Classes of dendritic information processing

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Abstract

Dendrites are much more than passive neuronal components. Mounting experimental evidence and decades of computational work have decisively shown that dendrites leverage a host of nonlinear biophysical phenomena and actively participate in sophisticated computations, at the level of the single neuron and at the level of the network. However, a coherent view of their processing power is still lacking and dendrites are largely neglected in neural network models. Here, we describe four classes of dendritic information processing and delineate their implications at the algorithmic level. We propose that beyond the well-known spatiotemporal filtering of their inputs, dendrites are capable of selecting, routing and multiplexing information. By separating dendritic processing from axonal outputs, neuron networks gain a degree of freedom with implications for perception and learning.

Highlights

- Dendritic compartmentalization is controlled and avoidable
- Compartmentalization combined with amplification allows neurons to withhold information distinct from what is being communicated by the cell body
- Network state, inhibition and neuromodulation can route information withheld in dendrites
- Dendrite-dependent burst firing can multiplex multiple streams of information

Introduction

Ever since the drawings of Santiago Ramon y Cajal[1], the dendritic arborization has become the most recognizable feature of neurons. When images of neurons are placed side by side, the striking diversity of patterns suggests an equally vast diversity of computational functions. Variants and invariants of dendritic properties—beyond their mere morphologies—may unveil new principles of neural information processing. Much is known about the basic input-output function of the cell body[2,3], yet we know just enough about dendrites to be bewildered and to have to rethink some fundamental questions: What is the nature of the information processing performed by the neuron as a whole? How do dendrite-bearing neurons allow neural networks to implement computations not achievable by point-neuron networks? For what algorithmic benefit?

These questions have been particularly challenging to frame within a tractable experimental framework. Historically, initial progress has largely relied on the theoretical work of Wilfrid Rall[4], who pioneered the use of digital computers in neuroscience. Rall demonstrated how the biophysical properties of membranes are at odds with an isopotential neuron. Other theoretical arguments leveraged features of inhibition[5] and NMDA receptor biophysics[6] to begin highlighting the rich repertoire of information processing strategies of dendrites. Since, the development of dendritic recordings and of several optical methods provided unprecedented abilities to interrogate dendritic properties[7,8]. These studies revealed a myriad of nonlinear dendritic responses including voltage-gated sodium and calcium channels,

calcium-induced calcium release and NMDA spikes[7,9–11]. Accumulating evidence suggests that these dendritic events are active parts of network dynamics and are operant *in vivo*[12–17]. As a result, questions are now shifting from whether dendrites have a role in information processing to how identified dendritic processing features implement defined algorithms[14,15,17–20].

Here we review recent contributions to our understanding of how dendritic processing gives rise to specific computations and coding principles. We delineate four broad types of dendritic information processing (Fig. 1): i) spatiotemporal filtering, ii) information selection, iii) information routing, and iv) information multiplexing. For each category, we highlight recent contributions that connect subcellular integration mechanisms and algorithmic-level function, connections that can be further explored and expanded with updated single-neuron models (Fig. 2).

Class I - Spatiotemporal filtering

A first step in characterizing dendritic computation is to determine the operation that transforms synaptic inputs into currents flowing into the soma. In the simplest case, a distant synaptic input will be attenuated and lowpass filtered before reaching the cell body[4]. However, the presence of both voltage-gated and ligand-gated ion channels in dendrites means that synaptic integration is inherently nonlinear, and jointly active synapses can thus combine in nontrivial ways. But this does not imply that the essence of dendritic integration cannot be captured by a linear process. As an example, the subthreshold somatic dynamics are well represented by a linear process despite the high density of ion channels[2,3]. In dendrites, just as in the cell body, nonlinearities can be either kept in check by the linearizing effect of background noise[21] or they can be captured by an equivalent linear process[22]. Thus, the combined effect of multiple synapses can result, at least approximately, in a linear sum at moderate noise. Such location-dependent attenuation and filtering combined with linear summation confers to dendrites the characteristics of a spatiotemporal filter (Fig. 1A). Importantly, within the class of spatio-temporal filters one can distinguish distinct dynamic modes such as low-pass filters or resonance[22,23].

Spatiotemporal filtering can contribute to powerful[24] and behaviourally relevant[25,26] computations. As an illustrous example, spatiotemporal filtering tunes the input delays in order to give rise to selectivity for interaural time difference (ITD)[25,27]. Thus our ability to perform azimuthal sound localization arises in part from the spatiotemporal class of dendritic computation. Recently, Remme and colleagues have shown that dendritic filtering properties are tuned to optimize this elemental computation without ostensibly increasing the metabolic energy expenditure[26]. This finding illustrates how dendritic ion channels densities must be tightly regulated to preserve spatiotemporal filtering despite the metabolic costs. Another recent study in crustacean somatogastric ganglia (STG) brings a complementary case forward[28]. Otopalik and colleagues have shown that the strong dendritic tapering observed in STG neurons curbs massively the electrotonic attenuation along the cable, to the extent that a dendritic tree obeying some morphological constraints becomes approximately isopotential. Together, these studies suggest two important principles for dendritic integration: first that even simple dendritic processing comes with a metabolic cost and second that attenuation is not an unavoidable consequence of dendritic structures.

At the algorithmic level, spatiotemporal filtering by dendrites can be substituted by other molecular mechanisms shaping the amplitude and time course of postsynaptic potentials. In this sense, this class of dendritic computation is captured by point-neuron models of input integration such as the linear-nonlinear Poisson (LNP) or generalized linear models (GLM; Fig. 2A)[2,29].

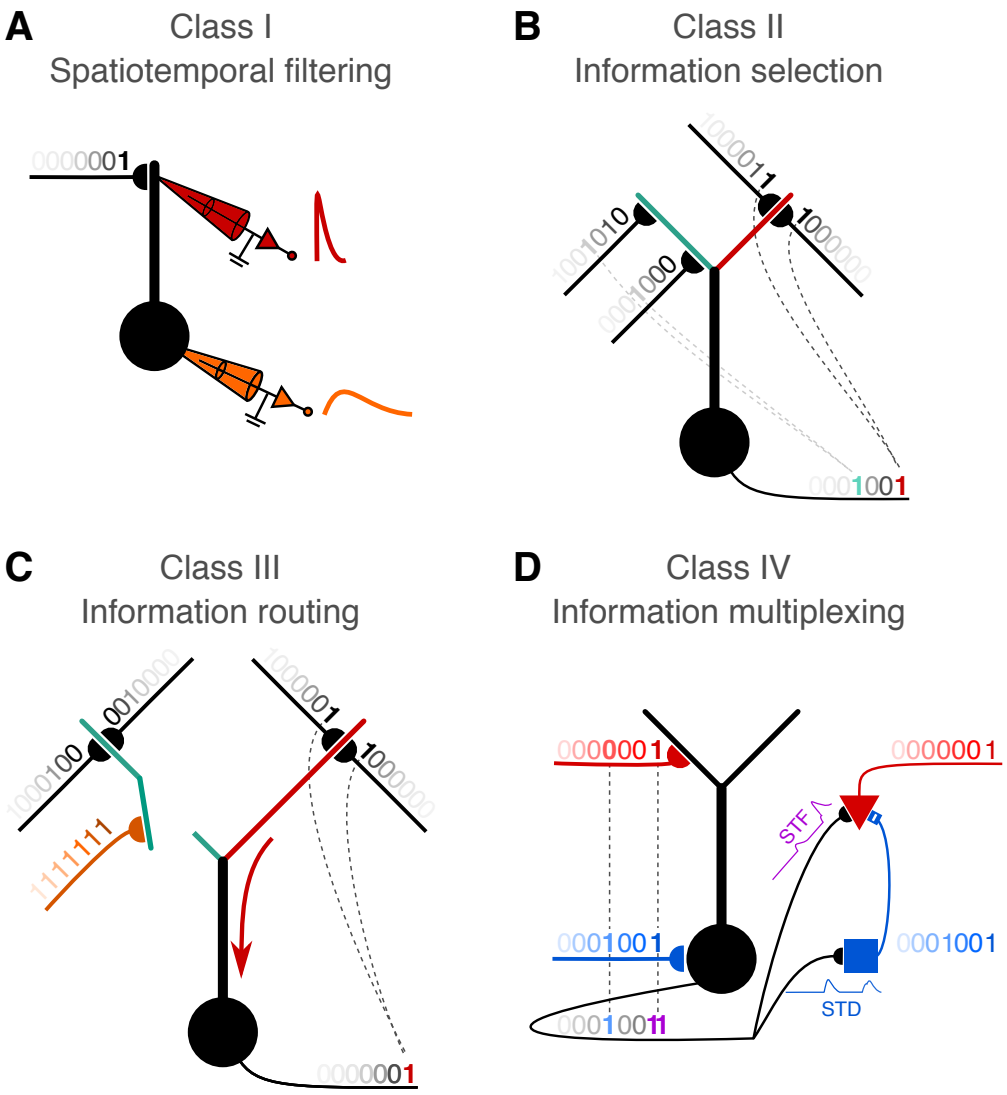

Figure 1 Four classes of dendritic information processing. In all panels, discretized spike trains appear above or near their respective axons, where lighter shading indicates more distant past. **Class I**: A spike arriving at a distal synapse evokes a local postsynaptic potential (red). Propagation results in a filtered voltage response at the soma (orange). **Class II**: Two independent distal dendritic branches (red and green) each receive synaptic inputs. Two coincident input spikes in either the red branch or the green branch can successfully contribute to a spiking output. The same number of input spikes distributed on different branches only causes a small depolarization that does not reach the soma, but that information can be important for local processing. **Class III**: Routing is schematically depicted by a switch circuit symbol on the green branch. Even though both the green and red branches receive equivalent input signals, a modulating input (orange) prevents the transmission of the information from the green branch. **Class IV**: Two contextually different input streams impinge on opposite poles of the neuron. When activated by the perisomatic (blue) stream alone, a single spike is fired by the postsynaptic neuron (blue 1 in bottom spike train). When present, the apical input (red) modulates the postsynaptic response by transforming a single spike into a burst (purple = blue + red). Short-term facilitation (STF) and depression (STD) and disynaptic inhibition (blue square synapse) can decode the multiplexed information.

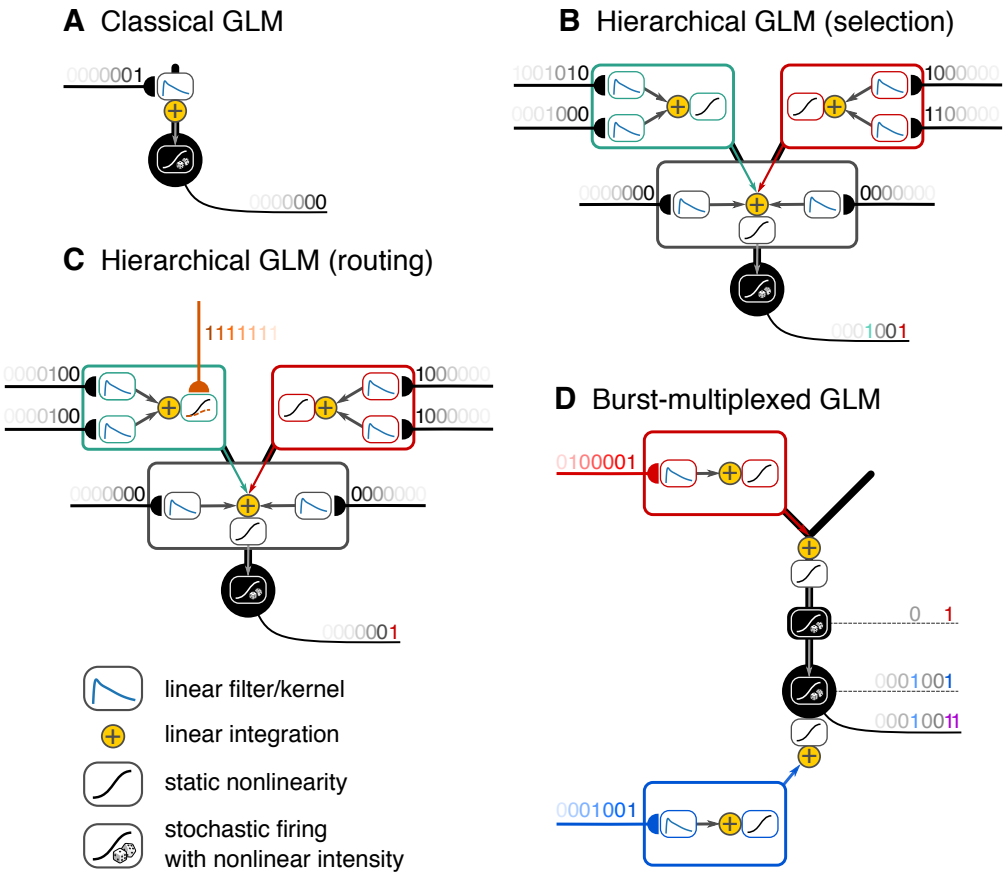

Figure 2 A hierarchy of Generalized Linear Models (GLMs). Only excitatory inputs are illustrated and postspike currents (e.g., afterhyperpolarization currents) are omitted to avoid cluttering the schematics. Their design was purposefully selected to enforce a link with Fig. 1. **A** In the "classical" GLM, input spike trains are convolved with linear filters and added together. The result is then fed to a pointwise nonlinearity and spikes are generated according to an inhomogeneous Poisson process. This model explicitly utilizes the spatiotemporal filtering of input spikes. **B** The hierarchical GLM is the model from Ref.[21] with an added random spike generator. **C** An extension of the hierarchical GLM can represent routing, for instance if a modulating input alters the nonlinearity of a dendritic branch. **D** The burst-multiplexed GLM involves two segregated integration zones. The bottom spike generator (illustrated by the black disk representing the soma) produces spikes randomly. Whenever such a spiking event occurs, the top spiking generator (black rectangle) is interrogated. A burst (purple 1's) is fired when the dendritic generator outputs 1, which loosely corresponds to the occurrence of a calcium spike.

Class II - Information selection

Cortical neurons amalgamate information from thousands of spike trains into a single sequence of discharges. Thus, from the vast amount of electrical and chemical information impinging on the cell surface, only a very small portion is selected for communication (Fig. 1B). Most of this information is lost in the act of pooling: by giving up knowledge on which postsynaptic potential came from which synapse, pooling discards information about the interspike intervals of individual presynaptic spike trains. Are there neural strategies to exploit some of the information lost to pooling?

Dendrites have now long been recognized to be parcelled in functional compartments. Such compartmentalization, however, acts as a double-edged sword: by preserving some of the information that would be lost to pooling in a point-neuron, compartmentalization increases the amount of information held within the cell, but it decreases the amount of information that makes its way to the cell body. This apparent paradox can be resolved if nonlinear mechanisms select part of the compartmentalized information and transiently facilitate its communication to the cell body[6,9,10,30–36]. Thus by combining compartmentalization with mechanisms for transient amplification, dendrites can increase the amount of information held within the cell without decreasing the amount of information that is communicated to the cell body. Consistent with that view, dendrites can control the degree of compartmentalization but also the amplification mechanisms by regulating the subcellular density of different classes of dendritic ion channels[28,37–41]. Also consistent with that view, supra-threshold activity in dendrites and the cell body tends to be correlated[14,42–44]. In sum, compartmentalization and transient amplification are seen as complementary mechanisms to increase local information while selecting part of it for communication.

Nonlinear amplification mechanisms increase the weight of some inputs at the expense of others and therefore contributes to a selection of information that ultimately determine the cell's output. What is being selected for communication can be formalized as a two-layer neural network, as proposed by Mel[6,45]. More recently, time-dependent extensions of this idea have been elaborated[21,46] (Fig. 2B). Alternatively, information selection may depend on bidirectional interactions with parent compartments. Indeed, as formalized by Senn and Larkum[9,31,33,47], the state of the cell body strongly affects and enriches feature of dendritic integration. This second point of view would require a modification to the model depicted in Fig. 2B so as to permit information back-propagating to the parent dendrites. Importantly, both cases require a distinction between locally withheld information, and information that is communicated by the cell body. This distinction between dendritic (local) and somatic (communicated) information relies on the presence of dendritic nonlinearities, as replacing subunit nonlinearities with a linear function in the hierarchical model of Fig. 2B would collapse the model onto a spatiotemporal filter (Class I; Fig. 2A). While the transmitted information is obviously the most important for network dynamics, the local information that is not communicated can still play a role in local processes, like plasticity[20,35,40,48–53]. For instance, developing CA1 dendrites are tuned to detect spatially-clustered and temporally co-active synaptic inputs that generates, through local calcium amplification, a local form of clustered plasticity[35]. Much recent interest has focused on the computational role of the type of information that is withheld from the cell body.

The recent work of Bono and Clopath (2017)[40] illustrates this point. First, they note that the decoupling of somatic and dendritic states is also associated with different forms of plasticity: a spike-timing dependent plasticity (STDP) for sodium spikes for perisomatic compartments, and a dendritic-spike dependent long-term potentiation (dLTP) in dendritic compartments[40,49]. Then, they show that this concerted compartmentalization of signal processing and plasticity rules increases the resilience of associative memories against ongoing activity. Here a learning-related signal restricted to the dendrites actively maintained synapses without the need to reactivate the Hebbian assembly.

This mechanism has a potent network-level function that is difficult to obtain in the absence of dendrites.

Other recent work[20,52] (see also Sacramento et al. (2017) on *arXiv*) articulates the relevance of dendrites for representing unit-specific learning signals similar to backprop and targetprop algorithms[54,55]. A key attribute in these approaches is that each unit can represent both a sensory feature and a learning signal. It is the conjunction of these signals that regulates plasticity. Spatial segregation within units with transient synchronization is a natural solution to this requirement. Therefore, learning algorithms such as those used in deep learning can be implemented using dendritic compartmentalization, an advantage that could go well beyond that provided by increasing the number of basic units.

Obtaining an adequate understanding of the full computational role of compartmentalized information poses a significant theoretical challenge. In this direction, dendritic states have been referred to as a teacher or target[33], a prediction[43,56,57], an error signal[20,52,58], a plasticity regulator[59,60], an associative signal[14,61] or attention signal[62]. We do not expect all dendrites to have the same function, nor do we believe these interpretations to all be mutually exclusive. Yet, irrespective of the interpretation, an algorithmic advantage may lie in dendrites holding information that is different from what that communicated by the cell body.

Class III - Information routing

Information routing refers to a modulation of the relative potency of dendritic subunits, thereby dynamically modifying the flow of information en route to the cell body. Figure 1C illustrates a case where the contribution to somatic activation of a defined dendritic compartment is adaptively attenuated relative to other active dendrites. In this illustration, a slow modulation prevents potent stimulation of a specific branch to trigger an action potential in the soma. Not included in the illustration but included in the class is the possibility that intrinsic plasticity routes information in the dendritic tree[63,64]. Importantly, routing can involve plasticity, neuromodulation, network state or synaptic inhibition but in all these cases it must act as a slow modulator rather than a driver of activity.

The line that separates drivers and modulators can be hard to draw, particularly for synaptic inhibition. Extending on the early work of Koch *et al.* (1983)[5], recent work[65,66] has shown that inhibition in general is a powerful mechanism for regulating dendritic activity, such that it may in principle subserve a conditional routing of information in a dendritic tree. However, inhibition–even when shunting–does not necessarily route information. To see this, we must distinguish inhibition accompanying direct excitation from slow inhibition coming from other, indirect, sources. Since feedforward inhibition is by definition correlated with excitation, the two effects can under some conditions be lumped together at the algorithmic level. Therefore, feedforward inhibition in dendrites will normally participate in information selection, as shown elegantly in the retina[67].

Specifically addressing the routing of information by inhibition, Yang and coworkers (2016) studied how the disinhibitory motif comprising vasointestinal peptide-positive (VIP) and somatostatin-positive (SOM) cells could select specific neural pathways by disinhibiting targeted dendrites on pyramidal neurons[68]. In a related study mutual inhibition between VIP and SOM neurons was shown to potently control the distribution of inhibition along the apical-somatic axis of pyramidal neurons[69]. Such inhibitory mechanisms are controlled by long-range feedback, but also by network state and neuromodulation[70–72]. At the algorithmic level, combining such context-dependent gating[73] with properties of synaptic consolidation[74] can overcome catastrophic forgetting in continual learning[75].

Network state[76] and neuromodulation[77] differentially engage distinct subcellular compartments. For instance, the

relative potency of subcellular compartments has been shown to be regulated by the amount of background noise present [36,37]. Since neuromodulators can trigger the emergence of noisy currents in cortical neurons [78], such noise-dependent dendritic routing mechanism provides a powerful means to implement a dynamic neuromodulatory control of information processing in cortical networks.

Class IV - Information multiplexing

Dendrites gather information from local and distant sources, information that is then propagated, selected and routed according to the mechanisms outlined in the previous sections. An intricate mapping is thus at play in transforming the incoming presynaptic spike patterns into a postsynaptic output spike train. As a corollary, one would reasonably expect this output to carry some visible signatures of the dendritic processing.

One salient feature that may encode such a signature is the presence of high-frequency bursts of spikes. Although burst firing is not exclusively dendrite-dependent [79–81], in many important cases bursts are facilitated by dendritic events [9,30,82] and show correlations in the behaving animal with calcium spikes and backpropagating action potentials [14,83,84]. These bursting mechanisms are conjunctive, since the co-occurrence of inputs in distinct compartments facilitates their generation (Figs. 1D and 2C). Given that apical dendrites largely receive higher-order cortical and thalamic inputs, conjunctive bursting constitutes a powerful associative mechanism between sensory-related inputs impinging on basal-proximal dendrites and context-related information streams targeting distal apical dendrites [18].

More generally, a recent theoretical study has shown that neurons can harness these conjunctive burst mechanisms and its associative properties to concomitantly represent multiple inputs into one spiking output, i.e. to multiplex several information-carrying sources [85]. Moreover, neural strategies combining short-term plasticity and disynaptic inhibition provide downstream networks with the ability to readily decode this spiking output and recover the multiple parent encoding streams [85]. This information can relate to purely sensory features, as shown recently in the drosophila [86]. However, information multiplexing should preferably involve input streams with different semantic contents. In the cortex, pyramidal cells could use bursts to multiplex feedforward and feedback information, where feedback relates to either attention [62,79,87], a binding signal [14,79,88,89] or a learning signal [19,20,52]. If multiplexing a learning signal with a representation of sensory features, neurons can communicate sensory evidence up the cortical hierarchy through the propagation of events while allowing a top-down credit signal to guide the plasticity through the modulation of bursting. While the nature of the information represented this way remains an open question, it is useful to note that the same mechanisms required for multiplexing are involved in learning, namely dendritic spikes [49,90], backpropagating action potentials [7] and bursting [16,90].

Conclusion: The Telegrapher's Office Metaphor

If the axon is a telegraph wire, dendritic arborization makes up the many aisles of the Telegrapher's building. External messages entering the office can fight their way through the building in order to influence the Telegrapher's actions. In this metaphor of dendritic computation, the Telegrapher perceives either all messages entering the building (the spatio-temporal filter) or a summary report of distinct corridors (information selection). The relative importance the Telegrapher gives to the different summary reports is either static, or it is allowed to change (information routing). The Telegrapher could then decide to communicate one summary report or invent a double entendre Morse code to communicate both the Telegrapher's summary or that of one of the corridors (information multiplexing). These different modes can very well be overlapping as, for instance, spatiotemporal filtering can be performed prior to

selection, routing or multiplexing.

While the capabilities of the Telegrapher's office are in the process of being understood, there clearly remains a number of future challenges, particularly in understanding to what extent distinct classes of dendritic information processing co-exist in the same cell, mapping out how these classes are distributed across brain areas, and relating such sub-cellular mechanisms to network-level computation.

Conflict of Interest

Nothing declared

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