An Intra-body Linear Channel Model Based on Neuronal Subthreshold Stimulation

Alireza Khodaei
Department of Computer Science and Engineering
University of Nebraska-Lincoln
Lincoln, Nebraska 68588 USA
Email: akhodaei@cse.unl.edu

Massimiliano Pierobon
Department of Computer Science and Engineering
University of Nebraska-Lincoln
Lincoln, Nebraska 68588 USA
Email: pierobon@cse.unl.edu

***Abstract*—Intra-body communication networks, where natural biological processes support the realization of links for the transmission, propagation, and reception of information, are at the cutting edge research for the pervasive interconnection of future wearable and implantable devices. In particular, the study of neurons as means to propagate information between these devices is encouraged by their ubiquitous distribution within the body and the existence of well-established techniques for their electrical interfacing. In this paper, a communication system is proposed based on the so-called subthreshold electrical stimulation of a neuron, and the propagation of this stimulation along the neuron length. This stimulation technique does not result in the generation of electrochemical spikes (action potentials), naturally carrying information within the nervous system, thus reducing the interference with the normal body functionalities. The use of subthreshold stimulation allows the analytical formulation of a linear channel model for the proposed communication system by stemming from the quasi-active model of the neuron's membrane from the neurophysiology literature. Numerical results from the developed analytical models are compared to simulation results obtained through the widely-used NEURON software.**

***Index Terms*—Neuron, Intra-body Communication, Linear Channel Model, Subthreshold Stimulation, Quasi-active Model**

I. Introduction

The latest advances in micro and nano technologies are enabling the development of novel sensing and computing devices that can be easily worn or implanted inside the human body, with an ever increasing ergonomics and biocompatibility [22]. These devices monitor numerous body parameters, (e.g., glucose monitors, activity trackers) as well as stimulate or actuate biochemical processes (e.g., pacemakers, insulin pumps), or even augment the functionalities of the human body itself (e.g., smart watches, smart glasses). The interconnection of a huge number of these devices actively interacting with the biological environment into Intra-Body communication Networks (IBNs) for their access, control, and collaborative processing, recently defined within the novel paradigm of Internet of Bio-Nano Things [2], will enable new advanced applications, mostly in the biomedical field.

These pervasive and ubiquitous IBNs cannot rely on the exchange of information through classical communication solutions based on electromagnetic or acoustic technologies, especially due to their invasiveness and/or possible negative effects on health [2]. Although solutions based on opto-ultrasonic communications [21] and Terahertz band communications [1] are recently being pursued, a valid alternative stands in the utilization of natural biological processes to support the realization of links for the transmission, propagation, and reception of information [13]. In particular, the study of neurons as means to propagate information between implantable devices is encouraged by their ubiquitous distribution within the body and the existence of well-established techniques for their electrical interfacing [19]. To realize this goal, novel communication and information theoretical models are needed to understand how information can be transmitted, propagated and received by utilizing neurons and their interconnections in the nervous system.

Previous literature on the communication theoretical modeling of information propagation through neurons has mainly focused on the analysis of neuro-spike communications, which are based on the active generation and propagation of electrochemical spikes (action potentials) naturally used by our body to transmit information through the nervous system [3], [24]. In particular, in [4], while the authors develop a detailed physical channel model of the natural propagation of neuro-spikes between two interconnected neurons, they do not suggest any means for their external stimulation and the propagation of non-naturally-generated information. In [5], a communication theoretical model is developed to capture the behavior of a specific part of a neuron, the dendritic tree, upon the reception of natural action potentials from another adjacent neuron. Other works in the literature are focused on future techniques for intra-body neuron stimulation of electrochemical spikes through implantable nanotechnology-enabled devices [15].

In this paper, we study the transmission of information through a neuron without active generation of action potentials, through the use of the so-called subthreshold electrical stimulation [18]. This technique has the potential to limit the interference with the natural neuro-spike communications within the nervous system, as the applied stimuli do not generally propagate from one neuron to another (through chemical synapses) [26], with the final goal of ensuring orthogonality between natural communications and IBNs. In addition, the subthreshold communications could minimize other adverse interfering phenomena caused by the stronger neuro-spikes electrical activity, such as those reportedly impacting axon

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myelination [25], plasticity and learning capabilities [8].

In particular, we define a communication system where the sender stimulates a neuron by injecting a modulated current at a particular neuron's location (soma), the neuron propagates the stimulus along its length, and the receiver recovers the stimulus by reading the voltage of the neuron's membrane at a location away from the sender. The study of a communication channel along a single neuron is motivated by the fact that a neuron length can reach over one meter within the human body (e.g., dorsal root ganglion that carries touch stimuli from the toe through the spinal cord towards the brain) [18], thus effectively serving the purpose of interconnecting devices placed at remote body locations. By ensuring a subthreshold stimulation at the sender, we analytically develop a linear channel model by stemming from the quasi-active model of the neuron's membrane from the neurophysiology literature [11]. Numerical results from the developed analytical models for a particular neuron physiology show a good match when compared to simulation results obtained through the NEURON [6] software, widely used in computational neuroscience.

The paper is organized as follows. In Sec. II the proposed communication system based on the electrical stimulation of a neuron is presented. In Sec. III we detail the analytical derivation of the linear channel model underlying the proposed communication system, while in Sec. IV we compare numerical results from the analytical model and the NEURON simulator. Finally, in Sec. V we conclude the paper.

II. A Neuron-based Communication System

We propose a communication system that utilizes a neuron cell (neuron) to transmit information signals between a sender and a receiver. For the purpose of the following analysis, a neuron can be considered as an electrically excitable structure that propagates electrical stimuli along its length. In particular, as shown in Fig. 1, a neuron is composed of a dendritic tree, a soma, and an axon [18]. The dendritic tree is an arbitrary branching of electrically-conductive projections from the cell body, the soma is the main cell's body that contains the nucleus and other organelles, and the axon is the projection from the soma that propagates the electrical excitation along its length. The electrical properties of the dendritic tree, the soma, and the axon derive from the fact that the neuron is bound by a lipid bylayered membrane that separates the intracellular from the extracellular environments, which in general have different concentrations of ions, or electrically-charged molecules. This concentration difference, created and maintained by specific mechanisms at the neuron membrane, results in an electrical potential across the membrane itself. We assume that when no external perturbation is applied to the neuron, the membrane potential is constant and homogeneous throughout the neuron, and equal to the resting potential E_m, in agreement with widely accepted models from the neurophysiology literature [23].

The communication system proposed in this paper, as shown in Fig. 1, is composed of a **Sender**, which modulates the injection of an electrical current into the soma according to

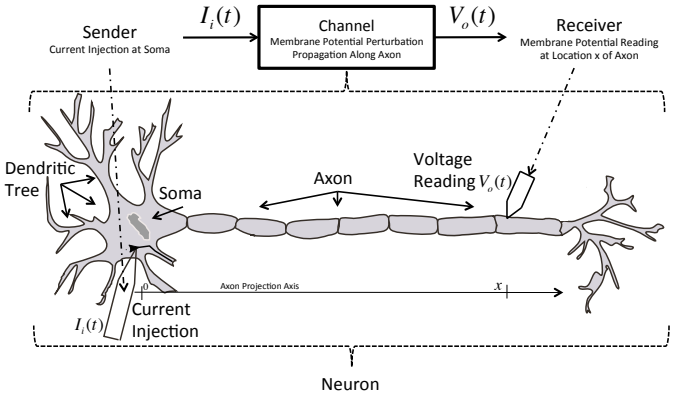

Fig. 1: Scheme of the proposed neuron-based communication system

a signal to be transmitted; a **Channel**, which corresponds to the membrane potential perturbation resulting from the current injection, and its propagation along the axon; and a **Receiver**, which recovers the transmitted signal by reading the membrane potential at a location along the axon away from the soma. In particular, we assume that the sender injects the current $I_i(t)$, as function of the time t, into the soma through a technique called somatic current injection [19], where a microelectrode penetrates the membrane at the soma and releases electrical current into the intracellular space. The injected current, and the consequent local perturbation of the membrane potential around the aforementioned resting potential, are propagated within the neuron in two main directions, namely, within the dendritic tree displaced around the soma, and along the axon. We assume that the receiver is realized through an intracellular electrode through which we read the membrane voltage $V_o(t)$ at a distance x along the axon projection axis from the soma.

Within the aforementioned system, we obtain a communication channel model based on the propagation of the membrane potential perturbation from the current injection to a location x along the axon. As detailed in Sec. III, while the physical processes underlying this model are in general characterized by non-linear behaviors, it is possible to obtain a linear channel model when the proposed communication system meets determinate conditions, i.e., subthreshold stimulation. The obtained channel model is deterministic, since within the scope of this paper we do not take into account noise arising from natural stochastic perturbations observed in neuronal membrane potential [14]. Nevertheless, we believe that this deterministic channel model is the first necessary step to explore the proposed communication system, and in our future work we plan to incorporate on top of it realistic models of the potential noise sources as well as the impact of interference with natural communication in the nervous system. We also plan to assess the performance of our model by analyzing throughput, packet loss, and average delay.

III. Linear Channel Model

We express a linear channel model of a neuron between a sender that injects the current $I_i(t)$, as function of the time t at the soma, and a receiver that reads the membrane potential

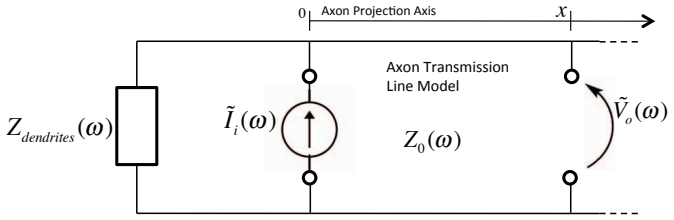

Fig. 2: Equivalent circuit of the linear channel model.

$V_o(t) = V(x,t)$ at distance x along the axon at time t. This model is expressed in the frequency ω domain as follows:

$$\tilde{V}_o(\omega) = Z(x,\omega)\tilde{I}_i(\omega)\,, \tag{1}$$

where $\tilde{I}_i(\omega)$ and $\tilde{V}_o(\omega)$ are the Fourier transforms of $I_i(t)$ and $V_o(t)$, respectively. The equivalent circuit of the linear channel model is shown in Fig. 2, which is valid if the injected current $\tilde{I}_i(\omega)$ satisfies the subthreshold stimulation conditions, expressed in Sec. III-A. In this circuit, the dendritic tree is modeled as an impedance $Z_{dendrites}(\omega)$ as function of the frequency ω, whose calculation is expressed in Sec. III-D, while the axon is modeled as an infinite transmission line extending from the soma with characteristic impedance $Z_0(\omega)$, expressed in (9). According to transmission lines and lumped circuit theory [16], the transimpedance $Z(x,\omega)$ as function of the distance x along the axon and the frequency ω is expressed as follows:

$$Z(x,\omega) = \frac{Z_{soma}(\omega)}{Z_0(\omega)} Z_{axon}(x,\omega)\,, \tag{2}$$

where $Z_{axon}(x,\omega)$ is the transimpedance of the axon at distance x from the soma and frequency ω, expressed in Sec. III-C, and $Z_{soma}(\omega)$ is the equivalent impedance at the soma where the sender injects the current $\tilde{I}_i(\omega)$, and it is expressed as the electrical parallel [16] between $Z_{dendrites}(\omega)$ and $Z_0(\omega)$:

$$Z_{soma}(\omega) = \frac{Z_{dendrites}(\omega)Z_0(\omega)}{Z_{dendrites}(\omega) + Z_0(\omega)}\,. \tag{3}$$

As detailed in the following, $Z_{dendrites}(\omega)$, $Z_{axon}(x,\omega)$, and $Z_0(\omega)$ are functions of the transmembrane impedance $Z_m(\omega)$ expressed in (5).

A. Subthreshold Stimulation Condition

Upon injection of electrical current, the membrane potential of a neuron varies around the aforementioned resting potential E_m. If the membrane potential of a neuron exceeds a value termed as threshold potential V_{th}, the neuron undergoes a process called action potential stimulation, where the membrane potential raises and falls with a predetermined trajectory as function of the time [18].

The linear channel model expressed in this section is valid only when the membrane potential maintains a value less than V_{th}, named subthreshold condition. This is realized when the current $\tilde{I}_i(\omega)$ injected by the sender in the neuron soma satisfies the subthreshold stimulation condition, expressed as

$$\tilde{I}_i(\omega) : \tilde{V}_o(x,\omega)\,|_{x=0} = Z_{soma}(\omega)\tilde{I}_i(\omega) < V_{th}\,, \tag{4}$$

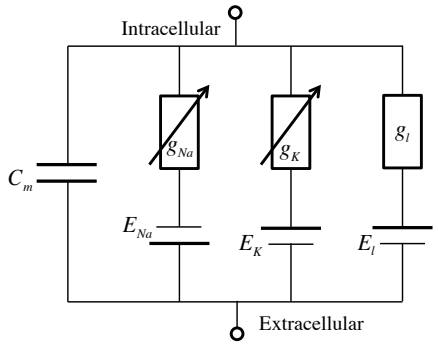

Fig. 3: Hudgkin-Huxley model of an isopotential membrane patch.

where $x = 0$ denotes the location of the soma along the axon coordinate x. If (4) is satisfied (at the soma), then the subthreshold condition is satisfied at any other membrane location, since the equivalent circuit in Fig. 2 is composed of passive elements other than the current injection at the soma [16]. V_{th} typically ranges from -60mV to -55mV, depending on the electrophysiological characteristics of the neuron [18].

B. Transmembrane Impedance $Z_m(\omega)$

The transmembrane impedance of a neuron is here defined as the ratio between the membrane potential $\tilde{V}_m(\omega)$ and the transmembrane current $\tilde{I}_m(\omega)$ of an area of neuron membrane where the membrane potential can be approximated as homogeneous, i.e., isopotential membrane patch. In this section, by applying the quasi-active neuron membrane model [11], we express of the transmembrane impedance as follows:

$$Z_m(\omega) = \frac{\tilde{V}_m(\omega)}{\tilde{I}_m(\omega)} = \frac{\alpha_3\omega^3 + \alpha_2\omega^2 + \alpha_1\omega + \alpha_0}{\beta_4\omega^4 + \beta_3\omega^3 + \beta_2\omega^2 + \beta_1\omega + \beta_0}\,, \tag{5}$$

where α_i, $i = 0,1,2,3$, and β_j, $j = 0,1,2,3,4$ are in (6) and (7), respectively. In the following, we motivate this result.

The relation between the membrane potential $v_m(t)$ and the transmembrane current $I_m(t)$ of an isopotential membrane patch of a neuron, as functions of the time t, is generally represented through the widely accepted Hudgkin-Huxley model as an electrical circuit with terminals at each side of the membrane [9], as shown in Fig. 3. The capacitance C_m models the lipid bilayer of the membrane patch, and the conductances g_{Na} and g_K model the voltage-gated ion channels, i.e., membrane pores that allow ions to pass through depending on the membrane voltage itself, for the sodium Na^+ and potassium K^+, respectively. The leak conductance g_l models leak channels, i.e., membrane pores that allow ions of various types to pass through independently from the membrane voltage, and the voltage sources E_{Na^+}, E_K, and E_l model the differences in the concentration of different ion species that drive the flow of ions through the membrane channels. The aforementioned resting potential E_m of the neuron is equal to the average of the voltage sources E_{Na^+}, E_K, and E_l weighted by each corresponding conductance. In general, the conductances g_{Na} and g_K are non-linear functions

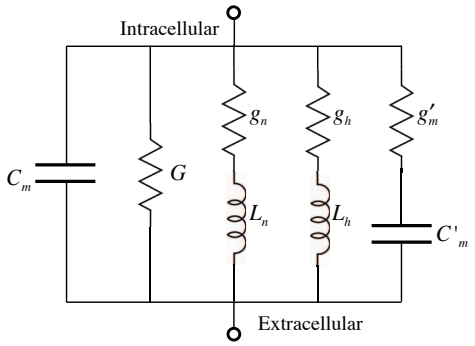

Fig. 4: Quasi-active model of an isopotential membrane patch in subthreshold condition.

of the membrane voltage $v_m(t)$, which results in a non-linear relation between $v_m(t)$ and the transmembrane current $I_m(t)$.

In the case when the membrane potential $v_m(t)$ satisfies the subthreshold condition at any isopotential membrane patch, corresponding to $v_m(t) < V_{th}$, the aforementioned Hudgkin-Huxley model for the isopotential membrane patch reduces to the quasi-active model detailed in [11]. This model corresponds to the electrical circuit shown in Fig. 4, which, in contrast to the Hudgkin-Huxley's, is composed of linear elements.

The expressions for the conductances G, g_n, g_h and g'_m, the inductances L_n and L_h, and the capacitance C'_m are provided in [12] as functions of the aforementioned Hudgkin-Huxley parameters, and omitted in this paper due to space constraints.

In this paper, we make the following assumptions: i) at the moment when the sender starts the injection of the current $I_i(t)$ into the soma, the membrane potential at any location of the neuron is equal to the aforementioned resting potential E_m; ii) during the injection of the current $I_i(t)$ into the soma, no other external perturbation is induced on the membrane potential; iii) The injection of the current $I_i(t)$ satisfies the subthreshold stimulation condition expressed in (4) for its Fourier transform $\tilde{I}_i(\omega)$.

As a consequence, during the transmission of information through the communication system proposed in this paper, every isopotential membrane patch of the neuron satisfies the aforementioned subthreshold condition, and can be modeled with the linear electrical circuit shown in Fig. 4.

By stemming from the quasi-active model, the relation between the Fourier transform $\tilde{V}_m(\omega)$ of the membrane potential $v_m(t)$ and the Fourier transform $\tilde{I}_m(\omega)$ of the transmembrane current $I_m(t)$ of an isopotential membrane patch, functions of the frequency ω, can be defined as the transmembrane impedance $Z_m(\omega)$ expressed in (5), computed at the terminals of the circuit in Fig. 4 by applying electrical circuit analysis [16]. The parameters α_i, $i = 0, 1, 2, 3$ in (5) have the following expressions:

$$\begin{aligned}
\alpha_0 &= G g_n g_h \\
\alpha_1 &= jG\left(L_n g_h + L_h g_n + C'_m g'_m g_h g_n\right) \\
\alpha_2 &= -G\left(L_n L_h + L_n C'_m g'_m g_h + L_h C'_m g'_m g_n\right) \\
\alpha_3 &= -jG L_n L_h C'_m g'_m ,
\end{aligned} \tag{6}$$

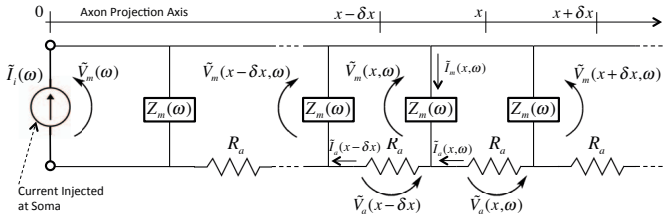

Fig. 5: Transmission line model of the axon obtained through the Cable Theory.

while the parameters β_j, $j = 0, 1, 2, 3, 4$ have the following expressions:

$$\begin{aligned}
\beta_0 &= g_n G + g_h G + g_h g_n \\
\beta_1 &= j\,(g_h g_n G C_m + C'_m g_h g_n G + L_n G + C'_m g'_m g_n G \\
&\quad + L_h G + C'_m g'_m g_h G + L_n g_h + L_h g_n + C'_m g'_m g_h g_n) \\
\beta_2 &= -\,(L_n g_h G C_m + L_h g_n G C_m + C'_m g'_m g_h g_n G C_m \\
&\quad + L_n C'_m g_h G + L_h C'_m g_n G + L_n C'_m g'_m G \\
&\quad + L_h C'_m g'_m G + L_n L_h + L_n C'_m g'_m g_h + L_n C'_m g'_m g_n) \\
\beta_3 &= -j\,(L_n L_h G C_m + L_n C'_m g'_m g_h G C_m \\
&\quad + L_h C'_m g'_m g_n G C_m + L_n L_h C'_m G + L_n L_h C'_m g'_m) \\
\beta_4 &= L_n L_h C'_m g'_m G C_m\,.
\end{aligned} \tag{7}$$

C. Axon Transimpedance $Z_{axon}(x, \omega)$

The axon transimpedance of a neuron is here defined as the ratio between the membrane potential $\tilde{V}(x, \omega)$ at distance x along the axon and the current $\tilde{I}_i(\omega)$ injected by the sender into the soma in the case where we exclude the electrical contribution of the dendritic tree, which corresponds to substituting the impedance of the dendritic tree in Fig. 2 with an open circuit, i.e., $Z_{dendrites}(\omega) \to \infty$. This is expressed as follows:

$$Z_{axon}(x, \omega) = 0.5 Z_0(\omega) \mathrm{e}^{-x\sqrt{\frac{4R_a}{Z_m(\omega) d_a}}}\,, \tag{8}$$

where $Z_0(\omega)$ is defined in (9), R_a is the membrane axial resistance, which is a parameter determined experimentally, and $Z_m(\omega)$ is the transmembrane impedance (5), respectively. In the following, we detail the derivation of (8).

The neuron axon is a projection from the soma, and its electrical properties in terms of the aforementioned impedance can be quantified by applying the Cable Theory [20] to the isopotential membrane patch model presented in Sec. III-B. In particular, the neuron axon is modeled through the electrical transmission line shown in Fig. 5, where $Z_m(\omega)$ is the transmembrane impedance of an isopotential membrane patch, expressed in (5), and R_a is the axial resistance of the axon, defined as the ratio between the membrane potential difference V_a of two adjacent membrane patches, and the ion current flowing in the axon intracellular environment (axoplasm) adjacent to the patches, termed axial current I_a. In agreement with [20], the axial resistance R_a is here considered constant and homogeneous along the axon. According to transmission

line theory [23], we define the characteristic impedance $Z_0(\omega)$ of the axon as

$$Z_0(\omega) = \sqrt{\frac{4R_a Z_m(\omega)}{\pi^2 d_a^3}}\,, \tag{9}$$

Where d_a is the diameter (average) of the axon. In the following derivations, we make the assumption [20] $L \gg \lambda$, where L is the length of the axon, and λ is the membrane's length constant, defined as follows [23]: $\lambda = \sqrt{\frac{\Re\{Z_m\}d_a}{4R_a}}$, where $\Re\{.\}$ denotes the real part. As a consequence, the electrical transmission line model shown in Fig. 5 has infinite extension in the axon projection direction. In addition, the soma is here considered as having negligible size with respect to the axon, and therefore approximated as a point at location 0 along the axon projection axis.

To analytically obtain the axon transimpedance $Z_{axon}(x,\omega)$, with reference to Fig. 5, we express the Kirchhoff's current law [16] at a location x along the axon as follows:

$$\tilde{I}_m(x,\omega) = \frac{\tilde{I}_a(x-\delta x,\omega) - \tilde{I}_a(x,\omega)}{\delta x} + \tilde{I}_i(\omega)\delta(x)\,, \tag{10}$$

where $\tilde{I}_m(x,\omega)$ and $\tilde{I}_a(x,\omega)$, are the Fourier transforms of the current per unit length flowing through the isopotential membrane patch and the current through the axial resistance R_a, respectively, at location x along the axon projection axis and frequency ω, and $\tilde{I}_i(\omega)$ is the Fourier transform of the current injected by the sender into the soma. δx is an infinitesimal distance along the axon projection axis, while $\delta(.)$ is the Dirac delta operator. Through electrical circuit analysis [16], we obtain the following expressions:

$$\begin{aligned}
\tilde{I}_a(x-\delta x,\omega) &= \frac{\pi d_a^2 \tilde{V}_a(x-\delta x,\omega)}{4R_a} = \frac{\pi d_a^2(\tilde{V}_m(x-\delta x,\omega) - \tilde{V}_m(x,\omega))}{\delta x 4R_a}\,,\\
\tilde{I}_a(x,\omega) &= \frac{\pi d_a^2 \tilde{V}_a(x,\omega)}{4R_a} = \frac{\pi d_a^2(\tilde{V}_m(x,\omega) - \tilde{V}_m(x+\delta x,\omega))}{\delta x 4R_a}\,,\\
\tilde{I}_m(x,\omega) &= \frac{\pi d_a \tilde{V}_m(x,\omega)}{Z_m(\omega)}\,,
\end{aligned}$$

where $\tilde{V}_a(x,\omega)$ and $\tilde{V}_m(x,\omega)$ are the voltage at the the axial resistance R_a and the membrane potential, respectively, at location x along the axon projection axis and frequency ω. By substituting (11) into (10), and taking the limit for $\delta x \to 0$, we obtain the following relation between the membrane potential $\tilde{V}(x,\omega)$ at distance x along the axon and the current $\tilde{I}_i(\omega)$ injected by the sender into the soma:

$$\frac{\pi d_a \tilde{V}_m(x,\omega)}{Z_m(\omega)} = \frac{\pi d_a^2}{4R_a}\frac{\partial^2 \tilde{V}_m(x,\omega)}{\partial x^2} + \tilde{I}_i(\omega)\delta(x)\,, \tag{11}$$

which corresponds to a second order linear partial differential equation with the following solution [11]:

$$\tilde{V}_m(x,\omega) = \frac{1}{2}\sqrt{\frac{4R_a Z_m(\omega)}{\pi^2 d_a^3}}\mathrm{e}^{-x\sqrt{\frac{4R_a}{Z_m(\omega)d_a}}}\tilde{I}_i(\omega)\,, \tag{12}$$

where $\tilde{V}_m(x,\omega)$ is the membrane potential at distance x along the axon and $\tilde{I}_i(\omega)$ is the current injected by the sender into the soma as functions of the frequency ω, R_a is the axon axial resistance, and $Z_m(\omega)$ is the transmembrane impedance expressed in (5). As a consequence, the axon transimpedance as defined above corresponds to the expression in (8).

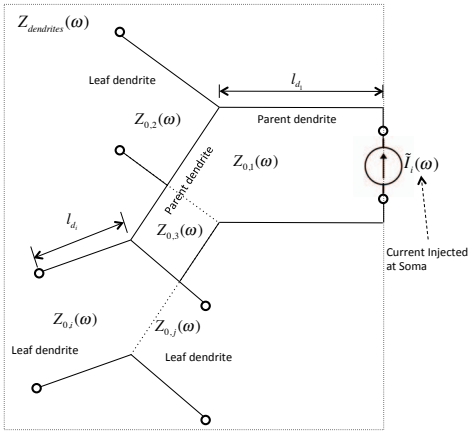

Fig. 6: Transmission line model of the dendritic tree obtained through the Cable Theory.

D. Dendritic Tree Impedance $Z_{dendrites}(\omega)$

The dendritic tree impedance of a neuron is here defined as the ratio between the membrane potential $\tilde{V}(0,\omega)$ at the soma and the current $\tilde{I}_i(\omega)$ injected by the sender into the soma in the case where we exclude the electrical contribution of the axon, which corresponds to substituting the axon transmission line model in Fig. 2 with an open circuit, i.e., $Z_{axon}(x,\omega) \to \infty$. This is computed recursively through a depth-first search with post-order traverse method [7] detailed in Algorithm 1.

Algorithm 1 Recursive Calculation of $Z_{dendrites}(\omega)$

```
1: procedure DendTreeImpedance (node dendrite)
2:     if dendrite != NULL then
3:         for node i : dendrite.GetChildren () do
4:             DendTreeImpedance (i)
5:             Compute Z_dendrites(ω) = Z_{d,i}(ω) with (13)
```

From the electrical perspective, the dendritic tree can be modeled through Cable Theory [20] as a branched transmission line, as shown in Fig 6, with characteristic impedance $Z_0(\omega)$, expressed in (9). In the transmission line model, each branch of the dendritic tree can be either a leaf dendrite, which have an open circuit as end load, or a parent dendrite, whose load is given by the equivalent load of the parallel branching transmission lines, named Children in Algorithm 1.

To analytically obtain the impedance $Z_{d,i}(\omega)$ of a dendrite i, we apply Transmission Line Theory [16] to compute the equivalent impedance of a transmission line having a characteristic impedance $Z_{0,i}(\omega) = \sqrt{4R_a Z_m(\omega)/(\pi^2 d_i^3)}$, d_i being the dendrite's diameter, a length equal to the physical length of the dendrite l_{d_i}, and a load $Z_{L,i}(\omega)$. This is expressed as

$$\begin{aligned}
Z_{d,i}(\omega) &= Z_{0,i}(\omega) \\
&\cdot \frac{Z_{L,i}(\omega)\cosh(\gamma(\omega)l_{d_i}) + Z_0(\omega)\sinh(\gamma(\omega)l_{d_i})}{Z_{L,i}(\omega)\sinh(\gamma(\omega)l_{d_i})Z_0(\omega)\cosh(\gamma(\omega)l_{d_i})}\,,
\end{aligned} \tag{13}$$

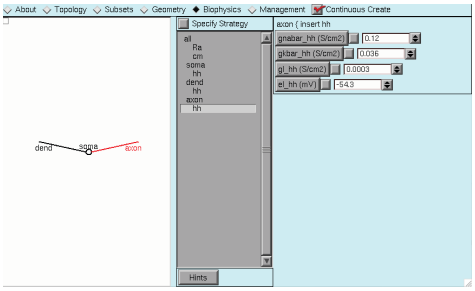

Fig. 7: NEURON software [6] screenshot showing the neuron morphology used to compute our numerical results.

where $\gamma(\omega) = \sqrt{4R_a/(Z_m(\omega)d_i)}$ and R_a is the axial resistance defined in Sec. III-C. If dendrite i is a leaf, the load $Z_{L,i}(\omega) \to \infty$, otherwise, if dendrite i is a parent, $Z_{L,i}(\omega)$ is expressed as the equivalent load of N parallel transmission lines branching from the dendrite i. This is expressed as follows:

$$Z_{L,i}(\omega) = \frac{\sum_{n=1}^{N} Z_{d,n}(\omega)}{\prod_{n=1}^{N} Z_{d,n}(\omega)}, \tag{14}$$

where N is the number of dendrites branching out from dendrite i, and $Z_{d,n}(\omega)$ is the impedance of the dendrite n computed at an earlier step in the recursion of Algorithm 1.

IV. Numerical Results

We present a preliminary comparison of numerical results, obtained by evaluating the analytical expressions of the linear channel model detailed in Sec. III, with results of simulations performed through the NEURON software [6], which is based on the numerical computation of the Hudgkin-Huxley (non-linear) model throughout a neuron with a defined shape, or morphology. We based our results on the biophysical parameters of the giant squid axon, which are considered as standard for neurophysiology model comparison [12]. For these preliminary results, we used a simplified dendritic tree having only one dendrite, as shown in the screenshot of the NEURON software in Fig. 7. The parameters are as follows: the lumped elements of the quasi-active model of a membrane patch in Fig. 4 are $G = 0.246$ mS/cm^2, $g_n = 0.894$ mS/cm^2, $g_h = 0.072$ mS/cm^2 , $g'_m = 0.432$ mS/cm^2, $L_n = 6.43$ H.cm^2, $L_h = 119$ H.cm^2 , $C_m = 1$ μF/cm^2 and $C'_m = 0.102$ μF/cm^2; the value of the membrane axial resistance is $R_a = 100$ ohm.cm; the length of the axon is $L = 1500$ μm and the length of the single dendrite is $l_{d_1} = 3400$ μm. Additional parameters used in the NEURON software are as follows: dendrites, soma, and axon diameters are equal to 50 μm, 50 μm, and 10 μm, respectively, the number of simulation segments is equal to 70, 5, and 50, respectively, and the length of the soma is equal to 100 μm, which can be considered negligible when compared to the axon and dendrite lengths. The parameter values of the Hudgkin-Huxley model for the giant squid axon [17] used in the NEURON simulations correspond to $\bar{g}_{Na} = 0.12$ S/cm^2, $\bar{g}_K = 0.036$ S/cm^2, $g_l = 0.0003$ S/cm^2, and $E_l = -54.3$ mV.

In Fig. 8 and Fig. 9 we show the numerical results in terms of magnitude and phase, respectively, of the neuron transimpedance $Z(x, \omega)$ when the receiver performs the voltage reading at a distance $x = 0.0675$ cm from the soma along the axon projection axis, as shown in Fig. 1. The analytical transimpedance values are computed with the linear channel model presented in this paper by evaluating the formulas in (2), (3), (5), (8), and Algorithm 1 for the aforementioned parameters. The simulation-based transimpedance values are computed by running the NEURON software [6] with the following parameters: initial membrane potential equal to the resting potential -65 mV, total simulation time 1000 msec, simulation time step 0.01 msec, and different voltage outputs are computed for sinusoidal injected currents with amplitude 5 nA, which satisfies the subthreshold condition as detailed in the following, and having frequencies from 1 Hz to 1000 Hz.

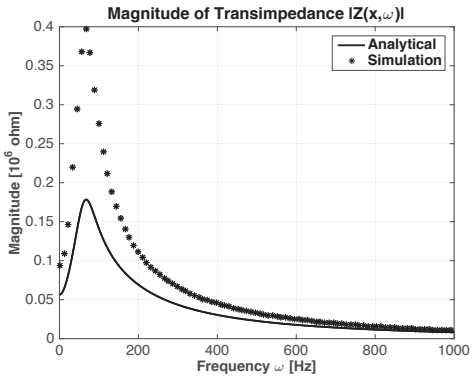

Fig. 8: Magnitude of the neuron transimpedance $|Z(x, \omega)|$ for a distance $x = 0.0675$ cm along the axon, and for frequencies ω ranging from 1 Hz to 1000 Hz.

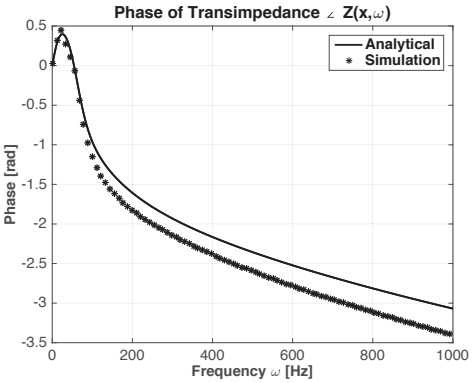

Fig. 9: Phase of the neuron transimpedance $\angle Z(x, \omega)$ (same parameters as in Fig. 8).

The preliminary results in Fig. 8 and Fig. 9 show as similar trend with numerical values of comparable magnitude computed through the linear channel model proposed in this paper and those computed through numerical simulation with the NEURON software. In particular, we notice that both the two strategies reveal a resonant frequency around 70 Hz, where the curves of the transimpedance magnitude $|Z(x, \omega)|$ show a maximum value. This is in agreement with experimental results, such as in [10]. We think that the main differences observed in the curves at low frequencies might be due to

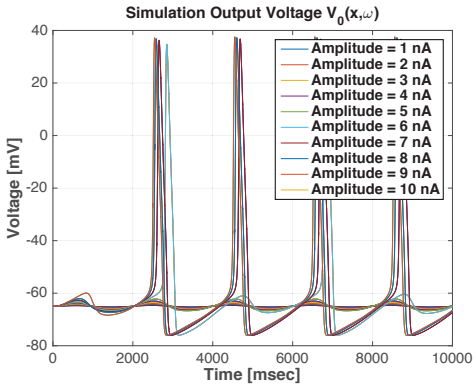

Fig. 10: Output voltage $V_o(x,t)$ from NEURON simulations upon sinusoidal injected currents with frequency 50 Hz and varying amplitude ranging from 1 nA to 10 nA.

the aforementioned simplified dendritic tree. In the future, we plan to validate our models on neurons with more realistic morphology and geometry

In Fig. 10 we show different values of the output voltage $V_o(x,t)$ from NEURON simulations corresponding to sinusoidal injected currents with frequency 50 Hz and varying amplitude ranging from 1 nA to 10 nA. We can observe that for low amplitudes of the injected current the output voltage maintains a sinusoidal shape with the same frequency, therefore confirming a linear behavior in subthreshold stimulation conditions. For high amplitudes, action potential stimulation occurs, and the output voltage shows the emergence of spikes.

V. Conclusion

In this paper, we have obtained a communication channel model based on the transmission of information through a neuron. Such a communication system is motivated by the need of intra-body communication links for the interconnection of the next generation wearable and implantable devices. Our proposed system is based on the so-called subthreshold electrical stimulation of a neuron, which does not stimulate neurospikes, and can potentially minimize the interference with the normal body functionalities. Moreover, by transmitting information through this type of stimulation, it is possible to express the communication channel with a linear model, which we analytically obtained by stemming from neurophysiology studies. Numerical results show agreement with simulations made with standard tools. While this preliminary model does not include stochastic effects that would be unavoidable in the proposed communication system, we plan to extend this work by incorporating the modeling of the major noise sources within the electrochemical processes of neurons. We believe that the results obtained in this preliminary study could encourage a new direction of investigation for the realization of sustainable intra-body communication systems.

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