

Modeling Refractoriness in Phenomenological Models of Electrically-Stimulated Auditory Nerve Fibers

Marko Takanen¹, Jean-Noël Weller, Bernhard U. Seeber²
Audio Information Processing, Technische Universität München
¹marko.takanen@tum.de, ²seeber@tum.de

Introduction

The ability of cochlear implants (CIs) to restore hearing for profoundly deaf people is based on electrical stimulation of the auditory nerve fibers (ANFs). Such stimulation allows CI users to understand speech in quiet conditions but researchers and device manufacturers are still optimizing coding strategies to improve the ability of CI users to cope in complex listening environments with multiple sound sources. Phenomenological models have proven themselves to be able to reproduce various response characteristics of the electrically stimulated ANF [1] and could, therefore, be used as an instrumental tool to aid the coding-strategy optimization by predicting ANFs' responses.

However, phenomenological models continue to face challenges with temporal phenomena related to inter-pulse interactions in pulse-train stimulation and only some of those models strive to predict the exact time of spiking [1, 2]. Both of these aspects are highly important for predicting responses to pulsatile stimulation used in modern CIs as well as the spatial hearing percepts of bilateral CI users. One of the fundamental temporal phenomena affecting the ANF's response to high-pulse-rate stimulation is refractoriness that limits the ability of the ANF to be excited again shortly after spiking. This aspect is accounted for by several phenomenological models [1]. However, we demonstrate here that the refractoriness can be captured well only when the spike timings and latency of the ANF are also being considered.

Modeling spiking of the ANF and its timing

In physiological sense, the electrical pulses charge up the capacitive cell membrane and excite the neuron to spike if the membrane potential reaches the neuron's threshold (THR) value. An action potential is then generated shortly later and therefore, there is always a stochastic delay, called latency, between the onset of the pulse and the time of spiking [3]. The aforementioned process is simulated in phenomenological models by integrating the charge delivered by the pulse. Figure 1 illustrates how the obtained estimate for membrane potential is compared in phenomenological leaky integrate-and-fire (LIF) models on a sample-by-sample basis to the stochastic threshold value and the time at which the THR value is exceeded is denoted as threshold crossing t_0 . By introducing a stochastic delay between t_0 and the subsequent spiking, phenomenological models can account for latency and jitter of the spike timing(s), and even stimulation-level dependency of those aspects [4, 5].

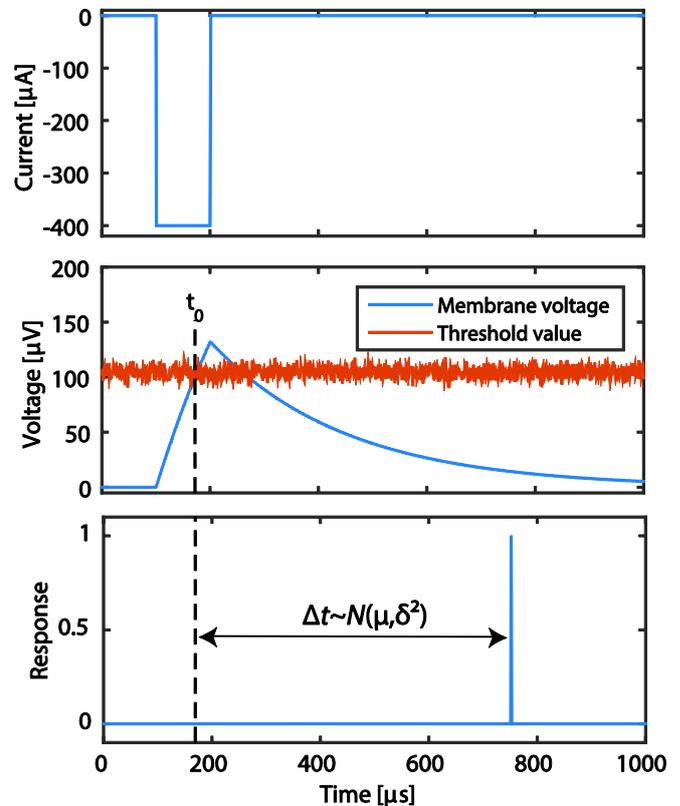


Figure 1: Modeling spiking of the electrically stimulated ANF with a phenomenological model [4]. The membrane voltage gets pushed above the stochastic threshold of the neuron, initiating an action potential to be generated after a random delay that accounts for the latency of firing.

Modeling refractoriness

The physiology behind refractoriness is also well established based on neurophysiological measurements (see, e.g. [2] for a review). Once an action potential has been generated, the ion channels remain inactive for a while, preventing the neuron to be excited during so-called absolute refractory period. Afterwards, the neuron gradually recovers to its resting state as more and more ion channels become active again. During this relative refractory period, the neuron can be excited but the THR is elevated as illustrated in Fig. 2. In phenomenological models, the refractory and recovery behavior of ANF is simulated by setting the threshold level first to an infinite value from the time of spiking t_{spk} onwards until the end of the absolute refractory period t_{arp} . Then, the threshold level is multiplied with an exponentially decaying function to simulate the gradual recovery of the neuron to its resting state. [1]

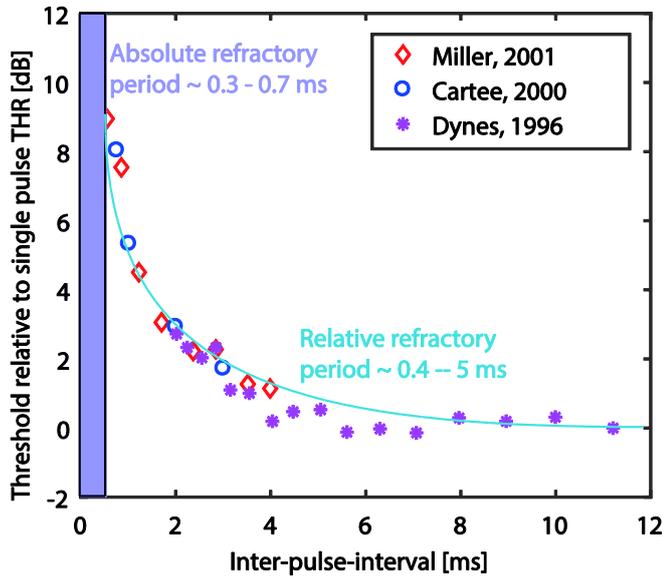


Figure 2: Threshold of an ANF as it recovers from previous excitatory stimulation. At first, the neuron cannot be excited again with any stimulation magnitude and afterwards the threshold gradually recovers to the single-pulse threshold level.

Identifying and solving the problem with timing in modeling refractoriness

The above-mentioned way of modeling refractoriness is elegant and allows phenomenological models to reproduce neurophysiological data. Unfortunately, there is an inconsistency between neurophysiological studies and models in the definitions of time constants. As shown in Figs. 3(a) and 2, neurophysiological studies consider the refractory period to begin from the onset of the supra-threshold pulse. Consequently, the second pulse in Fig. 3(a) following after a 0.9-ms-long inter-pulse-interval (IPI) would be considered able to excite the neuron as it is presented at +7 dB level compared to the nominal threshold.

However, the latency of the neuron to the first pulse is ignored when the absolute refractory period is defined to begin from the onset of the first pulse, and this causes problems for phenomenological models using time constants from neurophysiological measurements. The problem is demonstrated in Fig. 3 using the extended version of the biphasic leaky integrate-and-fire (BLIF) model [4] by Takanen and Seeber [6]. As shown in Fig. 3(c), the model predicts the neuron to spike to the first pulse with a latency of about 0.51 ms after the threshold crossing (Fig. 3). If the absolute refractory period is then thought to begin only after the time of spiking, the model would predict the neuron to be still in refractory state by the time of the second pulse (Fig. 3(b)). Consequently, the effective absolute refractory period of the model becomes too long for the model to spike to the second pulse, as expected based on neurophysiological data.

This problem can be circumvented by considering the refractory period to begin already when the generation of the action potential is initiated. After such a simple modification, the threshold level of the model is able to recover enough by the time of the second pulse - allowing also the second pulse to excite the model to spike.

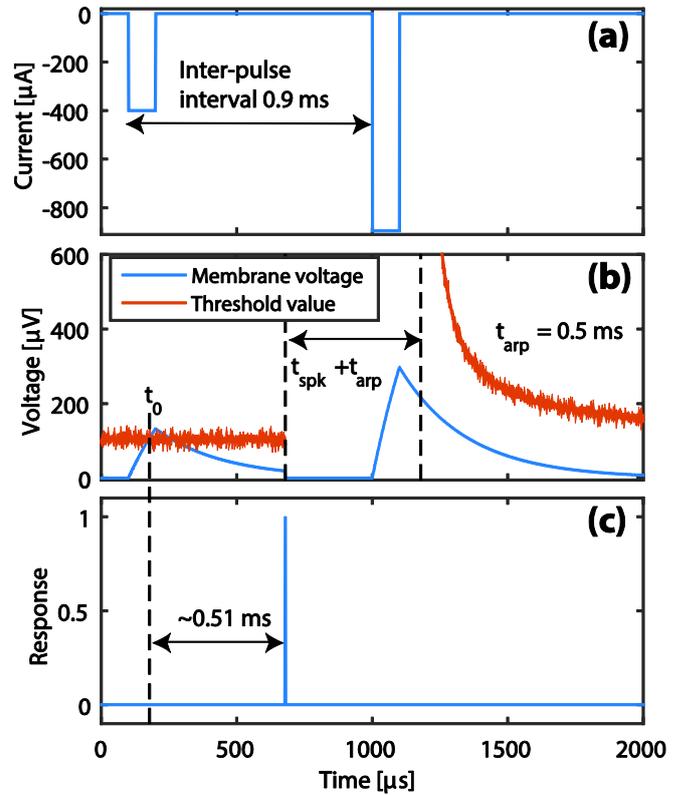


Figure 3: Problem in modeling refractoriness with the traditional approach of starting the refractory period from the time of spiking. Together with the latency to the first pulse, the effective refractory period becomes too long for the model to react to the second pulse.

Verification

To test the proposed solution, we simulated the experimental condition used in [7, 8, 9] using 40- μ s-long monophasic pulses at IPIs ranging from 0.5 to 12 ms (100 runs per IPI). We followed the traditional approach and multiplied the threshold level of the model with an exponential function [10, 6]

$$f(t) = \begin{cases} \infty, & t < t_{arp} \\ \left[\left(1 - \exp\left(\frac{-t + t_{arp}}{0.1\tau_{mp}}\right) \right) \dots \right]^{-1}, & t \geq t_{arp}. \\ \left(1 - 0.68 \exp\left(\frac{-t + t_{arp}}{\tau_{mp}}\right) \right) \end{cases}$$

The values for t_{arp} and τ_{mp} were chosen randomly for each neuron from Gaussian distributions having mean values of 0.3 ms (according to [9]) and 1.5 ms, and standard deviations of 0.05 ms and 0.4 ms, respectively, to account for the found variation in the neurophysiological data [7, 9]. The results from the simulations in Fig. 5 show accurate fit to the neurophysiological data, validating the suitability of the approach.

Summary

In this article, we demonstrated how phenomenological models for electrically stimulated auditory nerve fiber (ANF) can account for both latency and refractoriness data

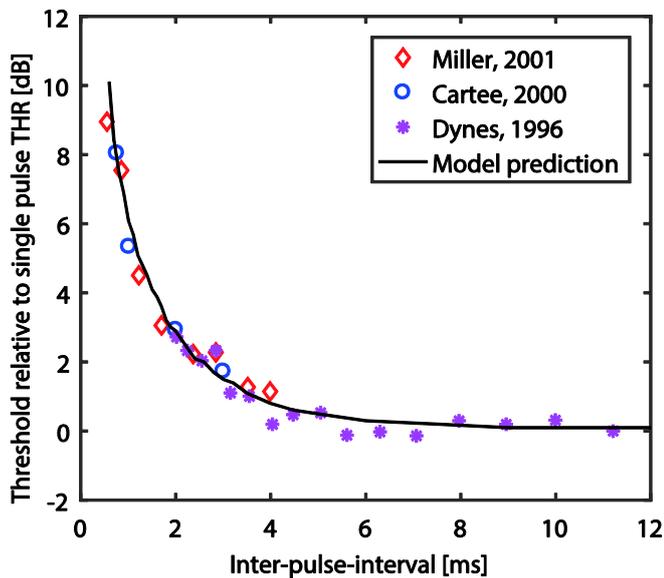


Figure 4: Results for modeling refractoriness of the ANF using the proposed approach. The model provides an accurate prediction for the neurophysiological data.

from neurophysiological literature. We also identified a problem in simulating refractoriness using time constants from such literature – resulting in too long effective refractory periods. The proposed solution allowed our phenomenological model [4, 6] to reproduce both latency and refractoriness data from literature and improving thus the model’s accuracy in predicting responses to high-pulse-rate stimulation. Similar solution can also be applied in other phenomenological models.

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References

[1] Takanen, M.; Bruce, I.C.; Seeber, B.U.: Phenomenological modelling of electrically stimulated

auditory nerve fibers: A review. *Network Comp. Neural.* 23 (2016), 157-185

[2] Boulet, J.; White, M.; Bruce, I.C.: Temporal considerations for stimulating spiral ganglion neurons with cochlear implants. *J. Assoc. Res. Otolaryngol.* 17 (2016), 1-17.

[3] Miller, C. A.; Abbas, P. J.; Robinson, B. K.; Matsuoka, A.: Electrically evoked single-fibre action potentials from cat: responses to monopolar, monophasic stimulation. *Hear. Res.*, 130 (1999), 197-218.

[4] Horne, C.; Sumner, C. A.; Seeber, B. U.: A phenomenological model of the electrically stimulated auditory nerve fiber: Temporal and biphasic response properties. *Front. Comput. Neurosci.* 10 (2016) 1-17.

[5] Joshi, S. N.; Dau, T.; Epp, B.: A Model of Electrically Stimulated Auditory Nerve Fiber Responses with Peripheral and Central Sites of Spike Generation. *J. Assoc. Res. Otolaryngol.* (2017) 1-20.

[6] Takanen, M.; Seeber, B.U.: Modeling pulse train stimulation of electrically stimulated auditory nerve fibers. *Fortschritte der Akustik -- DAGA '16* (2016), 40-42.

[7] Dynes, S.: “Discharge characteristics of auditory nerve fibers for pulsatile electrical stimuli”, PhD thesis, Massachusetts Inst. Technol., Cambridge, MA, 1996.

[8] Cartee, L. A.; van den Honert, C.; Finley, C. C.; Miller, R. L.: Evaluation of a model of the cochlear neural membrane. I: Physiological measurement of membrane characteristics in response to intrameatal electrical stimulation. *Hear. Res.* 146 (2000), 143-152.

[9] Miller, C.; Abbas, P.; Robinson, B.: Response properties of the refractory auditory nerve fiber, *J. Assoc. Res. Otolaryngol.* 2 (2001), 216–232.

[10] Hamacher, V.: “Signalverarbeitungsmodelle des elektrisch stimulierten Gehörs”, PhD thesis, RTWH Aachen, Germany, 2003.