



# Increased Computational Accuracy in Multi-Compartmental Cable Models by a Novel Approach for Precise Point Process Localization

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*Received July 16, 2004; Revised November 23, 2004; Accepted November 23, 2004*

Action Editor: Alain Destexhe

**Abstract.** Compartmental models of dendrites are the most widely used tool for investigating their electrical behaviour. Traditional models assign a single potential to a compartment. This potential is associated with the membrane potential at the centre of the segment represented by the compartment. All input to that segment, independent of its location on the segment, is assumed to act at the centre of the segment with the potential of the compartment. By contrast, the compartmental model introduced in this article assigns a potential to each end of a segment, and takes into account the location of input to a segment on the model solution by partitioning the effect of this input between the axial currents at the proximal and distal boundaries of segments. For a given neuron, the new and traditional approaches to compartmental modelling use the same number of locations at which the membrane potential is to be determined, and lead to ordinary differential equations that are structurally identical. However, the solution achieved by the new approach gives an order of magnitude better accuracy and precision than that achieved by the latter in the presence of point process input.

**Keywords:** compartmental models, dendrites, cable equation

## 1. Introduction

Compartmental models have become important tools for investigating the behaviour of neurons to the extent that a number of packages exist to facilitate their implementation (e.g. Hines and Carnevale, 1997; Bower and Beeman, 1997). These models are constructed by replacing the continuum description of a neuron by a

discrete description of the neuron formed by partitioning it into contiguous segments which interact with their nearest neighbours across common boundaries. A compartment is a mathematical representation of the morphological and biophysical properties of a segment, and a compartmental model is the collection of all compartments along with a specification of their connectivity. The efficacy of any formulation of a compartmental model depends on the faithfulness with which it captures the behaviour of the neuron that it represents, and

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41 it is in this respect that the new compartmental model  
42 developed in this article will be seen to perform bet-  
43 ter than existing compartmental models with a similar  
44 level of complexity.

45 The traditional approach to compartmental mod-  
46 elling (e.g., Rall, 1964; Segev and Burke, 1998) assigns  
47 a single potential to a compartment. This potential takes  
48 its value through an association with the average value  
49 of the current density crossing the membrane of the  
50 segment, and in a traditional compartmental model is  
51 approximated by the membrane potential at the cen-  
52 tre of the segment. However a compartment of this  
53 type is aesthetically unsatisfactory since it cannot act  
54 as the fundamental unit in the construction of a model  
55 dendrite, first, because two compartments are required  
56 to define axial current flow, and second, because half  
57 compartments are required to represent branch points  
58 and dendritic terminals. On the other hand, the new  
59 approach to compartmental modelling assigns two po-  
60 tentials to a compartment—one to represent the mem-  
61 brane potential at the proximal boundary of the segment  
62 and the other to represent the membrane potential at its  
63 distal boundary. The new compartment can exist as an  
64 independent entity and can therefore function as the  
65 basic building block of a multi-compartmental neu-  
66 ronal model. Another significant difference between  
67 a traditional compartmental model and the new com-  
68 partmental model lies in the novel procedure for the  
69 treatment of transmembrane current. In a traditional  
70 compartmental model the influence of transmembrane  
71 current on a segment is approximated by requiring these  
72 currents to act at the centre of the segment with the sin-  
73 gle potential assigned to the compartment representing  
74 the segment, and consequently these models do not re-  
75 flect accurately the influence of the precise location of  
76 point process input<sup>1</sup> on the segment. By contrast, the  
77 formulation of the new compartmental model makes  
78 it more responsive to the influence of the location of  
79 point process input to a segment, and in the presence of  
80 these inputs, is shown to be an order of magnitude more  
81 accurate than a comparable traditional compartmental  
82 model.

83 The accuracy of the new and traditional approaches  
84 to compartmental modelling is first assessed by calcu-  
85 lating the error in the somal potential of a test neuron  
86 when each approach is used to calculate this potential  
87 ten milliseconds after the initiation of large scale point  
88 current input. In a second comparison, the accuracy  
89 of the two approaches is assessed by comparing the  
90 statistics of the spike train output generated by each

type of compartmental model of the test neuron when  
subjected to large scale synaptic input.

## 2. Structure of Compartmental Models 93

We are concerned with compartmental models of den-  
drites. In this context, the fundamental morphological  
unit is the dendritic *section*, defined to be the length  
of dendrite connecting one branch point to a neigh-  
bouring branch point, to the soma or to a terminal.  
Compartmental modelling begins by subdividing each  
dendritic section into segments which are typically re-  
garded as uniform circular cylinders (e.g. Segev and  
Burke, 1998) or tapered circular cylinders (Hines and  
Carnevale, 1997). In the new approach to comparten-  
tal modelling, the known membrane potentials at the  
ends of a segment (rather than its centre) provide the  
basis for the development of a set of rules which enable  
the influence of precisely located point process input to  
be partitioned between the axial current at the proximal  
and distal boundaries of the segment. The mathematical  
equations of the compartmental model are constructed  
by enforcing conservation of axial current at segment  
boundaries, dendritic branch points and dendritic ter-  
minals.

### 2.1. Model Accuracy and the Partitioning of Point Process Input 114 115

The benefit in accuracy gained by taking into account  
the precise placement of point process input on a den-  
drite is best appreciated by considering how, in the ab-  
sence of this facility, small variations in the location of  
segment boundaries exert a large influence on the so-  
lution of a traditional compartmental model. Consider,  
for example, a point process close to a segment bound-  
ary. A small change in the position of that boundary  
may move the assigned location of this point process  
from the centre of one segment to that of an adjacent  
segment. With respect to a traditional compartmental  
model, the location of this point process is therefore de-  
termined only to an accuracy of half a segment length,  
and this indeterminacy will in turn generate a model  
solution that is particularly sensitive to segment bound-  
aries. Of course, with a small number of point process  
input, this problem can be avoided in the traditional ap-  
proach to compartmental modelling by arranging that  
only one point process falls on a segment, and that the  
location of this input coincides with the centre of the

segment. However, this strategy is not feasible when dealing with large scale point process input. What is required is a procedure which describes the effect of point process input on a dendritic section in a way that is largely insensitive to how that section is represented by segments.

The primary sources of error in the construction of a compartmental model are the well-documented effect of discretising a continuous dendrite, and the less well-documented error introduced by the placement of point process input on the dendrite. In the traditional approach based on a compartmental model with  $n$  compartments, the first type of error is  $O(1/n^2)$  (by analogy with the finite difference representation of derivatives), but it is not widely recognised that the second type of error is  $O(1/n)$  whenever the input does not naturally fall at the centre of segments. Since the accuracy of any model is governed by the least accurate contribution to the model, it is clear that *in practice* the traditional approach to compartmental modelling in the presence of point current and synaptic input is  $O(1/n)$  accurate. This theoretical observation is supported by the simulation studies of Sections 5.2 and 5.3, and by an example provided for us by an anonymous reviewer. This reviewer used the simulator NEURON to calculate the somal potential of the test neuron shown in Fig. 3 10 msec after the initiation of point current input. The results of this calculation are shown in Table 1.

The results shown in the middle panel of Table 1 (traditional compartmental model) are based on placing the exogenous point current input at the centre of

its nearest segment, whereas the results shown in the right hand panel (modified compartmental model) are based on the division of the point current input between the centres of adjacent compartments in proportion to the conductance between the location of the input and these centres. Several important differences between the two procedures for allocating the location of point current input are evident from the results set out in Table 1. The results based on dividing the current proportionately between the centres of neighbouring compartments converge smoothly and more rapidly to the true potential than those based on the traditional approach in which the current is placed at the centre of the compartment. An extrapolation procedure demonstrates that the potentials generated by the modified approach converge quadratically to the true somal potential as the number of compartments is increased. Moreover, not only does the solution following the traditional approach (middle panel) converge to the true potential more slowly than the modified approach (right hand panel), the former appears to oscillate as it approaches this potential. Finally, further evidence for the superior convergence of the modified approach is clear from the observation that the best estimate of the true potential using the traditional approach with 256 segments per branch section is achieved in the modified approach with approximately 28 segments per branch section. It will be seen in Section 4.1 that the procedure used by the reviewer to partition point current input is a special case of the general procedure for partitioning point process input. By contrast with the traditional

Table 1. The somal potential of the test neuron shown in Fig. 3 is given 10 msec after the initiation of point current input. The calculation is done for nine different levels of discretisation and two methods for the placement of exogenous point current input.

Segments per branch section	Point current input at centre of nearest segment		Point current input divided proportionately	
	V (mV)	$\Delta V$ (mV)	V (mV)	$\Delta V$ (mV)
1	10.2355		10.5692	
2	10.2311	$(-4.4616 \times 10^{-3})$	10.3357	$(-2.3352 \times 10^{-1})$
4	10.2367	$(5.6256 \times 10^{-3})$	10.2725	$(-6.3143 \times 10^{-2})$
8	10.2333	$(-3.4428 \times 10^{-3})$	10.2556	$(-1.6908 \times 10^{-2})$
16	10.2470	$(1.3754 \times 10^{-2})$	10.2519	$(-3.6550 \times 10^{-3})$
32	10.2509	$(3.8793 \times 10^{-3})$	10.2508	$(-1.1320 \times 10^{-3})$
64	10.2521	$(1.1874 \times 10^{-3})$	10.2506	$(-2.4666 \times 10^{-4})$
128	10.2530	$(8.8765 \times 10^{-4})$	10.2505	$(-6.3146 \times 10^{-5})$
256	10.2511	$(-1.9053 \times 10^{-3})$	10.2505	$(-1.5181 \times 10^{-5})$

approach, the new approach to compartmental modelling describes the influence of point process input to an accuracy of  $O(1/n^2)$ , and therefore one would anticipate that it does not degrade the overall accuracy of the model. The validity of this assertion is demonstrated through the simulation studies in Sections 5.2 and 5.3.

### 3. Distributed and Point Process Input to a Segment

In general, segments receive distributed and point process sources of input each of which require a different mathematical treatment. The current supplied by distributed input such as intrinsic voltage-dependent current or capacitive current is proportional to the surface area of the segment on which it acts, whereas the current supplied to a segment at a synapse or by an exogenous point input is independent of the size of the segment. An implicit assumption of a compartmental model is that distributed current input to a segment is small by comparison with axial current flowing along the segment.

To appreciate why this assumption is reasonable, consider a cylindrical dendritic segment of radius  $r$  (cm), length  $h$  (cm) and with membrane of constant conductance  $g_M$  (mS/cm<sup>2</sup>). Suppose that axoplasm has constant conductance  $g_A$  (mS/cm) and that a potential difference  $V$  (mV) exists between the segment boundaries, then the axial current along the segment is  $I_A = \pi r^2 g_A V/h$  ( $\mu$ A) and the total distributed current crossing the membrane of the segment is  $I_M = 2\pi r h g_M (V/2)$ . The ratio of the distributed current to the axial current is therefore

$$\begin{aligned} \frac{\text{Distributed current}}{\text{Axial current}} &= \frac{I_M}{I_A} = \frac{\pi r h g_M V}{\pi r^2 g_A (V/h)} \\ &= \frac{h^2 g_M}{r g_A} = \left(\frac{h}{r}\right)^2 \frac{r g_M}{g_A}. \quad (1) \end{aligned}$$

For a typical dendritic segment  $r g_M/g_A$  is small (say  $\approx 10^{-5}$ ), and therefore distributed current acting on a segment is small by comparison with axial current for “short” segments. On the other hand, segments several orders of magnitude longer than their radius can be expected to have distributed and axial currents of similar magnitude. An important property of a compartmental model is that segments are not excessively long by comparison with their radius (However, see Segev and Burke, 1998, Fig. 3b). In the treatment of distributed

current, the development of the new compartmental model makes explicit use of the assumption that distributed current is much smaller than axial current. This assumption may not be valid for point process input and will not be made for the treatment of this type of input in the new approach to compartmental modelling.

#### 3.1. Axial Current in the Absence of Transmembrane Current

The importance of the conclusion from Section 3 is that distributed transmembrane current acting on short segments is small compared with axial current, and may be neglected in a first approximation of the distribution of membrane potential on a segment. Thus in the absence of point process input, the axial current in a segment is well approximated from the potential drop across the segment. In the light of this approximation, consider Fig. 1 which illustrates a dendritic segment of length  $h$  in which  $\lambda \in [0, 1]$  is the fractional distance of a point of the segment from its proximal end ( $\lambda = 0$ ). Let  $r_P$  and  $r_D$  be the radii of the segment at its proximal and distal boundaries respectively, let  $V_P(t)$  and  $V_D(t)$  be the membrane potentials at these boundaries and let  $I_{PD}$  be the axial current in the segment in the absence of transmembrane current.

The membrane of the segment in Fig. 1 is formed by rotating the straight line PD about the axis of the dendrite to form the frustum of a cone of radius

$$r(\lambda) = (1 - \lambda)r_P + \lambda r_D, \quad \lambda \in [0, 1]. \quad (2)$$

Assuming that the segment is filled with axoplasm of constant conductance  $g_A$  and that no current crosses

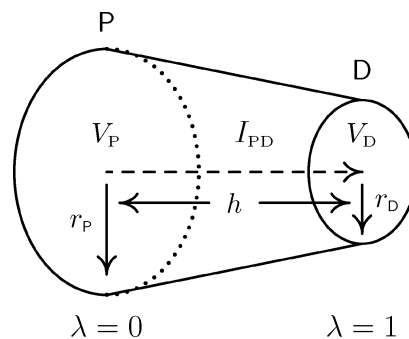


Figure 1. A segment of length  $h$  is illustrated. In the absence of transmembrane current, membrane potentials  $V_P$  and  $V_D$  at the proximal and distal boundaries of the segment generate axial current  $I_{PD}$ .

its membrane, then the relationship between  $V_P$ ,  $V_D$  and  $I_{PD}$  can be constructed by integrating the defining equation of axial current, namely  $I_{PD} = -g_A A(x) dV/dx$ , from the proximal to the distal boundary of a segment. For the conical segment illustrated in Fig. 1,  $A(x) = \pi r^2(\lambda)$ ,  $dV/dx = h^{-1} dV/d\lambda$  and the equation to be integrated is

$$I_{PD} = -\frac{g_A \pi}{h} [(1-\lambda)r_P + \lambda r_D]^2 \frac{dV}{d\lambda}$$

with boundary conditions  $V(0) = V_P$  and  $V(1) = V_D$ . The result of this calculation is that the the axial current  $I_{PD}$  and the potentials  $V_P$  and  $V_D$  are connected by the formula

$$I_{PD} = \frac{\pi g_A r_P r_D}{h} (V_P - V_D) \quad (3)$$

in the absence of transmembrane current. Moreover, the potential at the point  $\lambda$  is

$$V(\lambda) = \frac{V_P(1-\lambda)r_P + V_D\lambda r_D}{(1-\lambda)r_P + \lambda r_D}. \quad (4)$$

Note that Eq. (4) is valid for sections with taper and in the absence of taper will lead to a membrane potential which varies linearly along the length of a segment. The subsequent development of the new compartmental model assumes that sections may taper unless stated specifically that the section is uniform.

### 3.2. Partitioning Rule for Transmembrane Current

In compartmental modelling the effect of transmembrane current is represented in the model by input at points, or nodes, at which the membrane potential is known. In a traditional approach to compartmental modelling, these nodes are at the centre of segments, whereas in the new approach they are located at the boundaries of segments. The new approach partitions the effect of input at any location between the nodes at the proximal and distal boundaries of the segment. This procedure ensures that the solution of the compartmental model is insensitive to small changes in the location of segment boundaries because changes in these boundaries also affect how the input is partitioned between nodes. In the mathematical description of the new compartmental model, the effect of input to a segment is treated as perturbations  $I_P$  and  $I_D$  to the axial current  $I_{PD}$  at the proximal and distal boundaries of a segment. Axial current  $I_{PD} + I_P$  is assumed to

leave the proximal boundary of a segment in the direction of its distal boundary, while axial current  $I_{PD} + I_D$  is assumed to arrive at the distal boundary of a segment from the direction of its proximal boundary. The perturbations  $I_P$  and  $I_D$  must satisfy the conservation of current condition

$$(I_{PD} + I_D) - (I_{PD} + I_P) + h \int_0^1 J(\lambda, t) d\lambda = 0 \rightarrow I_P - I_D = h \int_0^1 J(\lambda, t) d\lambda \quad (5)$$

where  $J(\lambda, t)$  denotes transmembrane current. The task is to construct expressions for  $I_P$  and  $I_D$  that satisfy (5) for all constitutive forms for the current density  $J(\lambda, t)$ . The new approach to compartmental modelling requires a procedure or rule for partitioning transmembrane current between the proximal and distal boundaries of a segment. The rule used in this article is that transmembrane current flow to a boundary of a segment is proportional to the axial conductance of the segment lying between the point of application of the current and that boundary. If  $G_P(\lambda)$  is the axial conductance of the portion of segment lying between the point  $\lambda$  and the proximal boundary of the segment, and  $G_D(\lambda)$  is the axial conductance of the portion of segment lying between the point  $\lambda$  and the distal boundary of the segment, then

$$G_P(\lambda) = \frac{\pi g_A r_P r(\lambda)}{\lambda h}, \quad G_D(\lambda) = \frac{\pi g_A r_D r(\lambda)}{(1-\lambda)h} \quad (6)$$

and the rule for partitioning transmembrane current leads to the expressions

$$\begin{aligned} I_P &= h \int_0^1 \frac{G_P J(\lambda, t) d\lambda}{G_P + G_D} \\ &= h \int_0^1 \frac{(1-\lambda)r_P J(\lambda, t) d\lambda}{(1-\lambda)r_P + \lambda r_D}, \\ -I_D &= h \int_0^1 \frac{G_D J(\lambda, t) d\lambda}{G_P + G_D} \\ &= h \int_0^1 \frac{\lambda r_D J(\lambda, t) d\lambda}{(1-\lambda)r_P + \lambda r_D}. \end{aligned} \quad (7)$$

Clearly these expressions satisfy identically condition (5) for the conservation of current.



### 331 3.3. Specification of Transmembrane Current

332 Transmembrane current is usually assumed to consist  
333 of four distinct components: capacitive current, in-  
334 trinsic voltage-dependent current and point process in-  
335 put which is subdivided into synaptic current and ex-  
336 oogenous point current. Total transmembrane current is  
337 represented by

$$\int 2\pi r c_M \frac{\partial V}{\partial t} dx + \int 2\pi r J_{IVDC}(V) dx + \sum J_{SYN}(V_{syn}) + \sum I_{EX} \quad (8)$$

338 where the integrals and summations are taken over the  
339 length of a segment. In this expression  $c_M$  ( $\mu\text{F}/\text{cm}^2$ )  
340 is the specific capacitance of the segment membrane,  
341  $V(x, t)$  is the distribution of membrane potential at time  
342  $t$  (msec),  $J_{IVDC}(V)$  ( $\mu\text{A}/\text{cm}^2$ ) is the density of trans-  
343 membrane current due to intrinsic voltage-dependent  
344 channel activity,  $J_{SYN}(V_{syn})$  ( $\mu\text{A}$ ) describes synaptic  
345 input and  $I_{EX}$  ( $\mu\text{A}$ ) describes exogenous input. Al-  
346 though the specific capacitance of dendritic membrane  
347 is normally taken to be constant in neuronal modelling,  
348 it will be treated here as a function of position to show  
349 how transmembrane current of this type may be in-  
350 corporated into the new compartmental model. For a  
351 segment of length  $h$ , the expression for  $J(\lambda, t)$  corre-  
352 sponding to formula (8) is

$$hJ(\lambda, t) = 2\pi hr(\lambda)c_M(\lambda)\frac{\partial V(\lambda, t)}{\partial t} + 2\pi hr(\lambda)J_{IVDC}(V(\lambda, t)) + \sum_k J_{SYN}(V_{syn})\delta(\lambda - \lambda_k) + \sum_k I_{EX}(t)\delta(\lambda - \lambda_k) \quad (9)$$

353 where  $\lambda_k$  denotes the relative location of the  $k$ th  
354 synapse or exogenous input with respect to the proxi-  
355 mal boundary of the segment ( $\lambda = 0$ ).

## 356 4. The Partitioning of Transmembrane Current

357 Further progress requires expressions for  $I_P$  and  $I_D$   
358 in terms of the biophysical and morphological proper-  
359 ties of the segment and the membrane potentials at its  
360 proximal and distal boundaries. Each component of the  
361 transmembrane current (9) is examined separately.

### 4.1. Point Processes

We model synaptic current by the conventional con-  
stitutive equation  $\mathcal{I} = g(t)(V - E)$  where  $E$  is the  
reversal potential associated with the synapse and  $g(t)$   
is the time course of the synaptic conductance. Exoge-  
nous point current input takes the form  $\mathcal{I} = \mathcal{I}(t)$  where  
 $\mathcal{I}(t)$  is a known function of  $t$ . Suppose that  $\lambda_1, \dots, \lambda_n$   
are sites of point input  $\mathcal{I}_1, \dots, \mathcal{I}_n$  to the segment, then  
it follows from expressions (7) that the contributions  
made to  $I_P$  and  $I_D$  from these currents are

$$I_P = \sum_{k=1}^n \frac{r_P}{r_k} (1 - \lambda_k) \mathcal{I}_k, \quad -I_D = \sum_{k=1}^n \frac{r_D}{r_k} \lambda_k \mathcal{I}_k \quad (10)$$

where  $r_k = (1 - \lambda_k)r_P + \lambda_k r_D$ . In the special case of  
exogenous input alone,  $\mathcal{I}_k = \mathcal{I}_k(t)$  and expressions (10)  
give the exact partitioning of this input. The procedure  
used by the anonymous reviewer (see Section 2.1) is  
an application of Eq. (10) to a uniform segment, that  
is,

$$I_P = \sum_{k=1}^n (1 - \lambda_k) \mathcal{I}_k, \quad -I_D = \sum_{k=1}^n \lambda_k \mathcal{I}_k. \quad (11)$$

However, when synaptic input is present, expressions  
(10) for  $I_P$  and  $I_D$  will contain the (unknown) mem-  
brane potentials at the synapses, and its use will there-  
fore require these potentials to be estimated in terms of  
known functions and the potentials at the proximal and  
distal boundaries of the segment.

One obvious way to estimate the potential at the site  
of a synapse is to use the potential distribution (4).  
However, the efficacy of this approximation relies on  
the validity of the assumption that transmembrane cur-  
rent is negligible by comparison with axial current. In  
the presence of synaptic input, transmembrane current  
need not be negligible by comparison with axial cur-  
rent, and so the partitioning rule must be developed to  
include this possibility.

### 4.2. The Partitioning Rule in the Presence of Synaptic Input

The partitioning of point process input set out in  
Section 4.1 is developed by noting that this rule may  
be applied to the division of transmembrane current  
between nearest-neighbour sites of a point input, and  
that the proximal and distal boundaries of the segment  
are simply special cases of these sites. This application

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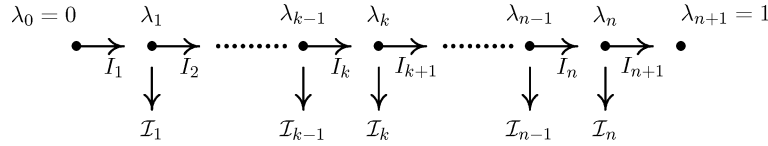


Figure 2. Configuration of point input to a dendritic segment of length  $h$ . Here  $\mathcal{I}_k = g_k(t)(V_k - E_k)$  in the case of synaptic input at  $\lambda_k$  or  $\mathcal{I}_k = \mathcal{I}_k(t)$  if the input is an exogenous point current.

of the partitioning rule is equivalent to considering the balance between axial current and point current at each site of input ignoring the influence of distributed transmembrane current between sites. The implementation of the partitioning rule for general point process input is done in two stages. The first stage of the discussion focusses on the construction of the equations satisfied by the potentials at the sites of the point input, and the second stage of the discussion describes how these equations may be solved numerically and is contained in appendix one.

**4.2.1. Equations for the Potentials.** In general, the locations of point process input can be taken to divide a segment into sub-segments, defined to be the lengths of the segment between the locations of these inputs. Figure 2 is a schematic representation of a segment of length  $h$  illustrating the relative locations  $\lambda_1, \dots, \lambda_n$  of  $n$  point inputs  $\mathcal{I}_1, \dots, \mathcal{I}_n$  on a segment. Suppose axial current  $I_k$  flows to the point  $\lambda_k$  from the point  $\lambda_{k-1}$  and that  $V_k$  is the potential at the point  $\lambda_k$ .

Since distributed current alone can flow across the membrane of a sub-segment, Equation (3) may be used to describe the axial current in the  $k$ -th sub-segment by replacing  $V_P$  and  $r_P$  with  $V_{k-1}$  and  $r_{k-1}$  respectively, by replacing  $V_D$  and  $r_D$  with  $V_k$  and  $r_k$  respectively, and by replacing  $h$  with  $h(\lambda_k - \lambda_{k-1})$ , the length of the sub-segment. If  $V_1, \dots, V_n$  are the potentials at the points  $\lambda_1, \dots, \lambda_n$  at which point process input is applied, then the axial currents  $I_1, \dots, I_{n+1}$  are related to the potentials  $V_1, \dots, V_n$  by the equations

$$I_k = \frac{\pi g_A r_{k-1} r_k}{h(\lambda_k - \lambda_{k-1})} (V_{k-1} - V_k),$$

$$k = 1, \dots, (n+1) \quad (12)$$

where it is understood that  $\lambda_0 = 0$ ,  $\lambda_{n+1} = 1$ ,  $r_0 = r_P$ ,  $r_{n+1} = r_D$ ,  $V_0 = V_P$  and  $V_{n+1} = V_D$ . Equation (12) are rearranged in the form

$$V_{k-1} - V_k = \frac{h}{\pi g_A} \frac{(\lambda_k - \lambda_{k-1})}{r_{k-1} r_k} I_k,$$

$$k = 1, \dots, (n+1).$$

By recognising that  $V_k - V_P$  is the sum of the potential differences across the first  $k$  sub-segments, it follows immediately from the previous equation that

$$V_k = V_P - \frac{h}{\pi g_A} \sum_{j=1}^k \frac{(\lambda_j - \lambda_{j-1})}{r_{j-1} r_j} I_j,$$

$$k = 1, \dots, n. \quad (13)$$

If  $\lambda_k$  is the point of application of an exogenous input of strength  $\mathcal{I}_k(t)$  then

$$I_{k+1} + \mathcal{I}_k(t) = I_k. \quad (14)$$

On the other hand, if there is a synapse at  $\lambda_k$ , then  $\mathcal{I}_k = g_k(t)(V_k - E_k)$  and conservation of current requires that

$$I_{k+1} + g_k(V_k - E_k) = I_k. \quad (15)$$

Formula (13) for  $V_k$  is now used to rewrite Eq. (15) in terms of axial currents to get

$$I_k - I_{k+1} + \frac{g_k h}{\pi g_A} \sum_{j=1}^k \frac{(\lambda_j - \lambda_{j-1})}{r_{j-1} r_j} I_j$$

$$= g_k(V_P - E_k), \quad k = 1, \dots, n. \quad (16)$$

Thus conservation of current at the points  $\lambda_1, \dots, \lambda_n$  gives rise to  $n$  equations for the  $(n+1)$  currents  $I_1, \dots, I_{n+1}$ . In order to complete the system of equations specifying  $I_1, \dots, I_{n+1}$ , note that the potentials at the proximal and distal boundaries of the segment are known, and that this condition constrains the currents  $I_1, \dots, I_{n+1}$  to satisfy

$$\sum_{j=1}^{n+1} \frac{(\lambda_j - \lambda_{j-1}) r_P r_D}{r_{j-1} r_j} I_j = \frac{\pi g_A r_P r_D}{h} (V_P - V_D). \quad (17)$$

Equation (17) is obtained from Eq. (13) by asserting that  $V_{n+1} = V_D$ . Note also that Eq. (17) has been

multiplied by the factor  $r_P r_D$  for the benefit of numerical work to make the coefficients of the currents in the rescaled equation order one. To summarise, the currents  $I_1, \dots, I_{n+1}$  are determined by solving the linear equations

$$\begin{aligned} I_k - I_{k+1} &= \mathcal{I}_k(t) \\ I_k - I_{k+1} + \frac{g_k h}{\pi g_A} \sum_{j=1}^k \frac{(\lambda_j - \lambda_{j-1})}{r_{j-1} r_j} I_j &= g_k (V_P - E_k), \\ \sum_{j=1}^{n+1} \frac{(\lambda_j - \lambda_{j-1}) r_P r_D}{r_{j-1} r_j} I_j &= \frac{\pi g_A r_P r_D}{h} (V_P - V_D) \end{aligned} \quad k = 1, \dots, n \quad (18)$$

where the first equation is used if  $\lambda_k$  is the location of an exogenous point input and the second equation is used if  $\lambda_k$  is the location of a synapse. The following example illustrates an application of Eq. (18) to the case of a single synapse and a single exogenous input.

**Example.** Consider a segment which receives synaptic input of conductance  $g_1(t)$  at  $\lambda_1$  and exogenous current  $\mathcal{I}_2(t)$  at  $\lambda_2$  where  $0 < \lambda_1 < \lambda_2 < 1$ . This partitioning of the segment gives rise to three currents  $I_1$ ,  $I_2$  and  $I_3$ . The determination of  $I_P$  and  $I_D$  will require expressions for  $I_1$  and  $I_3$  in terms of the known conductance  $g_1(t)$ , the known current  $\mathcal{I}_2(t)$ , the geometry of the segment, and finally, the potentials  $V_P$  and  $V_D$  at the proximal and distal boundaries of the segment. The formulation of this problem will involve the current  $I_2$  as an auxiliary variable, but the solution for  $I_2$  is not sought. It follows from Eq. (18) that  $I_1$ ,  $I_2$  and  $I_3$  satisfy

$$\begin{aligned} I_1 - I_2 + \frac{g_1(t)h}{\pi g_A} \frac{(\lambda_1 - \lambda_0)}{r_0 r_1} I_1 &= g_1(t)(V_P - E_1), \\ I_2 - I_3 &= \mathcal{I}_2(t), \\ \frac{(\lambda_1 - \lambda_0)r_0 r_3}{r_0 r_1} I_1 + \frac{(\lambda_2 - \lambda_1)r_0 r_3}{r_1 r_2} I_2 + \frac{(\lambda_3 - \lambda_2)r_0 r_3}{r_2 r_3} I_3 &= \frac{\pi g_A r_0 r_3}{h} (V_P - V_D). \end{aligned} \quad (19)$$

The first Equation in (19) is Eq. (16) applied at the location of the synapse ( $\lambda = \lambda_1$ ), and the second equation in (19) is Eq. (14) applied at the location of the exogenous current ( $\lambda = \lambda_2$ ). The last equation in (19) is the

the consistency condition expressed by Eq. (17). Equations (19) can be expressed in matrix form  $AX = B$  where  $X = [I_1, I_2, I_3]^T$  and

$$A = \begin{bmatrix} 1 + \frac{g_1(t)h}{\pi g_A} \frac{(\lambda_1 - \lambda_0)}{r_0 r_1} & -1 & 0 \\ 0 & 1 & -1 \\ \frac{(\lambda_1 - \lambda_0)r_3}{r_1} & \frac{(\lambda_2 - \lambda_1)r_0 r_3}{r_1 r_2} & \frac{(\lambda_3 - \lambda_2)r_0}{r_2} \end{bmatrix},$$

$$B = \begin{bmatrix} g_1(t)(V_P - E_1) \\ \mathcal{I}_2(t) \\ \frac{\pi g_A r_0 r_3}{h} (V_P - V_D) \end{bmatrix}.$$

It is a matter of careful algebra to show that the currents  $I_1$  and  $I_3$  are given by the expressions

$$\begin{aligned} I_1 &= \frac{\frac{\pi g_A r_0 r_3}{h} (V_P - V_D) + (1 - \lambda_1) \frac{r_0}{r_1} g_1(t)(V_P - E_1) + \mathcal{I}_2(t)(1 - \lambda_2) \frac{r_0}{r_2}}{1 + \frac{\lambda_1(1 - \lambda_1)h g_1(t)}{\pi g_A r_1^2}}, \\ I_3 &= \frac{\frac{\pi g_A r_0 r_3}{h} \left( 1 + \frac{\lambda_1 h g_1(t)}{\pi g_A r_0 r_1} \right) (V_P - V_D) - \frac{\lambda_1 r_3}{r_1} g_1(t)(V_P - E_1) - \mathcal{I}_2(t) \frac{r_3}{r_2} \left( \lambda_2 + \frac{\lambda_1(\lambda_2 - \lambda_1)h g_1(t)}{\pi g_A r_1^2} \right)}{1 + \frac{\lambda_1(1 - \lambda_1)h g_1(t)}{\pi g_A r_1^2}}. \end{aligned} \quad (20)$$

Of course, the complexity of these expressions for  $I_1$  and  $I_3$  is in part due to the fact that they combine the axial current in the segment in the absence of point input with the modification to this current due to the presence of the synaptic input at  $\lambda = \lambda_1$  and the exogenous input at  $\lambda = \lambda_2$ . The perturbations  $I_P = I_1 - I_{PD}$  and  $I_D = I_3 - I_{PD}$  to the axial current at the proximal and distal boundaries of the segment are now calculated from formulae (3) and (20) to give

$$\begin{aligned} I_P &= \frac{\frac{r_0(1 - \lambda_1)}{r_1} g_1(t)(\psi_1 - E_1) + \mathcal{I}_2(t)(1 - \lambda_2) \frac{r_0}{r_2}}{1 + \frac{\lambda_1(1 - \lambda_1)h g_1(t)}{\pi g_A r_1^2}}, \\ -I_D &= \frac{\frac{\lambda_1 r_3}{r_1} g_1(t)(\psi_1 - E_1) + \mathcal{I}_2(t) \frac{r_3}{r_2} \left[ \lambda_2 + \frac{g_1(t)h \lambda_1(\lambda_2 - \lambda_1)}{\pi g_A r_1^2} \right]}{1 + \frac{\lambda_1(1 - \lambda_1)h g_1(t)}{\pi g_A r_1^2}}. \end{aligned} \quad (21)$$



where  $\psi_1$  is the potential

$$\psi_1 = \frac{r_0(1 - \lambda_1)V_P + r_3\lambda_1 V_D}{r_1}. \quad (22)$$

It is clear from (4) that  $\psi_1$  would be the model potential at  $\lambda = \lambda_1$  in the absence of transmembrane current, and therefore  $g_1(t)(\psi_1 - E_1)$  would be the transmembrane current supplied by the synapse at  $\lambda = \lambda_1$  assuming that this synaptic current is negligible by comparison with the axial current. Furthermore, if the common denominator of expressions (21) is treated as unity, then expressions (21) simplify to

$$I_P = \frac{r_0(1 - \lambda_1)}{r_1} g_1(t)(\psi_1 - E_1) + \mathcal{I}_2(t)(1 - \lambda_2)\frac{r_0}{r_2}, \quad (23)$$

$$-I_D = \frac{\lambda_1 r_3}{r_1} g_1(t)(\psi_1 - E_1) + \mathcal{I}_2(t)\frac{r_3}{r_2} \lambda_2,$$

which are identical to Eq. (10) with  $\mathcal{I}_1 = g_1(t)(\psi_1 - E_1)$  and  $\mathcal{I}_2 = \mathcal{I}(t)$ . Expressions (23) are those that would follow from making the assumption that transmembrane current is negligible by comparison with axial current in the presence of synaptic input. Consequently, the use of expressions (23) for  $I_P$  and  $I_D$  would overestimate the true strength of both the synaptic and the exogenous input to a segment. In conclusion, synaptic and exogenous input do not act independently when a segment receives both types of point process input.

The second stage of the analysis deals with the construction and numerical solution of the equations constructed from the particular configuration of synapses and exogenous input, and is given in Appendix 1.

#### 4.3. Distributed Transmembrane Current

All distributed transmembrane current is treated using Eq. (7) with appropriate expressions for  $J(\lambda, t)$ , and with occurrences of the membrane potential approximated by expression (4). Capacitative current and intrinsic voltage-dependent current are considered separately.

**4.3.1. Capacitative Transmembrane Current.** The component of capacitative current in (9) is estimated by approximating the true membrane potential along

the segment by expression (4) to obtain

$$\begin{aligned} J^{\text{cap}}(\lambda, t) &= 2\pi c_M(\lambda)r(\lambda)\frac{dV(\lambda, t)}{dt} \\ &= 2\pi c_M(\lambda)\left[(1 - \lambda)r_P\frac{dV_P}{dt} + \lambda r_D\frac{dV_D}{dt}\right]. \end{aligned} \quad (24)$$

It now follows from expressions (7) that the contributions made by capacitative transmembrane current to  $I_P$  and to  $I_D$  are

$$\begin{aligned} I_P^{\text{cap}} &= 2\pi r_P h \left[ r_P \frac{dV_P}{dt} \int_0^1 \frac{(1 - \lambda)^2 c_M(\lambda) d\lambda}{(1 - \lambda)r_P + \lambda r_D} \right. \\ &\quad \left. + r_D \frac{dV_D}{dt} \int_0^1 \frac{\lambda(1 - \lambda)c_M(\lambda) d\lambda}{(1 - \lambda)r_P + \lambda r_D} \right], \end{aligned} \quad (25)$$

$$\begin{aligned} -I_D^{\text{cap}} &= 2\pi r_D h \left[ r_P \frac{dV_P}{dt} \int_0^1 \frac{\lambda(1 - \lambda)c_M(\lambda) d\lambda}{(1 - \lambda)r_P + \lambda r_D} \right. \\ &\quad \left. + r_D \frac{dV_D}{dt} \int_0^1 \frac{\lambda^2 c_M(\lambda) d\lambda}{(1 - \lambda)r_P + \lambda r_D} \right]. \end{aligned}$$

If the compartment is a uniform cylinder with constant specific membrane capacitance, the perturbations in axial current at the proximal and distal boundaries of the segment may be computed by evaluating the integrals in formulae (25) to get

$$\begin{aligned} I_P^{\text{cap}} &= \frac{C}{6} \left[ 2\frac{dV_P}{dt} + \frac{dV_D}{dt} \right], \\ -I_D^{\text{cap}} &= \frac{C}{6} \left[ \frac{dV_P}{dt} + 2\frac{dV_D}{dt} \right] \end{aligned} \quad (26)$$

where  $C$  is the total membrane capacitance of the segment. The calculation for tapered segments with non-uniform membrane specific capacitance is presented in Appendix 2.

**4.3.2. Intrinsic Voltage-Dependent Transmembrane Current.** The construction of  $I_P^{\text{cap}}$  and  $I_D^{\text{cap}}$  for a membrane with non-constant specific capacitance provides the framework for treating intrinsic voltage-dependent transmembrane current. For an ionic species  $\alpha$ , this current is usually described by the constitutive formula  $J = g_\alpha(\theta)(V - E_\alpha)$  where  $V$  is the membrane potential,  $E_\alpha$  is the reversal potential for species  $\alpha$  and  $g_\alpha(\theta)$  is a membrane conductance which depends on a set of auxiliary variables  $\theta$ , for example, the probabilities

556  $m$ ,  $n$  and  $h$  appearing in the Hodgkin-Huxley (1952)  
557 model.

558 In the case of a *passive* membrane, the conductance  
559  $g_\alpha(\theta)$  takes a constant (but different) value for each  
560 species. The total transmembrane current density is ob-  
561 tained by summing the transmembrane current densi-  
562 ties of each ionic species to get

$$J = \sum_{\alpha} g_{\alpha}(V - E_{\alpha}) = g_M(V - E),$$

$$g_M = \sum_{\alpha} g_{\alpha}, \quad E = \sum_{\alpha} \frac{g_{\alpha}}{g_M} E_{\alpha}. \quad (27)$$

563 Thus the constitutive equation for the transmembrane  
564 current density of a passive membrane is  $J = g_M(V -$   
565  $E)$  where  $g_M$  (mS/cm<sup>2</sup>) is the total membrane conduc-  
566 tance and  $E$  plays the role of a reversal potential. When  
567 the segment is a uniform cylinder with a membrane of  
568 constant conductance, the contributions to  $I_P$  and  $I_D$   
569 mimic formulae (26) for capacitive current and are  
570 respectively

$$I_P^{\text{IVDC}} = \frac{G}{6} [2(V_P - E) + (V_D - E)],$$

$$-I_D^{\text{IVDC}} = \frac{G}{6} [(V_P - E) + 2(V_D - E)] \quad (28)$$

571 where  $G$  is the total membrane conductance of the  
572 segment. The treatment of tapered segments with  
573 non-uniform membrane conductance is presented in  
574 Appendix 3.

## 575 5. Comparison of the Traditional and New 576 Approaches to Compartmental Modelling

577 Two simulation studies are used to compare the perfor-  
578 mance of the traditional and new compartmental mod-  
579 els. These studies are based on a branched model neu-  
580 ron with known expression for the somal potential in re-  
581 sponse to large scale exogenous input (see Appendix 4).  
582 The first study examines the accuracy with which each  
583 type of compartmental model estimates this somal po-  
584 tential, and uses the NEURON simulator (Hines and  
585 Carnevale, 1997) as an example of a traditional com-  
586 partmental model. The second study assesses the ac-  
587 curacy of the two types of models by comparing the  
588 statistics of the spike train output generated by each  
589 model when the test neuron is subjected to large scale  
590 synaptic input. Here a traditional compartmental model  
591 developed by the authors is used. This model gave re-  
592 sults identical to those of NEURON in the first study.

Finally, a time step of one microsecond is used in the  
numerical integration of each compartmental model to  
ensure that errors in temporal integration make no sig-  
nificant contribution to the error in the calculation of  
membrane potential.

### 5.1. The Test Neuron

One way to construct a branched test neuron with a  
closed form solution for the somal potential is to choose  
the radii and lengths of its sections such that the Rall  
conditions for an equivalent cylinder are satisfied (Rall,  
1964). These conditions require that the sum of the  
three-halves power of the diameters of the child limbs  
is equal to the three-halves power of the diameter of  
the parent limb at any branch point, and that the total  
electrotonic length from a branch point or the soma to  
a dendritic tip is independent of path. The test neuron  
illustrated in Fig. 3 satisfies these conditions. When the  
Rall conditions are satisfied, the effect at the soma of  
any configuration of input on the branched model of  
the neuron is identical to the effect at the soma of the  
unbranched equivalent cylinder with biophysical prop-  
erties and configuration of input determined uniquely  
from those of the original branched neuron (Lindsay  
et al., 2003).

The high degree of accuracy used in the specifica-  
tion of the dendritic radii and section lengths of the test  
neuron is required to ensure that the equivalent cylin-  
der is an adequate representation of the test neuron.  
The membrane of the test neuron is assigned a specific  
conductance of 0.091 mS/cm<sup>2</sup> ( $g_M$ ) and specific capaci-  
tance of 1.0  $\mu$ F/cm<sup>2</sup> ( $c_M$ ), and has axoplasm of conduc-  
tance 14.286 mS/cm<sup>2</sup> ( $g_A$ ). With these biophysical  
properties, the equivalent cylinder has length one elec-  
trotonic unit. The soma of the test neuron is assumed  
to have membrane area  $A_S$ , and specific conductance  
 $g_S$  and specific capacitance  $c_S$  identical to that of the  
dendritic membrane. The analytical expression for its  
somal potential is given in Appendix 4.

### 5.2. First Simulation Study

In this study, the performance of a traditional and  
the new compartmental model is compared by as-  
sessing the accuracy with which both models deter-  
mine the time course of the somal potential of the  
test neuron (Fig. 3) when the neuron is subjected to  
large scale exogenous point input. Each simulation dis-

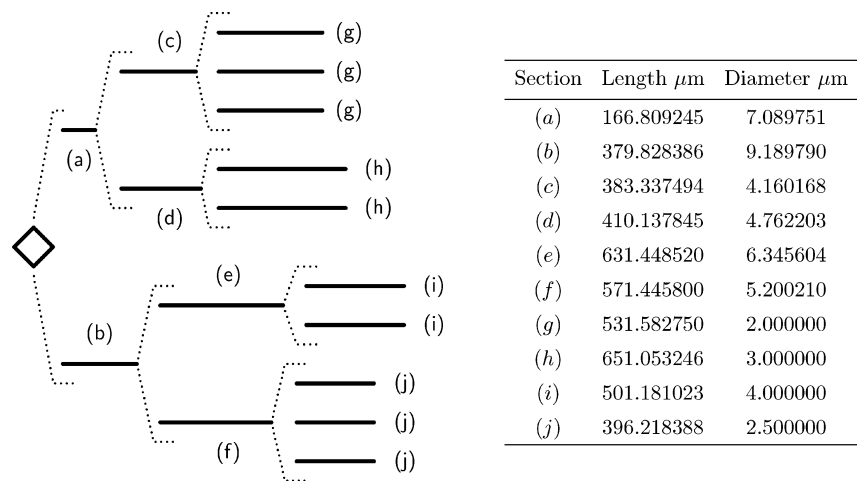


Figure 3. A branched neuron satisfying the Rall conditions. The diameters and lengths of the dendritic sections are given in the right hand panel of the figure. At each branch point, the ratio of the length of a section to the square root of its radius is fixed for all children of the branch point.

tributes 75 point inputs at random over the dendritic tree of the test neuron, where each input has strength  $2 \times 10^{-5} \mu\text{A}$ . These inputs are then mapped to positions on the Rall equivalent cylinder at the same electrotonic distance from the soma (assumed to be a sphere of diameter  $40 \mu\text{m}$ ). The time course of the potential at the soma of the equivalent cylinder due to the combined effect of these inputs is determined analytically and taken to be the reference potential against which error in both compartmental models is measured. The difference between a computed potential and its exact value is determined at one millisecond intervals in the first 10 milliseconds of the simulation, and each difference is divided by the exact potential at that time to get a relative measure of error. The simulation procedure is repeated 2000 times to determine the statistics of the relative error for each of 13 different levels of spatial discretisation (number of compartments).

**5.2.1. Results.** The results for this study are set out in Table 2. This table shows the common logarithms of the mean value of the modulus of the relative error and the standard deviation of that error estimated ten milliseconds after the initiation of the stimulus. Similar results (not shown) hold for all times at which the errors were estimated. The left hand panel of Fig. 4 shows regression lines of the common logarithms of the modulus of the mean relative error (denoted by  $\overline{RE}$ ) for the traditional (dashed line) and new (solid line) compartmental models on the

logarithm of the number of compartments (denoted by  $N$ ) used to represent the model neuron. These lines, based on the data in Table 2, have equations

$$\begin{aligned} \log_{10} \overline{RE}_{\text{traditional}} &= -1.09 - 1.17 \log_{10} N, \\ \log_{10} \overline{RE}_{\text{new}} &= -0.17 - 2.10 \log_{10} N \end{aligned} \quad (29)$$

in which the regressions are achieved with adjusted  $R^2$  values<sup>2</sup> of 97.4 and 99.5% respectively. In view of the very high  $R^2$  values for these regression equations, a number of conclusions can be drawn from this simulation study. For a fixed number of compartments, the error in the new compartmental model is always less than that of the traditional model. The regression Eqs. (29) support the argument made in Section 2.1 that the error in a traditional compartmental model in the presence of exogenous point current input is approximately  $O(1/n)$ , whereas the comparable error in the new compartmental model is approximately  $O(1/n^2)$ . In practical terms, for example, the regression results (29) suggest that the new compartmental model with 100 compartments achieves approximately the same level of accuracy as a traditional model with 500 compartments.

The standard deviation (SD) of the modulus of the relative error can be regarded as an indicator of the reliability of a single application of the model. The right hand panel of Fig. 4 shows regression lines of the common logarithms of the standard deviation of the modulus of the relative error for the traditional (dashed line) and new (solid line) compartmental models on the logarithm of the number of compartments used to

Table 2. The result of 2000 simulations for each of 13 different levels of discretisation used in the implementation of a traditional and new compartmental model. The common logarithms of the mean value of the modulus of the relative error and the standard deviation of that error are estimated at ten milliseconds after the initiation of the stimulus.

Compartments (log <sub>10</sub> (compartments))		Traditional new model log <sub>10</sub> (mean)		Traditional new model log <sub>10</sub> (standard dev.)	
17	(1.2305)	−2.41151	−2.71945	−2.62290	−3.19338
21	(1.3222)	−2.47233	−2.77674	−2.69851	−3.24583
34	(1.5314)	−2.94299	−3.41196	−3.06731	−3.88820
41	(1.6127)	−3.04729	−3.62138	−3.17081	−4.14997
54	(1.7323)	−3.21258	−3.89150	−3.34889	−4.41251
61	(1.7853)	−3.24692	−3.91268	−3.37653	−4.45051
75	(1.8750)	−3.35180	−4.12056	−3.46881	−4.65463
82	(1.9138)	−3.39846	−4.23567	−3.51591	−4.76498
93	(1.9684)	−3.45602	−4.30636	−3.57633	−4.82045
193	(2.2855)	−3.77417	−4.94731	−3.89829	−5.47886
293	(2.4668)	−3.94409	−5.31876	−4.07811	−5.84771
390	(2.5910)	−4.08234	−5.57349	−4.20025	−6.10791
495	(2.6946)	−4.15996	−5.78252	−4.28525	−6.32790

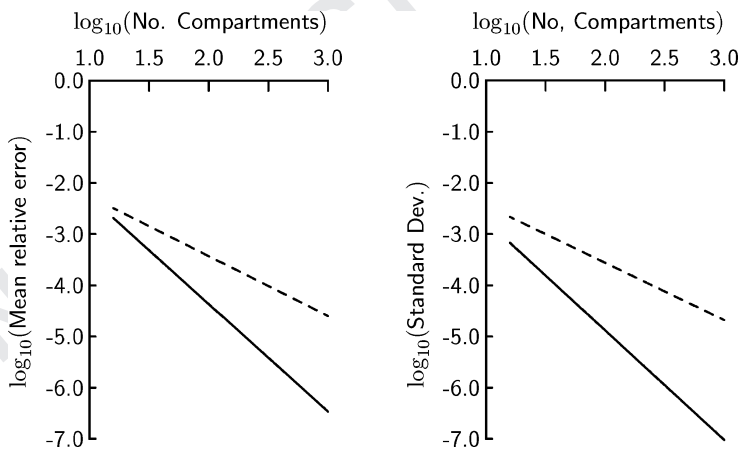


Figure 4. The left panel shows the regression lines of the common logarithm of the mean relative errors in the new compartmental model (solid line) and a traditional compartmental model (dashed line) against the common logarithm of the number of compartments. All errors are measured ten milliseconds after initiation of the stimulus. The right panel shows the regression lines for the standard deviations of the mean relative errors for the new compartmental model (solid line) and for a traditional compartmental model (dashed line).

represent the model neuron. These lines, based on the data in Table 2, have equations

$$\begin{aligned} \log_{10} \text{SD}_{\text{traditional}} &= -1.32 - 1.12 \log_{10} N, \\ \log_{10} \text{SD}_{\text{new}} &= -0.60 - 2.14 \log_{10} N \end{aligned} \quad (30)$$

in which the regressions are achieved with adjusted  $R^2$

values of 98.7 and 99.4% respectively. These regression lines show that the new compartmental model is more reliable than a traditional compartmental model. For example, a traditional compartmental model requires at least 100 compartments to give a standard deviation of the modulus of the relative error that is smaller than that of the new compartmental model using 40 compartments.

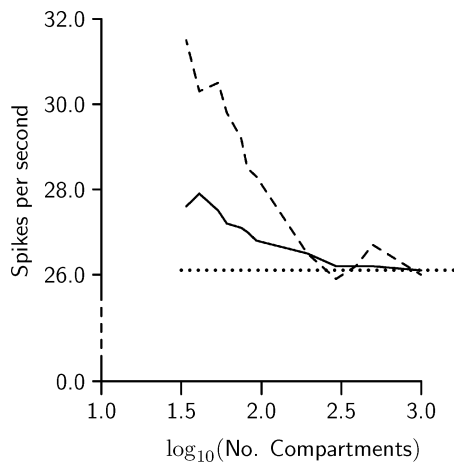


Figure 5. The spike rate plotted against the common logarithm of the number of compartments for a traditional compartmental model (dashed line) and the new compartmental model (solid line). The dotted line shows the expected spike rate.

Table 3. The spike rate estimated from a 10 second record of spike train activity obtained from a traditional and the new compartmental model at 12 different levels of spatial discretisation (number of compartments).

	Compartments (log <sub>10</sub> (Compartments))	Traditional model mean firing rate	New model mean firing rate
34	(1.5314)	31.5	27.6
41	(1.6127)	30.3	27.9
54	(1.7323)	30.5	27.5
61	(1.7853)	29.8	27.2
75	(1.8750)	29.2	27.0
82	(1.9138)	28.5	27.0
93	(1.9684)	28.3	26.8
193	(2.2855)	26.5	26.5
293	(2.4668)	25.9	26.2
390	(2.5910)	26.2	26.2
495	(2.6946)	26.7	26.2
992	(2.9965)	26.0	26.1

5.3. Second Simulation Study

In the second simulation study 100 synapses are distributed at random over the dendritic tree of the test neuron illustrated in Fig. 3. Each synapse is activated independently of all other synapses, has a maximum conductance of  $3 \times 10^{-5}$  mS and a rise time of 0.5 msec. Activation times for each synapse follow Poisson statistics with a mean rate of 30 pre-synaptic spikes per second. Spikes are generated by the soma of the test neuron using Hodgkin-Huxley kinetics. This study is based on 12 different levels of spatial discretisation (number of compartments) in which each simulation of the traditional and new compartmental models use identical synaptic firing times and identical numbers of compartments.

**5.3.1. Results.** Table 5 gives the spike rate of soma-generated action potentials based on 11 seconds of activity, the first second of which is ignored.

Figure 5 illustrates the data set out in Table 3 in which the spike rates for the traditional model (dashed line) and new model (solid line) are plotted against the common logarithm of  $N$ , the number of compartments used in each simulation. As  $N$  is increased, the spike rates generated by both models approach a common limit. However, the spike rate generated by the traditional model approaches this limit more slowly and appears to oscillate as the limit is approached. The spike rate obtained using the traditional model with 500 compartments is achieved in the new model with only

100 compartments. These differences in the number of compartments required to achieve the same level of accuracy in both models are identical to those observed in the first study.

**5.3.2. Comparison of Model-Generated Spike Trains.**

It is clear from Fig. 5 that the mean rate of the spike train generated by the new compartmental model converges more quickly to the theoretical mean spike rate than that generated by a traditional compartmental model. One would therefore infer from the behaviour of this summary statistic that the spike train generated by the former is a more accurate representation of the spiking behaviour of the test neuron in response to synaptic activity than that generated by the latter. To investigate the validity of this inference requires an accurate comparison of the times of occurrence of the spikes in the spike trains generated by each model with identical synaptic activity applied to the test neuron. We take as our reference the times of occurrence of the spikes generated in ten seconds using the new compartmental model with 100 compartments (spike train  $\mathcal{N}_{100}$ ). These spike times are compared with those generated by a traditional compartmental model with 100 compartments and with 500 compartments<sup>3</sup> (spike trains  $\mathcal{T}_{100}$  and  $\mathcal{T}_{500}$  respectively). The times of occurrence of spikes in the spike trains to be compared are taken to be identical if they occur within one millisecond of each other. The comparison between  $\mathcal{N}_{100}$  and  $\mathcal{T}_{100}$  revealed 244 spikes common to both spike trains (i.e. occurring



within one millisecond of each other). There were 24 spikes unique to  $\mathcal{N}_{100}$  and 39 spikes unique to  $\mathcal{T}_{100}$ . The comparison between  $\mathcal{N}_{100}$  and  $\mathcal{T}_{500}$  revealed 258 spikes common to both spike trains with 10 spikes unique to  $\mathcal{N}_{100}$  and 9 spikes unique to  $\mathcal{T}_{500}$ . Since the reference spike train  $\mathcal{N}_{100}$  is common to both comparisons, it is clear that as the number of compartments in a traditional model increases, the spike train generated by that model will conform more closely to that generated by the new compartmental model with significantly fewer compartments.

## 6. Concluding Remarks

We have demonstrated that it is possible to achieve a significant increase in the accuracy and precision of compartmental models by developing a new compartmental model in which compartments have two potentials—one at either end of the segment which the compartment represents. The new compartment acts as fundamental unit in the construction of a model of a branched dendrite. When these compartments are connected by requiring continuity of potential and conservation of current at segment boundaries, they provide a new type of compartmental model with a mathematical form identical to that of a traditional model in the sense that both types of compartmental model involve only nearest neighbour interactions. One demonstrated benefit of the new compartmental model is that it provides a mechanism to take account of the exact location of point process input by contrast with traditional compartmental models which would assign this input to an accuracy of half the length of a segment. We would anticipate that the application of the new compartmental model would be most useful in association with experiments in which the precise timing of spikes is thought to be important (e.g., Oram et al., 1999 and the references therein) or in studies investigating the influence of the location of synaptic input on the mean rate of the spike train output (e.g., Poirazi et al., 2003).

## Appendix 1: Numerical Estimation of Perturbations to Axial Current

The example in Section 4.2 demonstrates that synaptic and exogenous input do not act independently. This means that both types of point process input must be treated simultaneously in the construction of the equations to determine the perturbations  $I_P$  and  $I_D$  of the

axial current. The equations for the perturbations in axial current are constructed by replacing  $I_k$  in Eqs. (14), (16 and (17) by  $I_{PD} + \hat{I}_k$  where  $\hat{I}_k$  is the perturbation to  $I_k$ . If  $\lambda = \lambda_k$  is the site of an exogenous input then the appropriate equation for the perturbed currents is

$$\hat{I}_k - \hat{I}_{k+1} = \mathcal{I}_k(t), \quad (31)$$

whereas if  $\lambda = \lambda_k$  is the site of a synapse with conductance  $g_k(t)$ , the appropriate equation is

$$\hat{I}_k - \hat{I}_{k+1} + \frac{g_k h}{\pi g_A} \sum_{j=1}^k \frac{(\lambda_j - \lambda_{j-1})}{r_{j-1} r_j} \hat{I}_j = \mathcal{I}_k(t) \quad (32)$$

where the current  $\mathcal{I}_k(t)$  is defined by the formula

$$\mathcal{I}_k(t) = g_k(t) \left[ (1 - \lambda_k) \frac{r_P}{r_k} V_P + \lambda_k \frac{r_D}{r_k} V_D - E_k \right]. \quad (33)$$

The derivation of Eq. (32) takes advantage of the identity

$$\sum_{j=1}^k \frac{(\lambda_j - \lambda_{j-1})}{r_{j-1} r_j} = \frac{\lambda_k}{r_P r_k},$$

which can be established by induction. Note that expression (33) for  $\mathcal{I}_k(t)$  when  $\lambda = \lambda_k$  is a synapse is precisely the current that would be expected to flow at the synapse if the distribution of potential on the segment was described by expression (4). Finally, Eq. (17) simplifies to

$$\sum_{j=1}^{n+1} \frac{(\lambda_j - \lambda_{j-1}) r_P r_D}{r_{j-1} r_j} \hat{I}_j = 0 \quad (34)$$

where the constant multiplier  $r_P r_D$  has been added without loss to make the coefficients of this equation comparable to those appearing in the first  $n$  equations. Eqs. (31), (32) and (34) may be represented compactly in matrix notation by

$$A \hat{I} + GC \hat{I} = \mathcal{I} \quad (35)$$

where  $\hat{I} = [\hat{I}_1, \dots, \hat{I}_{n+1}]^T$  is the  $(n+1)$  dimensional column vector of perturbations in axial current,  $\mathcal{I} = [\mathcal{I}_1, \dots, \mathcal{I}_n, 0]^T$  and  $A$  is the  $(n+1) \times (n+1)$  matrix

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830

$$\begin{bmatrix} 1 & -1 & 0 & \cdots & \cdots & 0 \\ 0 & 1 & -1 & \cdots & \cdots & 0 \\ 0 & 0 & 1 & \cdots & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & \cdots & 1 & -1 \\ \frac{\lambda_1 r_P r_D}{r_0 r_1} & \frac{(\lambda_2 - \lambda_1) r_P r_D}{r_1 r_2} & \frac{(\lambda_3 - \lambda_2) r_P r_D}{r_2 r_3} & \cdots & \frac{(\lambda_n - \lambda_{n-1}) r_P r_D}{r_{n-1} r_n} & \frac{(1 - \lambda_n) r_P r_D}{r_n r_{n+1}} \end{bmatrix} \quad (36)$$

831 Briefly,  $G$  is an  $(n+1) \times (n+1)$  diagonal matrix  
 832 in which the  $(k, k)$  entry is zero if  $\lambda_k$  is the site of an  
 833 exogenous input and takes the value  $g_k(t)$  if  $\lambda_k$  is the  
 834 site of a synapse. The  $(n+1, n+1)$  entry of  $G$  is always  
 835 zero. The matrix  $C$  is a lower triangular matrix of type  
 836  $(n+1) \times (n+1)$  in which all the nonzero entries in the  
 837  $k^{\text{th}}$  column take the value  $(\lambda_k - \lambda_{k-1})/(\pi g_A r_{k-1} r_k)$ .

838 *Multiple Point Inputs*

839 To take account of the influence of the matrix  $GC$  in  
 840 the solution of Eq. (35), the algorithm

$$A \hat{I}^{(m+1)} = \mathcal{I} - GC \hat{I}^{(m)} \quad (37)$$

841 is iterated with initial condition  $A \hat{I}^{(0)} = \mathcal{I}$ . Although  
 842 it can be demonstrated that the matrix  $A$  has a simple  
 843 closed form expression for its inverse, it is not (numerically)  
 844 efficient to use this expression to solve Eq. (37).  
 845 Instead, we observe that  $A$  has an  $LU$  factorisation  
 846 in which  $U$  is the  $(n+1) \times (n+1)$  upper triangular  
 847 matrix with ones everywhere in the main diagonal, negative  
 848 ones everywhere in the super-diagonal and zero  
 849 everywhere else, and  $L$  is the  $(n+1) \times (n+1)$  lower  
 850 triangular matrix

$$\begin{bmatrix} 1 & 0 & 0 & 0 & \cdots & \cdots & 0 \\ 0 & 1 & 0 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & 1 & 0 & \cdots & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \frac{\lambda_1 r_P}{r_1} & \frac{\lambda_2 r_P}{r_2} & \frac{\lambda_3 r_P}{r_3} & \frac{\lambda_4 r_P}{r_4} & \cdots & \frac{\lambda_n r_P}{r_n} & 1 \end{bmatrix} \quad (38)$$

851 Since  $\mathcal{I}$  is a linear combination of  $V_P$ ,  $V_D$  and a voltage  
 852 independent term, then the solution to Eq. (37) has  
 853 general representation

$$\hat{I} = \phi_1(t)V_P + \phi_2(t)V_D + \phi_3(t) \quad (39)$$

where  $\phi_1(t)$ ,  $\phi_2(t)$  and  $\phi_3(t)$  satisfy

854

$$\begin{aligned} A \phi_1 &= \left[ g_1(1 - \lambda_1) \frac{r_P}{r_1}, \dots, g_n(1 - \lambda_n) \frac{r_P}{r_n}, 0 \right]^T \\ &\quad - GC \phi_1, \\ A \phi_2 &= \left[ g_1 \lambda_1 \frac{r_D}{r_1}, \dots, g_n \lambda_n \frac{r_D}{r_n}, 0 \right]^T - GC \phi_2, \\ A \phi_3 &= -[g_1 E_1, \dots, g_n E_n, 0]^T - GC \phi_3. \end{aligned} \quad (40)$$

The Eqs. (40) for  $\phi_1(t)$ ,  $\phi_2(t)$  and  $\phi_3(t)$  may be solved  
 easily by an iterative procedure based on the sparse  
 $LU$  factorisation of  $A$ . If the conductances  $g_1, \dots, g_n$   
 are sufficiently small, the solution of Eqs. (40) is well  
 approximated by ignoring the second term on the right  
 hand side of Eqs. (40). This approximation is equivalent  
 to using the partitioning rule (7) in combination with  
 formula (4) for the membrane potential.

863 *Special Case of Exogenous Input*

If  $\lambda_1, \dots, \lambda_n$  are sites of exogenous input  $\mathcal{I}_1, \dots, \mathcal{I}_n$   
 then  $G = 0$  in Eq. (37) and  $\mathcal{I}$  is the vector of exogenous  
 currents. In this case, expressions (10) for  $I_P$  and  $I_D$   
 are obtained immediately as the first and last entries in  
 the solution  $\hat{I}$  of equation  $A \hat{I} = LU \hat{I} = \mathcal{I}$ .

869 **Appendix 2: The Partitioning of Capacitive  
870 Current on Tapered Cylinders**

Recall from expressions (7) that the contributions made  
 to the proximal and distal perturbations to the axial current  
 as a consequence of capacitive transmembrane  
 current on a tapered segment with membrane of variable  
 specific capacitance are respectively

$$\begin{aligned} I_P^{\text{cap}} &= 2\pi r_P h \left[ r_P \frac{dV_P}{dt} \int_0^1 \frac{(1 - \lambda)^2 c_M(\lambda) d\lambda}{(1 - \lambda) r_P + \lambda r_D} \right. \\ &\quad \left. + r_D \frac{dV_D}{dt} \int_0^1 \frac{\lambda(1 - \lambda) c_M(\lambda) d\lambda}{(1 - \lambda) r_P + \lambda r_D} \right], \\ -I_D^{\text{cap}} &= 2\pi r_D h \left[ r_P \frac{dV_P}{dt} \int_0^1 \frac{\lambda(1 - \lambda) c_M(\lambda) d\lambda}{(1 - \lambda) r_P + \lambda r_D} \right. \\ &\quad \left. + r_D \frac{dV_D}{dt} \int_0^1 \frac{\lambda^2 c_M(\lambda) d\lambda}{(1 - \lambda) r_P + \lambda r_D} \right]. \end{aligned} \quad (41)$$

876 For tapered segments ( $r_P \neq r_D$ ) with membranes of  
 877 non-uniform specific capacitance, the integrals in (41)  
 878 have values

$$\begin{aligned} I_P^{\text{cap}} &= 2\pi h r_P [c_P \psi(r_P, r_D) + c_D \phi(r_P, r_D)] \frac{dV_P}{dt} \\ &\quad + 2\pi h [c_P r_D \phi(r_P, r_D) + c_D r_P \phi(r_D, r_P)] \frac{dV_D}{dt}, \\ -I_D^{\text{cap}} &= 2\pi h [c_P r_D \phi(r_P, r_D) + c_D r_P \phi(r_D, r_P)] \frac{dV_P}{dt} \\ &\quad + 2\pi h r_D [c_P \phi(r_D, r_P) + c_D \psi(r_D, r_P)] \frac{dV_D}{dt} \end{aligned} \quad (42)$$

879 where  $c_M(\lambda) = (1 - \lambda)c_P + \lambda c_D$  and the auxiliary  
 880 functions  $\phi(x, y)$  and  $\psi(x, y)$  are defined by

$$\begin{aligned} \phi(x, y) &= \frac{x}{6(x-y)^3} \\ &\quad \times \left[ x^2 - 5xy - 2y^2 + \frac{6xy^2}{x-y} \log \frac{x}{y} \right], \\ \psi(x, y) &= \frac{x}{6(x-y)^3} \\ &\quad \times \left[ 2x^2 - 7xy + 11y^2 - \frac{6y^3}{x-y} \log \frac{x}{y} \right]. \end{aligned} \quad (43)$$

881 The evaluation of the integrals in expression (41) is  
 882 facilitated by defining the auxiliary integrals

$$\begin{aligned} \mathcal{K}_1 &= \int_0^1 \frac{(1-\lambda)^2 \hat{c}_M(\lambda) d\lambda}{\hat{r}(\lambda)}, \\ \mathcal{K}_2 &= \int_0^1 \frac{\lambda(1-\lambda) \hat{c}_M(\lambda) d\lambda}{\hat{r}(\lambda)}, \\ \mathcal{K}_3 &= \int_0^1 \frac{\lambda^2 \hat{c}_M(\lambda) d\lambda}{\hat{r}(\lambda)} \end{aligned}$$

883 and observing that  $\mathcal{K}_1$ ,  $\mathcal{K}_2$  and  $\mathcal{K}_3$  can be determined  
 884 easily from the identities

$$\begin{aligned} \mathcal{K}_1 + 2\mathcal{K}_2 + \mathcal{K}_3 &= \int_0^1 \frac{\hat{c}_M(\lambda) d\lambda}{\hat{r}(\lambda)}, \\ r_P \mathcal{K}_1 + r_D \mathcal{K}_2 &= \int_0^1 (1-\lambda) \hat{c}_M(\lambda) d\lambda, \\ r_P \mathcal{K}_2 + r_D \mathcal{K}_3 &= \int_0^1 \lambda \hat{c}_M(\lambda) d\lambda. \end{aligned}$$

885 The results given in Section 4.3.1 for a uniform segment  
 886 ( $r_P = r_D$ ) are obtained from formulae (42) by replac-  
 887 ing  $\phi(x, y)$  and  $\psi(x, y)$  with their respective limiting

values of  $1/12$  and  $1/4$  where each limit is taken as  $x \rightarrow y$ .

### Appendix 3: Partitioning of Voltage-Dependent Current on Tapered Cylinders

The construction of  $I_P^{\text{cap}}$  and  $I_D^{\text{cap}}$  for a membrane with non-constant specific capacitance provides the framework for treating intrinsic voltage-dependent transmembrane current. For tapered segments with non-constant membrane conductance, the contributions to the perturbations in the axial current at the proximal and distal boundaries of the segment are identical to expressions (42) with  $c_P$  replaced by  $g_P(V_P; \theta)$  and  $c_D$  replaced by  $g_D(V_D; \theta)$ . These contributions are

$$\begin{aligned} I_P^{\text{IVDC}} &= 2\pi h r_P [g_P(V_P; \theta) \psi(r_P, r_D) \\ &\quad + g_D(V_D; \theta) \phi(r_P, r_D)] (V_P - E) \\ &\quad + 2\pi h [g_P(V_P; \theta) r_D \phi(r_P, r_D) \\ &\quad + g_D(V_D; \theta) r_P \phi(r_D, r_P)] (V_D - E), \\ -I_D^{\text{IVDC}} &= 2\pi h [g_P(V_P; \theta) r_D \phi(r_P, r_D) \\ &\quad + g_D(V_D; \theta) r_P \phi(r_D, r_P)] (V_P - E) \\ &\quad + 2\pi h r_D [g_P(V_P; \theta) \phi(r_D, r_P) \\ &\quad + g_D(V_D; \theta) \psi(r_D, r_P)] (V_D - E) \end{aligned} \quad (44)$$

where the auxiliary functions  $\phi(x, y)$  and  $\psi(x, y)$  are defined in (43).

### Appendix 4: Analytical Solution for Soma Potential of Test Neuron

It may be shown that  $V(t)$ , the deviation of the somal transmembrane potential from its resting value as a result of a distribution  $\mathcal{I}(x, t)$  of current on a uniform cylindrical dendrite of radius  $a$  and length  $l$  attached to a soma is

$$\begin{aligned} V(t) &= e^{-t/\tau} \left[ \phi_0(t) + \sum_{\beta} \phi_{\beta}(t) e^{-\beta^2 t / L^2 \tau} \cos \beta \right], \\ L &= l \sqrt{\frac{2g_M}{ag_A}} \end{aligned} \quad (45)$$

where  $\tau$  is the time constant of the somal and dendritic membranes and  $g_M$  and  $g_A$  have their usual meanings. The summation is taken over all the solutions  $\beta$  of the transcendental equation  $\tan \beta + \gamma \beta = 0$  where  $\gamma$  (constant) is the ratio of the total membrane area of the soma

915 to the total membrane area of the dendrite. The func-  
916 tions  $\phi_0(t)$  and  $\phi_\beta(t)$  are solutions of the differential  
917 equations

$$\begin{aligned}\frac{d\phi_0}{dt} &= -\frac{e^{t/\tau}}{C_D + C_S} \left[ \mathcal{I}_S(t) + \int_0^l \mathcal{I}(x, t) dx \right], \\ \frac{d\phi_\beta}{dt} &= -\frac{2e^{(1+\beta^2/L^2)t/\tau}}{C_D + C_S \cos^2 \beta} \left[ \int_0^1 \mathcal{I}(x, t) \cos \beta \right. \\ &\quad \left. \times (1 - x/l) dx + \cos \beta \mathcal{I}_S(t) \right] \quad (46)\end{aligned}$$

918 with initial conditions  $\phi_0(0) = \phi_\beta(0) = 0$ , that is,  
919 the neuron is initialised at its resting potential. The  
920 parameters  $C_S$  and  $C_D$  denote respectively the total  
921 membrane capacitances of the soma and dendrite, and  
922  $\mathcal{I}_S(t)$  is the current supplied to the soma.  
923 In the special case in which point currents  
924  $\mathcal{I}_1(t), \dots, \mathcal{I}_n(t)$  act at distances  $x_1, \dots, x_n$  from the  
925 soma of the uniform cylinder, the corresponding co-  
926 efficient functions  $\phi_0$  and  $\phi_\beta$  satisfy

$$\begin{aligned}\frac{d\phi_0}{dt} &= -\frac{e^{t/\tau}}{C_D + C_S} \left[ \mathcal{I}_S(t) + \sum_{k=1}^n \mathcal{I}_k(t) \right], \\ \frac{d\phi_\beta}{dt} &= -\frac{2e^{(1+\beta^2/L^2)t/\tau}}{C_D + C_S \cos^2 \beta} \\ &\quad \times \left[ \sum_{k=1}^n \mathcal{I}_k(t) \cos \beta (1 - x_k/l) + \cos \beta \mathcal{I}_S(t) \right]. \quad (47)\end{aligned}$$

## 927 Acknowledgment

928 A.E. Lindsay would like to thank the Well-  
929 come Trust for the award of Vacation Scholarship  
930 (VS/03/GLA/8/SL/TH/FH).

## Notes

1. Following the terminology of Hines and Carnevale (Hines97, a point process is taken to mean either synaptic input (voltage-dependent) or an exogenous point current input (voltage-independent). 932 933 934 935
2.  $R^2$  measures the proportion of the total variation of the dependent variable about its mean value that is explained by the regression, and necessarily takes a value between zero and one expressed as a percentage. 936 937 938 939
3. All the simulations were run on a PC with dual Athlon 1500MP processors. The times required to simulate 10 seconds of spike train data were 61 minutes for the new compartmental model with 100 compartments, 41 minutes and 353 minutes for a traditional compartmental model with 100 and 500 compartments respectively. In the presence of point current input alone, the computational times for both models are identical. 940 941 942 943 944 945 946 947

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