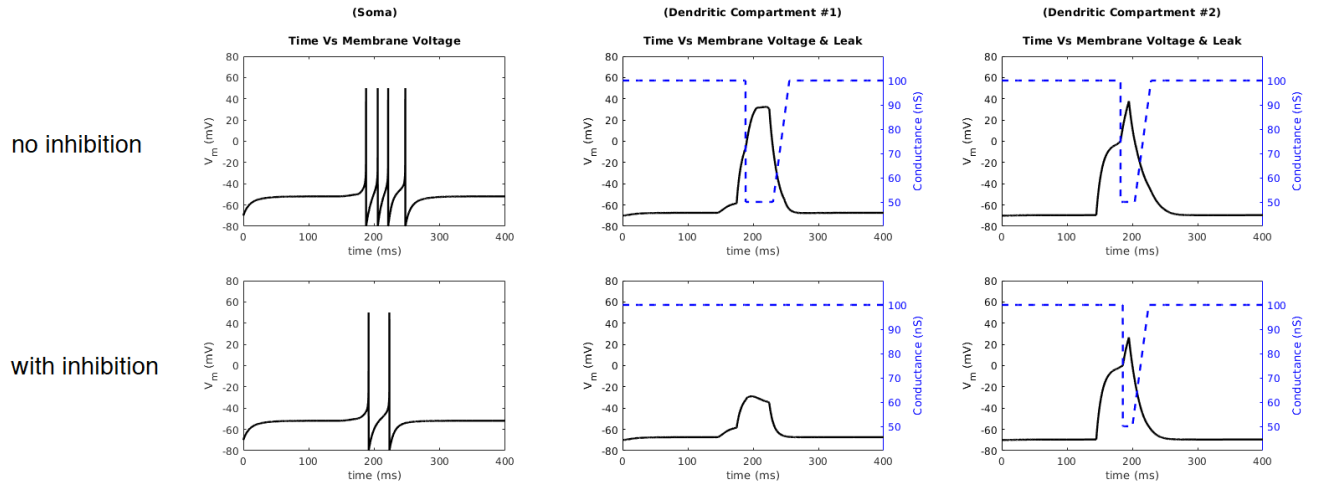


Fig. 5. *Top row*: Without inhibition of 'A' by 'B' firing first the response to motion is not as directionally specific. Contrast this -30ms delay of 'B' to that of Fig. 4. There the direction of motion is opposite of this, but the response is essentially identical. *Bottom row*: The same experimental setup as the top row, but 'B' firing before 'A' causes inhibition at the synapse of 'A' onto the motion neuron. See Fig. 3 for the overall effect of inhibition on the mean firing rate.

Especially for motion modeling of the eye and later on in the dorsal visual stream.

The invention and history of the computer could be retroactively labeled as a failed attempt to recreate the brain. The term computer was originally used to refer to women who did arduous mathematical computations by hand. The boolean algebra underlying the discrete logic of computers today began as a systematic attempt to capture human thinking in mathematical terms. Von Neumann's original 60 page manuscript outlining his Von Neumann architecture (EDVAC) cited only the work of McCulloch & Pitts (P.11), and he seemingly lectured more on that type of material than he did of Turing's ideas [7]. Memory is called memory in a computer system for a reason, not by

accident. Who would have thought to use electricity to think? Nature did several hundred million years ago. Nowadays with the modern hype around AGI, we create artificial selective pressures for machines that do everything a person can do. We have the same end goal yet many expect engineering and purely mathematical efforts to get us there. Our cultural evolution is not so clever at search and design that we should be quick to go a different route than the one our brain evolved upon. It is for these reasons and others that understanding and modeling biology has and will remain the best source of useful AI design [3].

## V. FUTURE WORK

- Dendritic voltage ceiling related to synaptic equilibrium potentials
- Spine search dynamics
- Learning of weights
- Dendritic branching
- Active dendritic properties (eg NMDA, Ca++, Na+ spikes)
- Ensure parameters are biologically realistic
- Add non-instantaneous and non-binary growth and decay dynamics for the compartment's variable conductances.
- COBA instead of CUBA (non-instantaneous current injection)
- Make PSPs travel speed conditioned on conductance and resistance (e.g. like the effects of myelin sheaths).

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