

Dynamic Compartmentalization in HTM Dendrites

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February 2018

Introduction

Neuron dendrites do not function as a single monolithic entity, but rather distant regions of a dendrite function independently of each other. This property known as ‘dendritic compartmentalization’ has been found experimentally in neurons [2], and has been shown to be crucial for neuron models to function correctly [1]. The HTM model [1] of cortical pyramidal neurons simplifies each neuron’s distal dendrites into a static set of independent areas of the dendrite. A recent study [2] examines how a dendrite’s electrical impedance separates areas of the dendrite. They find that distant areas of a dendrite can cooperate and that nearby areas of a dendrite can become separated by inhibitory synapses.

This report introduces a computational dendrite model which attempts to capture the complex dynamics of [2] without unnecessary details of biology and electronics. It is implemented, analysed, integrated into the HTM model, and tested on the Numenta Anomaly Benchmark [4] where it performs as well as Nupic’s HTM model with static dendritic compartments.

Dendrite Model

Dendrite Structure

Dendrites are modeled as a binary tree of dendrite segments. Each dendrite segment contains a list of synaptic spines, which are physically located along the segment in 1 unit intervals.

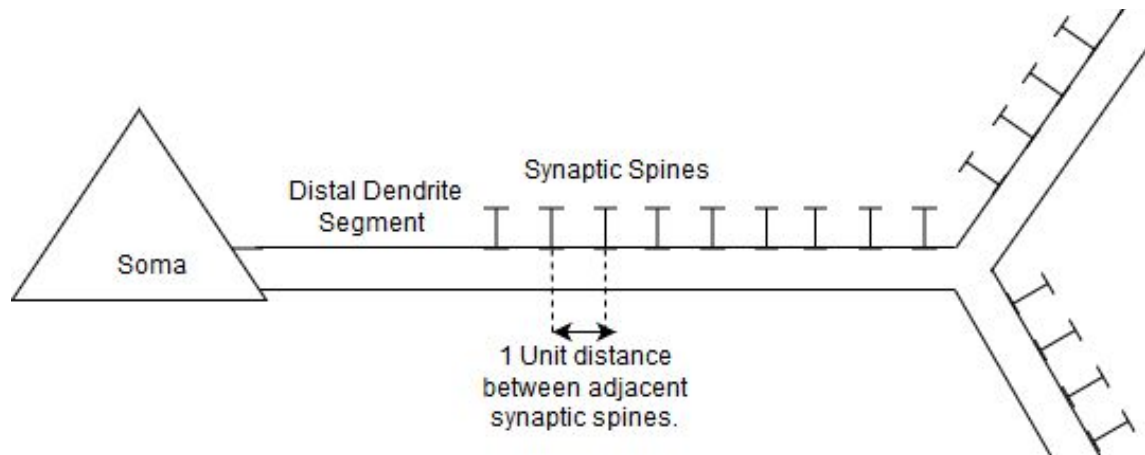


Figure 1: Diagram of a dendrite.

Excitement

This model does not simulate the effects of electricity. Instead this model uses units of excitement, where 1 unit of excitement is the amount of excitement a synapse receives when it emits an excitatory postsynaptic potential (EPSP). Each EPSP event increases the excitement at all locations in the dendrite, starting at the synapse which emitted it and exponentially decaying with distance from that synapse. For a brief duration of time, the excitement from many EPSP events accumulates at synaptic spines. At the end of the period of time, every synaptic spine whose excitement reached the NMDA spiking threshold activates.

EPSP Events

The separation factor describes how the effects of an EPSP decay as a function of distance from the EPSP.

Equation 1: Separation Factor = α^{distance}

The total excitement at a location in the dendrite is a function of all EPSPs throughout the dendrite. Since each EPSP emits exactly one unit of excitement, the separation factor is also the amount of excitement delivered by an EPSP to a location.

Equation 2: $\text{Excitement}(\text{Loc}) = \text{Sum}(\text{Separation Factor}(\text{Loc, synapse}) \text{ for synapse in EPSPs})$

The variable α can be redefined in terms of variable "period" which has units of distance.

Equation 3: $\alpha = 1 - 1 / \text{period}$

The sum of excitement throughout the dendrite caused by a single EPSP can be calculated with the following equation. It also describes the maximum excitement which any location will receive.

Equation 4: Maximum Excitement = $-2 / \ln(\alpha)$

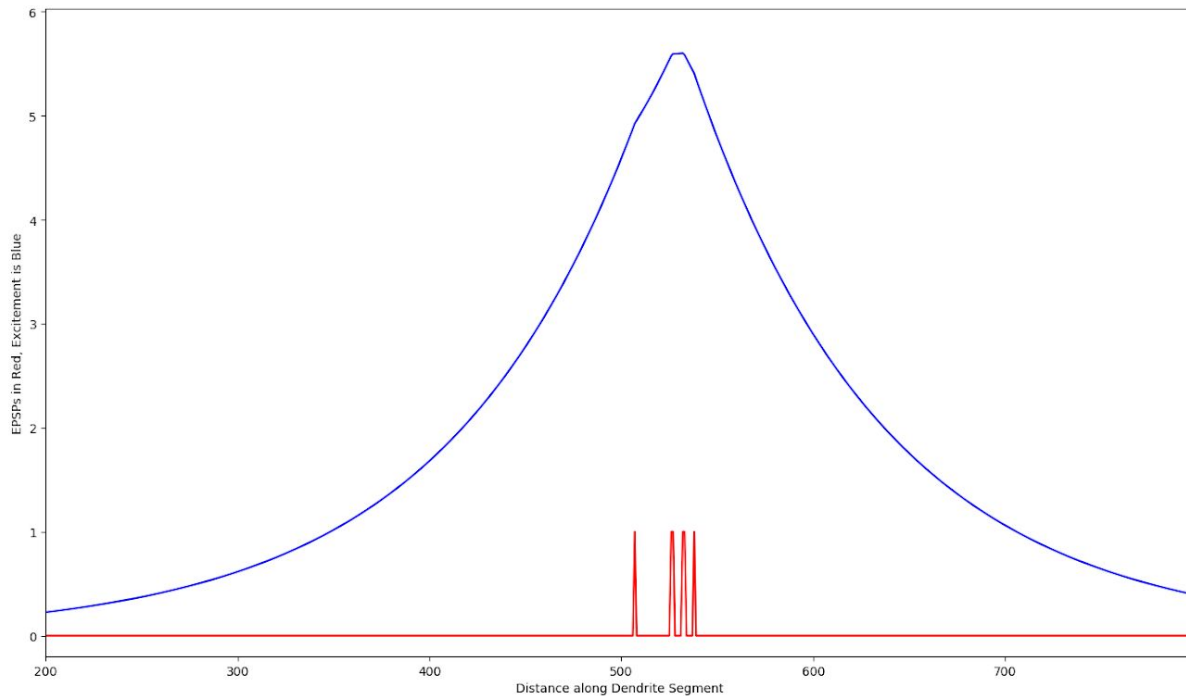


Figure 2: Excitement emitted by a cluster of 6 EPSPs on a segment.

Dendritic Trees

Equation 1 does not account for the branching structure of the dendritic tree, it only works for the special case of a single long dendrite and does not consider what's attached to either end of it. When excitement reaches a bifurcation it is divided equally among the branches, regardless of which if segments are parents, children, or siblings. Excitement is conserved across bifurcations. The model actually uses equation 5 to determine the separation factor. When excitement reaches the leaves or root of the tree it is removed, not conserved.

Equation 5: Separation Factor = $(\alpha^{\text{distance}}) * (\frac{1}{2}^{\text{Bifurcations}})$

Where “Bifurcations” is the number of bifurcations that lay along the distance being measured.

Synapse Placement

New segments are created when the HTM model detects a prediction failure. New segments are created on available areas of the dendrite, with a preference for areas closer to the root. Areas of the dendrite are considered available if they are mostly devoid of synapses.

Methods

Dendrite Algorithm

The excitement at every synapse location in the dendrite tree is calculated in three traversals through the locations. This is possible because the effects of each EPSP decays exponentially with respect to distance. This allows the calculation to be factored and each factor incrementally computed. For example consider the effects of two EPSPs, separated by 1 unit, on location A which is 1 unit away from them:

$$\text{Excitement}(\text{Location A}) = \alpha^1 + \alpha^2$$

$$\text{Excitement}(\text{Location A}) = (1 * \alpha + 1) * \alpha$$

Then consider the combined effect of these two EPSPs on location B, which is 1 unit beyond location A and 2 units away from the EPSPs.

$$\text{Excitement}(\text{Location B}) = \alpha^3 + \alpha^2$$

$$\text{Excitement}(\text{Location B}) = (1 * \alpha + 1) * \alpha * \alpha$$

Notice that the adjacent locations are different by a factor of α .

$$\text{Excitement}(\text{Location B}) = \text{Excitement}(\text{Location A}) * \alpha$$

This proves a property of exponential decays, that they can be added together if they decay at the same rate.

Algorithm Steps:

- 1) For each presynaptic AP, notify all potentially connected synapses about the AP. If the synapse is in a connected state then an EPSP is registered inside of the synapse.
- 2) Perform a depth first traversal of each neurons dendritic tree.
 - a) On the preorder traversal through the tree, the excitement from EPSPs is distributed towards the leaves. The excitement accumulates at each synapse location.
 - b) On the returning postorder traversal, the excitement from EPSPs is distributed towards the root. This excitement also accumulates at the synapse locations. When a bifurcation is reached, excitement which needs to be distributed to the sibling branches accumulates at the roots of the sibling branches, it will be distributed in step 3.
- 3) Perform a second depth first traversal of each neurons dendritic tree in order to finish distributing the excitement which goes first towards the root and then down a branch towards a leaf. After distributing this, the total excitement at each synapse location is known. At this time detect supra-threshold events and reset the synapse states.

Implicit Synapses

The data structures for complete dendrite trees are not created at program startup, instead dendrites and synapses are created when needed. The dendritic trees expand from the root towards the leaves, yielding a compact layout. This frees unused dendrites and synapses from being represented in the computer's memory and used by the model. The model accounts for

the implicit synapses which may exist at the leaves of the dendrite. The implementation does not account for any implicit synapses beyond an implicit bifurcation.

Hierarchical Temporal Memory

The model is implemented as a modification to the Nupic temporal memory model [3]. The temporal memory model needed to be modified to work with dynamic dendrite compartments, which have no fixed size or shape and can span multiple branches of a dendrite. I introduce a dendrite event class, which represents contiguous areas of supra-threshold dendrite. It provides an interface much like the prior fixed area segments had and much of Nupic's code remains unchanged.

Parameter Choices

This model introduced a single parameter, "period" which is set to 128, the same value as the temporal memory's maximum synapses per segment. The temporal memory parameters were not changed, with the exception of the distal synapses initial permanence, which was raised to 0.5 to match the distal synapses connected permanence. This change was needed so that newly created synapses are initially connected. Without this change newly created segments fail to activate for lack of synapses, and they never learn because they do not meet the matching threshold. Swarming or another parameter optimization technique might marginally improve this model because the model has changed and so parameters previously optimal with Nupic may no longer be optimal. The parameters used by the HTM model can be found in Nupic Github Repository [3] in the file:

[nupic/src/nupic/frameworks/opf/common_models/anomaly_params_random_encoder/best_single_metric_anomaly_params_tm_cpp.json](https://github.com/numenta/nupic/blob/master/src/nupic/frameworks/opf/common_models/anomaly_params_random_encoder/best_single_metric_anomaly_params_tm_cpp.json)

Results

Numenta Anomaly Benchmark

The model is tested on the Numenta Anomaly Benchmark (NAB) [4]. The benchmark was run three times with different random seeds and the range of scores is reported in the following table.

Model	Standard Profile	Low False Positive Profile	Low False Negative Profile
Numenta	70.5-69.7	62.6-61.7	75.2-74.2
Dendrite	65.3-65.8	57.2-57.8	70.0-70.9
NumentaTM	64.6	56.7	69.2

Table 1: NAB scores. The Numenta model is the current leaderboard (range of three shown), the dendrite model is introduced by this report (range of three shown), and the NumentaTM model is the original version of HTM which the dendrite model is an extension of. The leaderboard does not use biological methods.

Analysis

Examine the distribution of excitement throughout the dendrite model. The excitement is graphed and then correlated in figures 3 and 4.

For illustrative purposes figures 3 and 4 were created using different model parameters. This model has 4 cells per column instead of 32, which causes more synapses to grow on each dendrite. This model uses a maximum of 64 synapses per segment instead of 128, which creates more frequent bifurcations. This model has a dendrite period of 64. This NAB dataset used was `realKnownCause/ambient_temperature_system_failure.csv` which contains 7267 time series records.

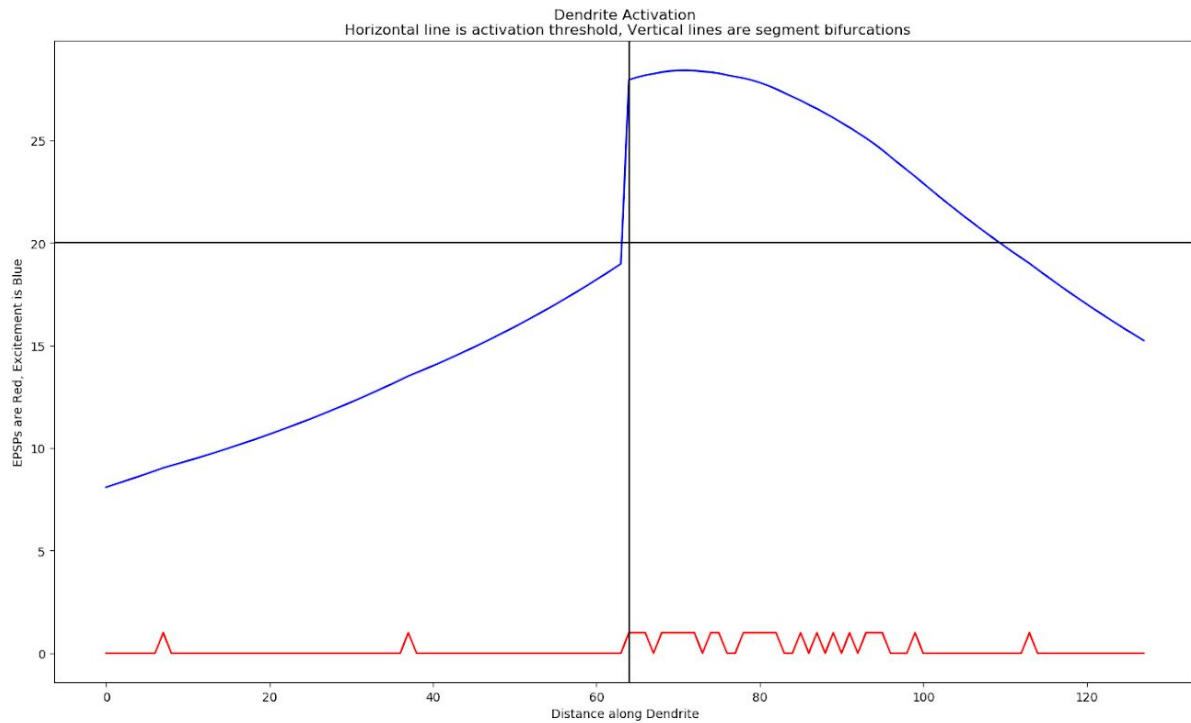


Figure 3: Excitement across the length of a dendrite. The dendrite's root is at distance 0; at distance 64 the dendrite bifurcates and only one of the branches is shown. An area of the dendrite has reached the activation threshold. This area is bounded on one side by the bifurcation which divides the effect of its excitement in half, and the other side is bounded by the exponential decay of the activations excitement.

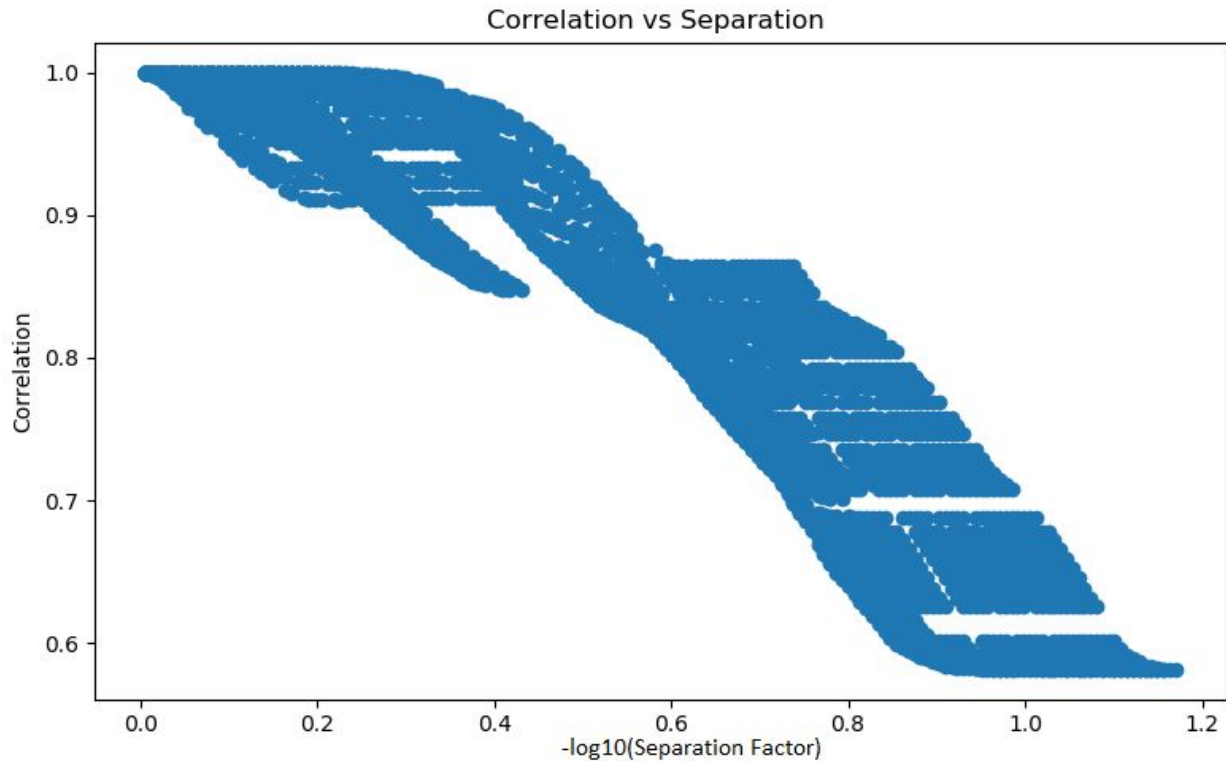


Figure 4: Correlation of excitement in an active (supra-threshold) dendrite versus the separation factor. The excitement was sampled at random locations on every activation for several thousand cycles. The separation factor is transformed with the function “ $f(s) = -\log_{10}(s)$ ” which makes the trend visible. The clear downward trend shows that the separation factor does separate areas of the dendrite. Nearby areas have a high correlation indicating that they function as a single unit to sum their inputs linearly, while distant areas have a lower correlation indicating that they still cooperate but in a more independent way.

Performance

It takes approximately 10 hours for the Dendrite model to run the whole NAB. For comparison, it takes approximately 1 hour for the NumentaTM model to run the whole NAB on the same computer.

Discussion

The contribution of this work is to introduce a computational model of dendrites which operates in a manner consistent with the biology and which performs as well as other leading dendrite models. This model captures the inner workings of a dendrite in a manner that can be easily computed.

The future work for this model is to determine how dendrites are modulated internally and externally. Externally, the level of detail offered by this model is just right for modeling the

inhibitory interneurons which interact with dendrites. SOM interneurons apply shunting inhibition [5] with the effect of separating areas of the dendrite [2]. These interneurons could be modeled with synapses which emit a negative amount of excitement.

Internally, the activity of the dendrites can be modulated by changing the alpha parameter. Alpha can be controlled at the following resolutions: synapse, dendrite segment, dendritic subtree, neuron, and globally. It can be used to increase or decrease the cooperativity or the number of compartments in a context dependant manner. Another potential use for changing the alpha parameter is this: alpha could be used to control the effective distance between synapses, if it weren't defined at 1 unit of distance. This would allow dendrite areas to change synapse densities, without changing total area and without representing unused or non-existent synapses.

Works Cited

[1] Hawkins J and Ahmad S (2016) Why Neurons Have Thousands of Synapses, a Theory of Sequence Memory in Neocortex. *Front. Neural Circuits* 10:23. doi: 10.3389/fncir.2016.00023

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[5] Burkhalter A (2008). Many specialists for suppressing cortical excitation. *Front. Neurosci.* 2:2. doi: 10.3389/neuro.01.026.2008