



Dendritic computations captured by an effective point neuron model

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Complex dendrites in general present formidable challenges to understanding neuronal information processing. To circumvent the difficulty, a prevalent viewpoint simplifies the neuronal morphology as a point representing the soma, and the excitatory and inhibitory synaptic currents originated from the dendrites are treated as linearly summed at the soma. Despite its extensive applications, the validity of the synaptic current description remains unclear, and the existing point neuron framework fails to characterize the spatiotemporal aspects of dendritic integration supporting specific computations. Using electrophysiological experiments, realistic neuronal simulations, and theoretical analyses, we demonstrate that the traditional assumption of linear summation of synaptic currents is oversimplified and underestimates the inhibition effect. We then derive a form of synaptic integration current within the point neuron framework to capture dendritic effects. In the derived form, the interaction between each pair of synaptic inputs on the dendrites can be reliably parameterized by a single coefficient, suggesting the inherent low-dimensional structure of dendritic integration. We further generalize the form of synaptic integration current to capture the spatiotemporal interactions among multiple synaptic inputs and show that a point neuron model with the synaptic integration current incorporated possesses the computational ability of a spatial neuron with dendrites, including direction selectivity, coincidence detection, logical operation, and a bilinear dendritic integration rule discovered in experiment. Our work amends the modeling of synaptic inputs and improves the computational power of a modeling neuron within the point neuron framework.

dendritic computation | synaptic current | synaptic integration | single-neuron dynamics | point neuron model

A single neuron performs extensive computations through active dendrites with rich biophysical properties and morphological structures (1, 2). In general, it is difficult to understand information processing in a neuron when receiving broadly distributed synaptic activities on its dendrites. Despite the complexity of dendrites, the information is presumably encoded via action potentials generated at the soma of a neuron. Therefore, for a large set of issues regarding neuronal information coding, one usually simplifies a spatial neuron as a single point representing its soma with the membrane potential dynamics modeled as a resistance–capacitance circuit (3, 4),

$$C \frac{dV}{dt} = I_{ion} + I_{syn}, \quad [1]$$

where C is the membrane capacitance and V is the membrane potential at the soma. Here, I_{ion} is the intrinsic ionic current, and I_{syn} is the synaptic current. By modeling different I_{ion} , one can obtain a class of point neuron models, such as the leaky integrate-and-fire neuron and the Hodgkin–Huxley neuron (5). For the

synaptic current I_{syn} , in general, the integration of all individual synaptic inputs originated from dendrites is phenomenologically incorporated into a linear summation of 2 effective excitatory (E) and inhibitory (I) synaptic currents arriving at the soma, that is,

$$I_{syn} = g_E(\varepsilon_E - V) + g_I(\varepsilon_I - V), \quad [2]$$

where g_E and g_I are the effective E and I synaptic conductances at the soma, respectively; and ε_E and ε_I are the E and I reversal potentials, respectively.

Point neuron models with synaptic current taking the form of Eq. 2 have been extensively applied to both experimental and theoretical studies, including synaptic current decomposition (6, 7), synaptic conductance estimation (8–10), dynamic clamp stimulation (11, 12), and neuronal network dynamics modeling (13–20), etc. Despite the simplicity of the point neuron model in analysis and simulation, various important questions remain to be addressed. For instance, do the E and I synaptic currents arriving at the soma of a spatial neuron with dendrites follow

Significance

Modeling single-neuron dynamics is the first step to quantitatively understand brain computation. Yet, the existing point neuron models fail to capture dendritic effects, which are crucial for neuronal information processing. We derive an effective point neuron model, which incorporates an additional synaptic integration current arising from the nonlinear interaction between synaptic currents across spatial dendrites. Our model captures the somatic voltage response of a neuron with complex dendrites and is capable of performing rich dendritic computations. Besides its computational efficiency in simulations, our model suggests reexamination of previous studies involving the decomposition of excitatory and inhibitory synaptic inputs based on the existing point neuron framework, e.g., the inhibition is often underestimated in experiment.

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Data deposition: The source code for our model has been deposited on GitHub at https://github.com/songting858/DIF_model.

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a linear summation as described in Eq. 2? Can the point neuron model reflect dendritic integration effects and implement dendritic computations? If not, how do we establish a point neuron model to capture the essence of dendritic functions?

Results

Integration of E and I Synaptic Currents Revealed in Electrophysiological Experiments. We first investigate these questions in a CA1 pyramidal neuron of rat hippocampal slices. The whole-cell recording is made from the soma of the pyramidal neuron with sampling frequency 100 kHz, and fluorescent dye Alexa Fluor 488 is loaded into the neuron via the recording pipette to visualize the dendritic tree (Fig. 1A). Microiontophoretic applications of E transmitter glutamate and I transmitter γ -aminobutyric acid (GABA) at the apical dendrite induce rapid membrane depolarizations and hyperpolarizations, respectively, with kinetics similar to those of natural excitatory postsynap-

tic potentials (EPSPs) and inhibitory postsynaptic potentials (IPSPs) elicited by extracellular electrical stimulation in the CA1 region, respectively (Fig. 1B) (21). For convenience, these iontophoretic responses are referred to hereafter as EPSPs and IPSPs. To assess the validity of the synaptic current modeling (Eq. 2), we first need to determine the intrinsic ionic current and the passive parameters in the point neuron description of this pyramidal neuron (Eq. 1). Early experiments demonstrate that, within the subthreshold regime, the dynamics of the somatic membrane potential of a pyramidal neuron can be described as a leaky integrator (22, 23). Therefore, in the absence of action potentials, the ionic current I_{ion} can be well characterized as $I_{ion} = g_L(\varepsilon_L - V)$, where ε_L is the resting potential about -60 mV measured from the soma of the pyramidal neuron. The passive parameters are determined as $g_L \sim 11.67$ nS and $C \sim 129.67$ pF by giving a hyperpolarizing step current -50 pA at the soma of the pyramidal neuron. By convention, we rescale the leak conductance and the capacitance by dividing the estimated area of the neuron to obtain $g_L = 0.134$ mS \cdot cm $^{-2}$ and $C = 1$ μ F \cdot cm $^{-2}$.

We next examine whether the E and I synaptic currents follow a linear summation as described in Eq. 2 when the pyramidal neuron receives synaptic inputs from its dendrites. In the experiment, when an E input is elicited by an iontophoretic pipette placed at the dendritic trunk ~ 100 μ m away from the soma, an EPSP denoted as V_E is recorded at the soma. To eliminate the numerical error when taking the temporal derivative of the EPSP, we smooth the EPSP trace by performing simple moving average with time window 5 ms. Using the smoothed EPSP (Fig. 1B), the corresponding effective excitatory postsynaptic current (EPSC) denoted as I_E is derived based on the form of the point neuron model (Eq. 1), that is, $I_E = C \frac{dV_E}{dt} - g_L(\varepsilon_L - V_E)$. Similarly, when an I input is elicited by an iontophoretic pipette placed at the dendritic trunk ~ 50 μ m away from the soma, an IPSP denoted as V_I is recorded at the soma and smoothed by simple moving average (Fig. 1B), and the corresponding effective inhibitory postsynaptic current (IPSC) denoted as I_I is derived, that is, $I_I = C \frac{dV_I}{dt} - g_L(\varepsilon_L - V_I)$. Using the information of the EPSC and the IPSC, we further determine the effective E and I conductances at the soma as $g_E = I_E/(\varepsilon_E - V_E)$ and $g_I = I_I/(\varepsilon_I - V_I)$, respectively, with the E reversal potential $\varepsilon_E = 0$ mV and the I reversal potential $\varepsilon_I = -66$ mV measured from the experiment.

When both the E and I inputs are elicited simultaneously with the input strengths and locations the same as given individually, a summed somatic potential (SSP) denoted as V_S is recorded at the soma and smoothed by simple moving average (Fig. 1B), and the corresponding summed somatic current (SSC) denoted as I_S is derived as $I_S = C \frac{dV_S}{dt} - g_L(\varepsilon_L - V_S)$. Based on the synaptic current description (Eq. 2) in the point neuron model, the SSC is presumably made of the linear summation of the E and I synaptic currents, that is, $I_S \equiv g_E(\varepsilon_E - V_S) + g_I(\varepsilon_I - V_S)$. However, by constructing the E and I synaptic currents, i.e., $g_E(\varepsilon_E - V_S)$ and $g_I(\varepsilon_I - V_S)$, using the resolved conductances g_E and g_I and the postsynaptic potential V_S (Fig. 1C), the SSC is found to be significantly different from instead of equal to the linear summation of the E and I synaptic currents (Fig. 1D). This fact demonstrates that the synaptic current description (Eq. 2) is insufficient to characterize the synaptic current arriving at the soma as a result of dendritic integration.

To analyze the integration of synaptic currents quantitatively, we denote the difference between the SSC and the linear sum of the EPSC and the IPSC as the synaptic integration current ΔI_{syn} , that is, $\Delta I_{syn} = I_S - g_E(\varepsilon_E - V_S) - g_I(\varepsilon_I - V_S)$. If we cast this integration current in the form of Ohm's law as $\Delta I_{syn} = \Delta g(\varepsilon_E - V)$ with Δg defined as the integration conductance, by randomly varying the strengths of the E and I synaptic inputs with their input locations fixed, the integration conductance is found to

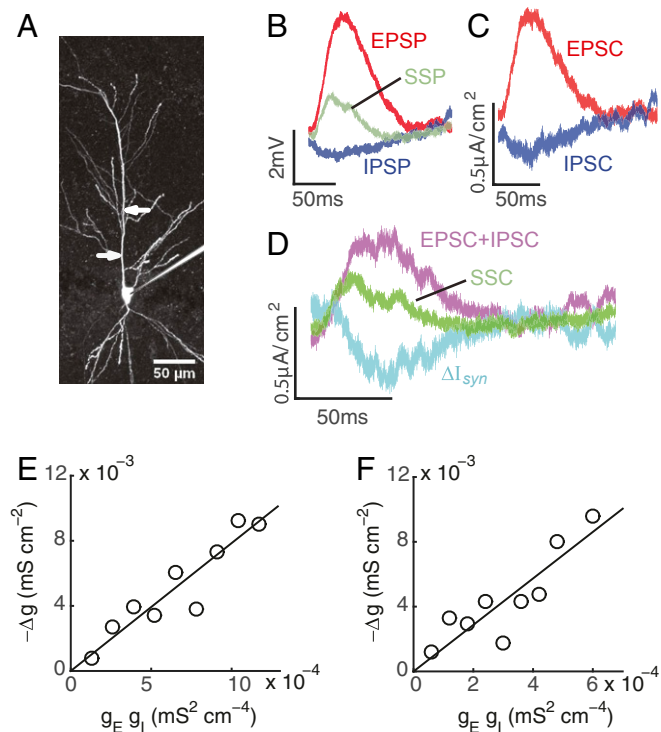


Fig. 1. Experimental measurement of the bilinear conductance relation for a pair of E and I inputs. (A) Image of a CA1 pyramidal neuron. Arrows indicate pipettes for iontophoresis of glutamate and GABA at about 100 and 50 μ m from soma, respectively. (Scale bar: 50 μ m.) (B) A set of individual EPSP, individual IPSP, and SSP induced by both E and I inputs recorded in the experiment. A simple moving average with time window of 5 ms is applied to smooth each trace. (C) Constructed EPSC and IPSC using the SSP and the E and I conductances estimated from the EPSP and IPSP in B. (D) The SSC estimated from the SSP in B, the linear sum of the constructed EPSC and IPSC in C, and the difference between them denoted as ΔI_{syn} . (E) The bilinear relation between Δg and the multiplication of g_E and g_I at the time when the EPSP reaches its peak value. The E and I inputs are given simultaneously. Line indicates linear fit (slope, $-\alpha_{EI} = 7.86$ k $\Omega \cdot$ cm 2 , $R^2 = 0.87$). (F) The same as E except that the I input is given 20 ms preceded to the E input. Line indicates linear fit (slope, $-\alpha_{EI} = 14.35$ k $\Omega \cdot$ cm 2 , $R^2 = 0.76$). In E and F, by varying the E and I input strengths, the amplitude of EPSP ranges from 1 to 8 mV, and the amplitude of IPSP ranges from -1 to -3 mV. For the purpose of denoising, we first measure values of g_E , g_I , and Δg for each set of EPSP, IPSP, and SSP; then, we construct a scatterplot of $g_E g_I$ vs. Δg , and finally, we divide the range of $g_E g_I$ into 9 bins and average all of the data points within each bin. In addition, similar results can be obtained by replacing moving average with low-pass filtering, such as the elliptic filter.

obey a bilinear rule throughout the response period until g_E or g_I vanishes (i.e., $\Delta g = \alpha_{EI} g_E g_I$, where α_{EI} is the proportional coefficient independent of the input strengths but dependent of time). Note that, when the synaptic integration current is cast in the form of Ohm's law, the reversal potential here is set to be the E reversal potential ε_E . We point out that the bilinear relation of the conductances remains valid when a different value of reversal potential is chosen (*SI Appendix*, Fig. S1), which will be further discussed in *Discussion*. The bilinear relation at a particular time point around the peak of the EPSP is illustrated in Fig. 1E (with coefficient of determination $R^2 = 0.87$). In addition, the bilinear relation remains valid even when there is a time delay between the E and I input arrival times. A particular case of the bilinear relation is shown in Fig. 1F ($R^2 = 0.76$) in which the I input is elicited 20 ms earlier than the E input. The proportional coefficients α_{EI} in both the concurrent and nonconcurrent inputs cases are not identical, indicating that α_{EI} is sensitive to input arrival time difference. Therefore, from our experiment, the synaptic current description (Eq. 2) in the point neuron framework should be modified to incorporate the synaptic integration current ΔI_{syn} , and the corresponding integration conductance Δg follows a bilinear rule with the proportional coefficient α_{EI} independent of input strengths but dependent of time. For the ease of discussion, we refer to α_{EI} as the integration coefficient.

Integration of E and I Synaptic Currents Revealed in Realistic Neuron Simulations. To further confirm the existence and the structure of the synaptic integration current, we perform realistic neuron simulations in which the time derivatives of voltage can be precisely obtained to estimate the conductance values accurately. Here, a hippocampal CA1 pyramidal neuron model is built with a complex dendritic morphology (Fig. 2A) and active ionic channels (details of the model are in *Materials and Methods*). The E α -amino-3-hydroxy-5-methyl-4-isoxazolepropionic acid (AMPA) receptor and I GABA_A receptor are implemented on the dendrites of the neuron with kinetics consistent with experimental recordings (21). The resting and reversal potentials are set as $\varepsilon_L = -70$, $\varepsilon_E = 0$, and $\varepsilon_I = -80$ mV. Similar to the experimental procedure, we first determine the passive parameters in the point neuron description of the pyramidal neuron model by injecting a step current at the soma of the neuron: $g_L = 0.11$ mS \cdot cm $^{-2}$ and $C = 1$ μ F \cdot cm $^{-2}$. Then, in the simulation of the neuron model, an EPSP or an IPSP is measured at the soma (Fig. 2B) after eliciting an individual E synaptic input on the dendrite about 350 μ m away from the soma or an individual I synaptic input about 280 μ m away from the soma, respectively. The effective E and I conductances at the soma g_E and g_I are determined from the measured EPSP and IPSP, respectively. The neuron is then stimulated given both the E and I synaptic inputs simultaneously with the input strengths and input locations the same as given individually; an SSP is measured at the soma of the neuron, and the corresponding SSC is calculated. Consistent with our experimental observations, after constructing the EPSC and IPSC (Fig. 2C) using the E and I conductances and the SSP, the SSC is found to be significantly different from the linear summation of the constructed EPSC and IPSC (Fig. 2D). This indicates the existence of the synaptic integration current and challenges again the validity of the synaptic current form (Eq. 2) in the point neuron framework.

Following the notation of the synaptic integration current ΔI_{syn} to denote the difference between the SSC and the linear summation of the constructed EPSC and IPSC, we next verify whether the integration conductance Δg obtained from ΔI_{syn} still follows a bilinear relation with the E and I conductances as observed in experiment. Assuming that ΔI_{syn} takes the form of Ohm's law [i.e., $\Delta I_{syn} = \Delta g(\varepsilon_E - V)$], by randomly varying the strengths of the E and I inputs with their input locations fixed, the integration conductance Δg is indeed shown to be proportional

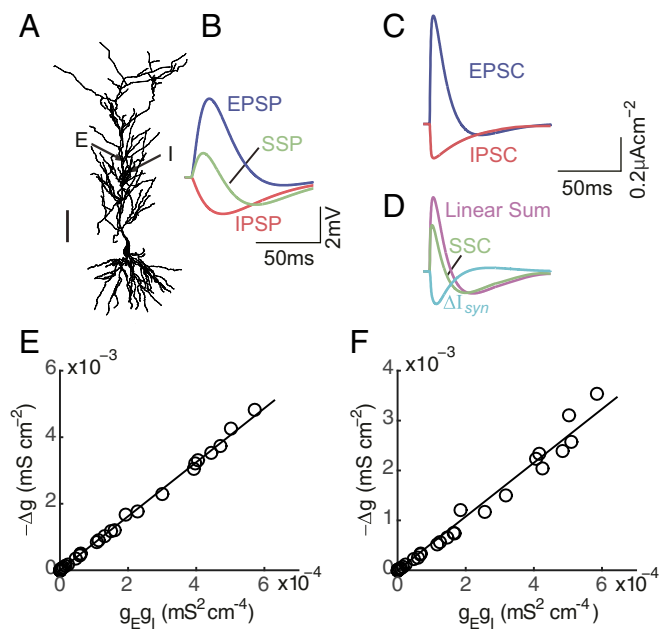


Fig. 2. Realistic neuron simulation result of the bilinear conductance relation for a pair of E and I inputs. (A) The reconstructed hippocampal CA1 pyramidal neuron. Arrows indicate that the I and E inputs are given on the dendritic trunk about 280 and 350 μ m away from the soma. (Scale bar: 100 μ m.) Model details can be found in refs. 21, 24, and 25. (B) A set of simulated individual EPSP, individual IPSP, and SSP induced by both E and I inputs. (C) Constructed EPSC and IPSC using the SSP and the E and I conductances estimated from the EPSP and IPSP in B. (D) The SSC estimated from the SSP in B, the linear sum of the constructed EPSC and IPSC in C, and the difference between them denoted as ΔI_{syn} . (E) The bilinear relation between Δg and the multiplication of g_E and g_I at the time when the E conductance reaches its peak value. The E and I inputs are given simultaneously. Line indicates linear fit (slope, $-\alpha_{EI} = 8.12$ k $\Omega \cdot$ cm 2 , $R^2 = 0.998$). (F) The same as E except that the I input is given 20 ms preceded to the E input. Line indicates linear fit (slope, $-\alpha_{EI} = 5.39$ k $\Omega \cdot$ cm 2 , $R^2 = 0.979$). In E and F, by varying the E and I input strengths, the amplitude of EPSP ranges from 0 to 6 mV, and the amplitude of IPSP ranges from 0 to -3 mV. Each circle corresponds to a set of EPSP, IPSP, and SSP.

to both g_E and g_I at each time point, confirming the bilinear relation $\Delta g = \alpha_{EI} g_E g_I$. The bilinear relation at the peak time of the E conductance is illustrated in Fig. 2E ($R^2 = 0.998$). Furthermore, the bilinear relation remains valid when the E and I inputs arrive nonconcurrently. As an illustration, a particular case of the bilinear relation is shown in Fig. 2F ($R^2 = 0.979$) when the I input is elicited 20 ms earlier than the E input. Consistent with our experimental observations, the integration coefficient α_{EI} in the bilinear conductance relation is found to be independent of input strengths but is dependent of input arrival times (*SI Appendix*, Fig. S2).

Mechanism Underlying the Synaptic Current Integration. To investigate the origin of the synaptic integration current ΔI_{syn} , we perform the static 2-port analysis and show that it emerges from the interaction of synaptic inputs across the spatial dendrites (*SI Appendix* has details). In particular, from our analysis, the integration coefficient α_{EI} in the bilinear conductance relation can be expressed as

$$\alpha_{EI} \approx K_{SS} \left(1 - \frac{K_{EI}}{K_{ES}} \right) + K_{SS} \frac{\varepsilon_I}{\varepsilon_E} \left(1 - \frac{K_{EI}}{K_{IS}} \right), \quad [3]$$

where K_{EI} , K_{ES} , and K_{SS} are the transfer resistances between the locations of the E and I inputs, between the locations of the E input and the soma, and at the soma, respectively.

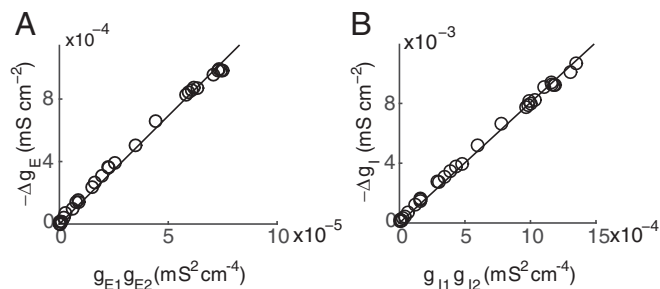


Fig. 3. Realistic neuron simulation result of the bilinear conductance relation for a pair of synaptic inputs of the identical type. (A) The bilinear relation between Δg_E and the multiplication of g_{E1} and g_{E2} . Data are collected by randomly changing the amplitude of EPSP from 0 to 4 mV. Line indicates linear fit (slope, $-\alpha_{EE} = 13.85 \text{ k}\Omega \cdot \text{cm}^2$, $R^2 = 0.994$). (B) The bilinear relation between Δg_I and the multiplication of g_{I1} and g_{I2} . Data are collected by randomly changing the amplitude of IPSP from 0 to -3 mV. Line indicates linear fit (slope, $-\alpha_{II} = 8.06 \text{ k}\Omega \cdot \text{cm}^2$, $R^2 = 0.999$). In A and B, the 2 E (I) inputs are given simultaneously on the dendritic trunk about 280 and 350 μm away from the soma, and the data are measured at the time when one of the E (I) conductances reaches its peak value.

Therefore, only in the limiting case when the E and I inputs are given at the soma, we have $K_{EI} = K_{ES} = K_{IS}$. In this case, according to Eq. 3, the integration coefficient α_{EI} vanishes as does the synaptic integration current ΔI_{syn} , hence the validity of the synaptic current description (Eq. 2). However, a neuron in general receives E and I inputs on the dendrites where $K_{EI} \neq K_{ES}$ and $K_{EI} \neq K_{IS}$. In such a case, according to Eq. 3, α_{EI} deviates from zero; thus, the synaptic current description (Eq. 2) fails to characterize the synaptic current arriving at the soma of a spatial neuron with dendrites. Note that our 2-port analysis shows that the synaptic integration current is mostly negative (*SI Appendix* has details), indicating an additional I effect at the soma coming from the synaptic integration in addition to hyperpolarizing and shunting effects of I inputs. Consequently, the form of the synaptic current (Eq. 2) in the traditional point neuron framework underestimates the inhibition effect.

Integration of Identical-Type Synaptic Currents Revealed in Realistic Neuron Simulations. Via realistic neuron simulations, we further discover that the synaptic integration current and the bilinear conductance relation exist for cases of both a pair of E inputs and a pair of I inputs. When 2 inputs of the same type are elicited simultaneously on the dendrites of the realistic neuron about 350 and 280 μm away from the soma, the SSC derived from the point neuron model is found to deviate from the linear sum of 2 individual synaptic currents when elicited individually. The difference between them is also denoted as ΔI_{syn} and casted by the form of Ohm's law: that is, $\Delta I_{syn} = \Delta g_k (\varepsilon_k - V)$, where ε_k ($k = E, I$) is the E or I reversal potential depending on the input type. By randomly varying the strengths of the 2 inputs without changing the input locations, the bilinear conductance relation can be observed as $\Delta g_E = \alpha_{EE} g_{E1} g_{E2}$ and $\Delta g_I = \alpha_{II} g_{I1} g_{I2}$, where α_{EE} and α_{II} are the integration coefficients independent of input strengths and g_{k1} and g_{k2} ($k = E, I$) are the conductances measured when the 2 inputs are given separately. The bilinear relation at the time when one of the conductances reaches its peak value is illustrated in Fig. 3A for the case of 2 E inputs ($R^2 = 0.994$) and in Fig. 3B for the case of 2 I inputs ($R^2 = 0.999$). Additional simulation results demonstrate that the integration coefficients vary at different time points (Fig. 4A) and are dependent of input arrival times. Note that, for the cases of both a pair of E inputs and a pair of I inputs, the expressions of the integration coefficients α_{EE} and α_{II} in the bilinear conductance relation can be similarly obtained as in Eq. 3 using our 2-port analysis (*SI Appendix* has details),

indicating the existence of the synaptic integration current in these cases.

Spatiotemporal Dependence of the Integration Coefficients. We next investigate the spatial dependence of the integration coefficients α_{EI} , α_{EE} , and α_{II} in realistic neuron simulations. For a pair of E and I inputs, when the I input location is fixed, the dependence of the integration coefficient α_{EI} on the E input location shows a clear asymmetry for proximal vs. distal E input locations. To be specific, given an I input on the dendritic trunk, $-\alpha_{EI}$ decreases rapidly as the distance between the E and I sites increases when the E input site is located between the soma and the I input site but remains constant when the E input site is located farther away from the soma than the I input site (Fig. 4B). In contrast, for a pair of E inputs, when 1 E input location is fixed, the dependence of the integration coefficient α_{EE} on the other E input location shows a clear symmetry for proximal vs. distal E input locations. Also, $-\alpha_{EE}$ is largest when the 2 E input sites overlap with each other and decays when the distance between the 2 E inputs increases (Fig. 4C). The spatial dependence of α_{II} is similar to that of α_{EE} (Fig. 4D). Accounting for the fact that a neuron receives the majority of synaptic inputs from its dendritic branches, we also investigate the spatial dependence of the integration coefficients on the whole dendrites. We find that the above spatial dependence of the integration coefficient still holds when 1 input site is fixed on the dendritic trunk and the other input site is scattered on the dendritic arbor (*SI Appendix*, Fig. S3). In addition, when 1 input site is fixed on a dendritic branch, the integration coefficient is significantly non-zero only when the other input site is within the same branch (*SI Appendix*, Fig. S3), consistent with the theory that each dendritic branch is an independent functional computational unit (26, 27). It has been further noticed that the integration coefficient for a pair of inputs within a branch is in general larger than that for 2 inputs at the dendritic trunk (*SI Appendix*, Fig. S3). All of these spatial properties of the integration coefficients observed in the simulations can be successfully explained from our 2-port analysis (*SI Appendix* has details).

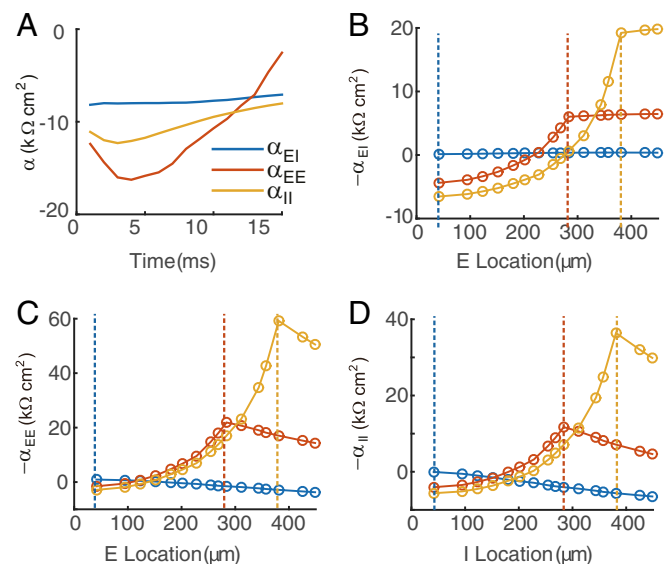


Fig. 4. Spatiotemporal properties of the integration coefficients. (A) α_{EE} , α_{II} , and α_{EI} as a function of time. (B) The spatial dependence of $-\alpha_{EI}$. For each color-coded curve, the I input is fixed at the location marked by the dashed line with identical color, and the E input moves along the dendritic trunk from the soma toward the distal dendrites. (C and D) The spatial profiles of $-\alpha_{EE}$ and $-\alpha_{II}$, respectively.

direction selectivity. As predicted by Rall's cable theory (29), the activation of a train of E inputs can promote the firing of a neuron when the inputs are received sequentially from the distal dendrite toward the soma but demote the firing when the E inputs are received in the reverse direction (Fig. 6B). In this way, the neuron has a preferred direction of input sequence. The sensitivity to spatiotemporal sequences of synaptic activation in cortical pyramidal neuron dendrites was observed in later experiments (2). In our derived synaptic integration current, the information of the input direction can be encoded in an ordered sequence of integration coefficients. In particular, the early activation of a pair of distal E inputs corresponds to the synaptic integration current with a large negative α_{EE} , and the late activation of a pair of proximal E inputs corresponds to the synaptic integration current with a small negative α_{EE} (*SI Appendix* has details). Therefore, given a temporal sequence of identical E inputs to the point neuron, its firing will be promoted by sequentially activating the set of α_{EE} with values that are in an increasing order but demoted by activating the set of α_{EE} in the reversed order (Fig. 6B).

Coincidence detection. Similarly, a point neuron with the synaptic integration current can play the role of coincidence detector. In the early auditory pathway, neurons that receive bilateral inputs have bipolar dendrites, with each dendritic tree receiving input from only 1 ear (30). These neurons can detect input coincidence with submillisecond temporal resolution in their role of computing interaural arrival time difference, which is a cue for sound localization (Fig. 6C). In the point neuron model with the synaptic integration current, the detection of coincident inputs can be facilitated by a small negative α_{EE} in the synaptic integration current for a pair of E inputs representing the case of the inputs received on separate dendrites and will be depressed by a large negative α_{EE} in the corresponding synaptic integration current representing the case of the inputs received on the same dendrite (Fig. 6C and *SI Appendix* have details).

Logical operation. The synaptic integration current enables a point neuron to perform logical operation. Previous studies have shown that one of the important functions of dendrites is to perform logical computation (3, 26). For instance, given a pair of E and I inputs, the I input is found to be maximally effective to silence the E input when the I input is received between the soma and the location of the E input, known as the "on-the-path effect" (3, 26). Therefore, given a pair of distal E synapse and proximal I synapse, to observe an output at the soma, it is required that the E synapse is activated, while the I synapse remains inactivated. Therefore, this pair of E and I inputs performs the logical operation of "E AND (NOT I)." In contrast, for an I input located farther away from the soma than the location of the E input—the out-of-the-path configuration—studies have shown that the I input exerts a weak influence on the E input. Therefore, this pair of E and I inputs no longer performs the logical operation of E AND (NOT I) but simply the gate of E. In addition, a pair of E inputs received at 2 separated branches in general will produce larger response at the soma of a neuron than a pair of E inputs received at the same branch. If the neuron requires at least 2 inputs to generate an output, the inputs are preferred to be at different branches. Therefore, 2 separate E inputs can play the role of an AND gate, while 2 nearby E inputs cannot. When a neuron receives multiple inputs distributed on the dendrites, the combination of the above-mentioned simple logical gates can give rise to complex logical operations. All of these logical operations can be easily achieved in the point neuron framework by measuring values of the integration coefficients in the synaptic integration current (Eq. 5), because the integration coefficients encode the locations of inputs that determine the type of logical computations.

Discussion

In this work, by using electrophysiological experiments, realistic neuronal simulations, and theoretical analyses, we have derived a form of synaptic current in the point neuron framework as a result of dendritic integration. In addition to the traditional form of the synaptic current (Eq. 4), our derived synaptic integration current described by Eq. 5 indicates that the interaction between each pair of synaptic inputs on the complex nonlinear active dendrites can be reliably captured by the bilinear interaction between their corresponding synaptic conductances. In addition, we have shown that the point neuron model with the synaptic integration current incorporated is able to capture many dendritic phenomena, including counterintuitive dendritic filtering, and a bilinear rule of dendritic integration discovered in a recent experiment, and the model possesses the computational ability of a spatial neuron with dendrites, including direction selectivity, coincidence detection, and logical operation.

When describing the synaptic integration current measured in our experiments and the simulations, we have chosen the reversal potential to be the E reversal potential. In fact, there is a degree of freedom for choosing the value of the reversal potential within the regime in which the ratio of the postsynaptic potential to the reversal potential is small, and the value of the integration coefficient α_{EI} depends on the choice of the reversal potential (*SI Appendix* has details). However, we stress that the bilinear interaction between the conductances remains valid when choosing a different reversal potential value (e.g., the I reversal potential), which has been justified in both our theoretical analysis (*SI Appendix*) and numerical simulations (*SI Appendix*, Fig. S1).

To reveal the mechanism underlying the existence of the synaptic integration current, for the simplicity of illustration, we have performed the steady-state analysis. By noticing that the static analysis fails to describe the temporal integration of synaptic inputs, we have also developed a strict analysis based on the dynamical cable equation when the model neuron receives time-dependent synaptic inputs. The dynamical analysis also gives rise to the identical form of synaptic integration current with time-dependent integration coefficients as a result of spatiotemporal dendritic integration.

According to the nonlinear integration between E and I conductances in the synaptic integration current, it behooves one to reexamine the ramifications of previous works involving the decomposition of E and I synaptic inputs. In many previous works, based on the form of the traditional synaptic current (Eq. 2), by holding the somatic membrane potential at various levels using the voltage clamp, the E and I synaptic conductances (9) and currents (10) are estimated from the linear I–V relation where the slope is the total conductance $g_E + g_I$ and the intercept is the reversal current $g_E E_E + g_I E_I$. The measured conductances are often used to evaluate the state of a network (31). However, our work shows that the E and I conductances are not linearly separable but interact with each other nonlinearly. Therefore, the interpretation of the measured E and I components based on the traditional point neuron model is questionable.

We illustrate the issue of conductance measurement using realistic neuron simulations as shown in *SI Appendix*, Fig. S4. When a pair of E and I inputs is given at the dendritic trunk 350 and 280 μm away from the soma of the realistic neuron model separately, we calculate the E and I conductances in the corresponding point neuron model as the reference conductances. Note that the reference conductance is different from the local conductance at the dendrite; instead, it reflects directly the functional impact of local synaptic inputs on the somatic membrane potential change and thereby, neuronal information processing at the soma. When the same pair of E and I inputs is given at

the dendritic trunk simultaneously, by using the voltage clamp, the measured E and I conductances based on Eq. 2 significantly deviate from the reference conductances. In addition, in the case shown in *SI Appendix, Fig. S4*, the fact that inhibition is dominant to excitation can be misinterpreted as that E and I are approximately balanced. Through our analysis, the error is induced by neglecting the nonlinear integration between currents across the spatial dendrites when using the traditional point neuron framework.

It has been broadly believed that many dendritic phenomena, such as the integration of spatially distributed synaptic inputs, are beyond the scope of the existing point neuron models (32, 33). However, the dendritic integration process is known to have a strong impact on the action potential generation and thereby, neuronal information coding. Here, we have developed an effective point neuron model (i.e., a point neuron model with the synaptic integration current incorporated) that can capture many dendritic effects, and it has succinct structure for analysis and simulation. We have shown that the effective point neuron model can achieve the same order of accuracy for the somatic voltage dynamics as a detailed multicompartment model with substantially low computational costs (Fig. 5D).

Therefore, it is promising to develop fast algorithms for neuronal simulations to capture the dynamics of a neuron with realistic dendritic morphology. To be specific, the spatiotemporal profile of the integration coefficients encoding the information of synaptic inputs can be measured in advance and recorded in a library for future simulations. When simulating the point neuron model, the dendritic integration effect can be accurately captured by simulating the synaptic integration current with the integration coefficient read out from the library. It has been found in our simulation that the library of the integration coefficients is very sparse (*SI Appendix, Fig. S5*) (i.e., the majority of the coefficients are not large enough to induce a 5% change of SSP). This is consistent with previous works showing that the nonlinear interaction between a pair of inputs is mainly localized within a branch (26, 27). The sparsity of bilinear synaptic interactions benefits the simulation efficiency of our point neuron model. Consequently, the simulation speed is expected to be improved tremendously in comparison with simulating the realistic neuron model with full dendrites. The developed point neuron model in this work only describes the subthreshold regime without accounting for active channels associated with spike generation. However, this limitation could be potentially overcome by modeling the spike time as when the voltage reaches a firing threshold (i.e., the integrate-and-fire-type neuron). Another limitation of the developed point neuron model is that the integration current derived in our model so far

only takes into account the second-order interaction of synaptic inputs; therefore, it may not be capable of capturing highly nonlinear dendritic phenomena, such as dendritic spikes and plateau potentials. Capturing these phenomena may involve the voltage dependence of the integration coefficients and higher-order interactions of synaptic inputs.

Furthermore, the form of the synaptic integration current reshapes the synaptic input modeling in both experiments and simulations. For instance, dynamic clamp has been extensively used in electrophysiological experiments, in which realistic E and I synaptic currents are generated at the soma of a neuron (34, 35) to mimic synaptic current dynamics. Based on our results, these synaptic currents are far from reality because of the neglect of the synaptic integration current. An appropriate way suggested by our results is to generate synaptic currents by incorporating the synaptic integration current (Eq. 5) in future studies.

Materials and Methods

Slice Electrophysiology. The experimental procedure of whole-cell recording and microiontophoresis on hippocampal CA1 pyramidal neurons in acute brain slices (350- μ m thick) of juvenile Sprague-Dawley rats (postnatal days 15 to 20) followed the methods described in our previous study (21). The animal experimental protocols were approved by the Animal Use and Care Committee of the State Key Laboratory of Cognitive Neuroscience & Learning at Beijing Normal University (IACUC-BNU-NKLCNL-2016-02).

Realistic Neuron Simulation. We adapted the multicompartment neuron model used in our previous studies (21, 24, 25) for our realistic pyramidal neuron simulation. The morphology of the reconstructed pyramidal neuron, which includes 200 compartments, was obtained from the Duke-Southampton Archive of Neuronal Morphology (36). The passive cable properties and the densities of active conductances in the neuron model were based on published experimental data obtained from the hippocampal and cortical pyramidal neurons (27, 37–48). In particular, the multicompartment neuron model included the voltage-gated sodium channel, the delayed rectifier potassium channel, 2 variants of the A-type potassium channel, and the hyperpolarization activated channel. The E and I synaptic inputs were given through AMPA and GABA_A receptors, respectively. The resting potential was set to $V_r = -70$ mV, and the E and I reversal potentials were set to $E_{AMPA} = 0$ and $E_{GABA_A} = -80$ mV. We used the NEURON software Version 7.4 (49) to simulate the model with a time step of 0.1 ms.

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