

Low-pass filter effects in biological neurons as a feature to facilitate representation of tactile information

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Abstract— Here we simulate the tactile sensory information processing in a fully recurrent network of excitatory and inhibitory neurons. The neuron model has previously been shown to capture essential aspects of the Hodgkin-Huxley biological neuron model. We specifically explore the impact of noise in the spike generation of the tactile sensors, and how the time constants of the biological neurons in a network may be adapted to cope with such noise. We find that in networks with short time constants, and hence higher temporal precision, the risk is high that the network will segregate noise (i.e. as in overfitting) in the spike generation rather than the underlying haptic input signal, which is composed of features distributed across somewhat longer periods of time. Hence, low-pass filtering effects that arise because of these time constants can be beneficial for a biological neuronal network processing tactile information, to focus its available capacity on the main underlying haptic input features.

I. INTRODUCTION

The properties of biological tactile information processing remain a source of inspiration for engineered haptic systems. An important aspect of understanding biological sensory systems is to understand how the biological brain can represent and use the information [1], [2]. This is in turn to a large extent defined by the properties of the neuronal networks of the brain [3]–[5]. Recent data of both anatomical and physiological nature indicate that the neocortical system handling tactile information is globally interconnected [6], [7]. Hence, it is likely a network which is extensively recursive. Other data indicate that neuronal spike generation, which is the means by which neurons transfer information to other neurons, is inevitably stochastic [8]. Stochasticity will at least to some extent render neurons noisy. Even tactile sensors are neural, implying that tactile sensors have a limited temporal precision. Unlike deterministic systems, neuronal systems will hence to some degree need to rely on probabilistic representation of tactile data and find the most efficient way to work with such data. Another aspect of biological neuronal transmission of information is that it is low-pass filtered, due to the transformation of an electrical signal, the axon action potential or spike, to a chemical signal and then back to an electrical signal in the receiving neuron through the process of synaptic transmission.

Here we simulate sensors and processing neuronal networks to elucidate the limitations that different noise levels would imply for the neural representation and segregation of

tactile information in recurrent neuronal networks. The neuron model is a simplified, non-spiking, version of a biological neuron working according to Hodgkin-Huxley principles, which has previously been shown to capture all central generic biological neuron properties while also being highly advantageous in preventing activity saturation and spurious noise generation in perpetually active, fully recurrent networks [9], [10]. In this neuron model, as in biology, the transmission of information between neurons is always mildly low-pass filtered.

With this work we aim to examine the effects of noise in emulated tactile sensors, superimposed on one and the same underlying signal, on the variance of the responses in a neuronal network. Additionally, we explored the effect of sensor noise on the ability of a network to generate separable neuron output responses for two different underlying tactile sensory inputs.

II. MATERIALS AND METHODS

A. Neuron Model

In this study we used a non-spiking Linear Summation neuron Model (LSM) that was designed to capture the important characteristics of a H-H conductance-based model [9]. LSM output activity (A , (1-2)) was given by a sum of weighted (w) input synaptic activity (a), that was normalized using static leak (k_{static}) and dynamic leak (τ_{dyn}) components. The static and dynamic leak components mimic the effect of the RC circuit created by the ion channels and the capacitance of the membrane. The output activity of this neuron model was given by the following equations,

$$\tau_{dyn} \frac{dA}{dt} = \frac{\sum(w_i * a_i)}{k_{static} + \sum|w_i * a_i|} \quad (1)$$

$$\text{if } A < 0, \text{ then } A = 0. \quad (2)$$

The $k_{static} = 1$ and $\tau_{dyn} = 1/150$, these values were kept constant for this study.

B. Network Structure

A densely connected neuronal network configuration, comprising of both excitatory and inhibitory neurons was used in this study (Fig. 1A). The excitatory neurons (Ns , blue circles) were connected to all other neurons in the network via excitatory synapses (blue arrows, Fig. 1A) whereas inhibitory neurons (INs , red circles) were connected only to excitatory neurons via inhibitory synapses (red arrows, Fig. 1A). In this study, the network comprises 5 excitatory and 5 inhibitory neurons, where two of the excitatory neurons (neuron #1, #2) received external sensory inputs. All the synaptic weights

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were pseudo-randomly generated as normal distribution with a mean (μ) of 0.3 and standard deviation (σ) of 0.1. The weights of inhibitory synapses were set negative and the excitatory were set positive.

C. Pseudo-random Inputs

In this study, we used two sets of pseudo-random inputs (Input #1 & #2, Fig. 1B, C). Each of the two input sets comprised two sensory signals (Sensor #1 & #2, Fig. 1B, C). For each input, we generated two pseudorandom spike trains with uniform normal distribution at a mean frequency of 50 Hz. A MATLAB function “*randi*” was used to generate these spike time distributions. Further these spike trains were convoluted to mimic post-synaptic potentials, using the following kernel function,

$$a = \frac{\tau_m}{\tau_d - \tau_r} * \left[\exp\left(\frac{-t - \tau_l - t^*}{\tau_d}\right) - \exp\left(\frac{-t - \tau_l - t^*}{\tau_r}\right) \right]. \quad (3)$$

where, t^* is the input spike time, τ_d is the decay time (4 ms), τ_r is the rise time (12.5 ms), τ_m is the constant to calculate ratio between rise time and decay time (21.3 ms), and τ_l is the latency time which is zero in this case. These values were chosen based on the previous work (Rongala et al., 2018). The convoluted signals were given as sensory inputs (Fig. 1B, C) to two excitatory neurons in the network.

A gain value (synaptic time constant gain, Fig. 3) was used as multiplication factor to the base time constants (of τ_d , τ_r & τ_m , as reported above) to achieve a wide range of synaptic time constants.

D. Input Spike Noise (ISN)

Noise was implemented in two different ways. First, we provide temporal noise to the input spike trains. Secondly, ‘white’ noise was added to the signal of each neuron, and this noise was varied with respect to amplitude.

To study the effect of input noise on the network dynamics, we have provided the network with a given sensory input for 25 repetitions. During each repetition, a defined amount of noise was added to the sensory input spike times. The noise was generated as uniform distribution within the given range. We have explored different levels of input noise, ranging between ± 0 to ± 50 ms (Fig. 2).

Additionally, a random gaussian noise ($\mu = 0.025$ and $\sigma = 0.001$) was added to the neuron activity (neuron activity noise, *NAN*) across all neurons in the network.

E. Statistical Analysis

1) Cross correlation analysis

A cross correlation measure was used to calculate the similarities between neuron output activity (Fig. 2, 3). A cross correlation index value of “0” indicates high dissimilarity between the signals that were compared, and a value of “1” indicates high similarity. An inbuilt MATLAB function “*xcorr*” (with zero-lag) was used to compute this cross-correlation measure.

2) Frequency analysis

A continuous wavelet transform was performed (using inbuilt MATLAB function “*cwt*”) to define the frequency

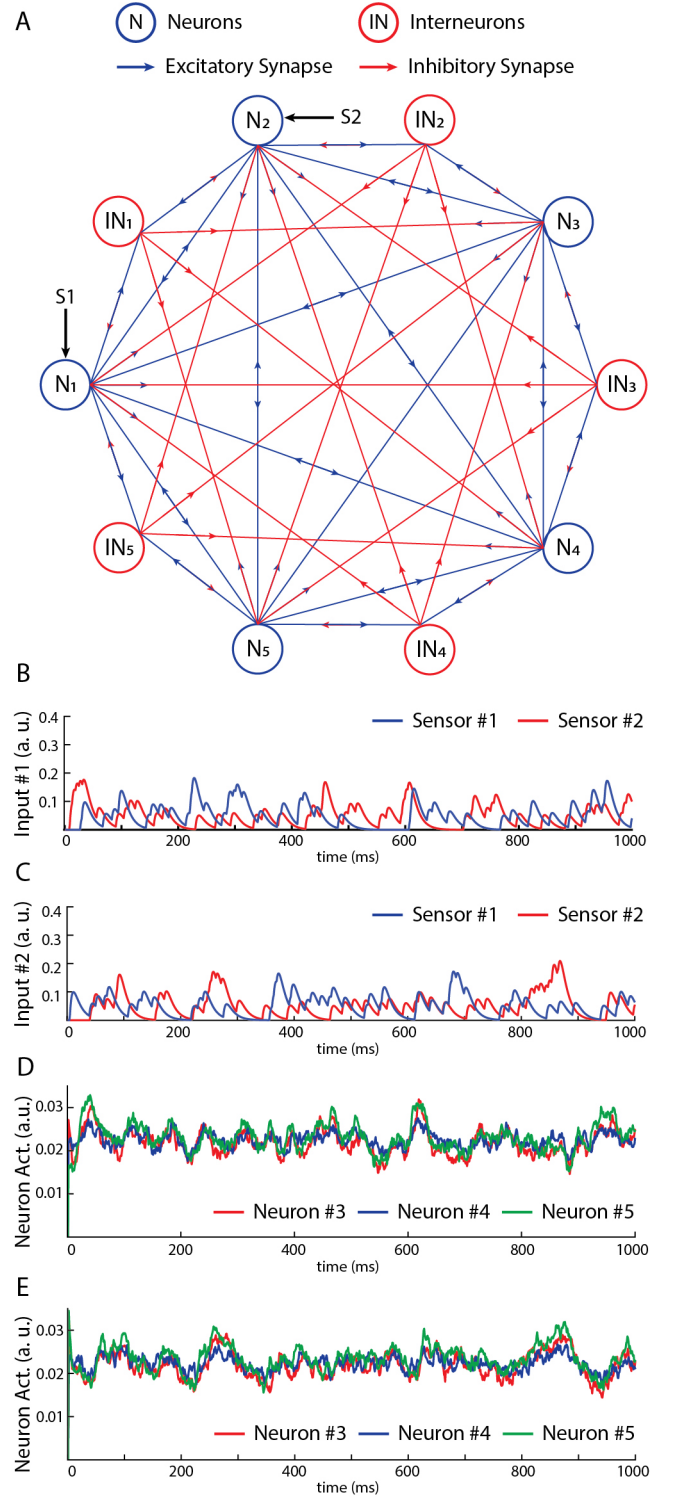


Figure 1 (A) The network that was studied. A densely connected neuronal network comprising of 5 excitatory neurons (N, blue circles) and 5 inhibitory neurons (IN, red circles). The neurons were interconnected using excitatory and inhibitory synaptic connection that were indicated using blue and red lines/arrowheads respectively. (B) Convoluted sensory signals (see Methods) of Input #1. (C) Convoluted sensory signals of Input #2. (D) Neuron output activity (Neuron #3-5) for a given Input #1. (E) Neuron output activity (Neuron #3-5) for a given Input #2.

composition of the neuron output activity over time. The power across each frequency band averaged over time for a

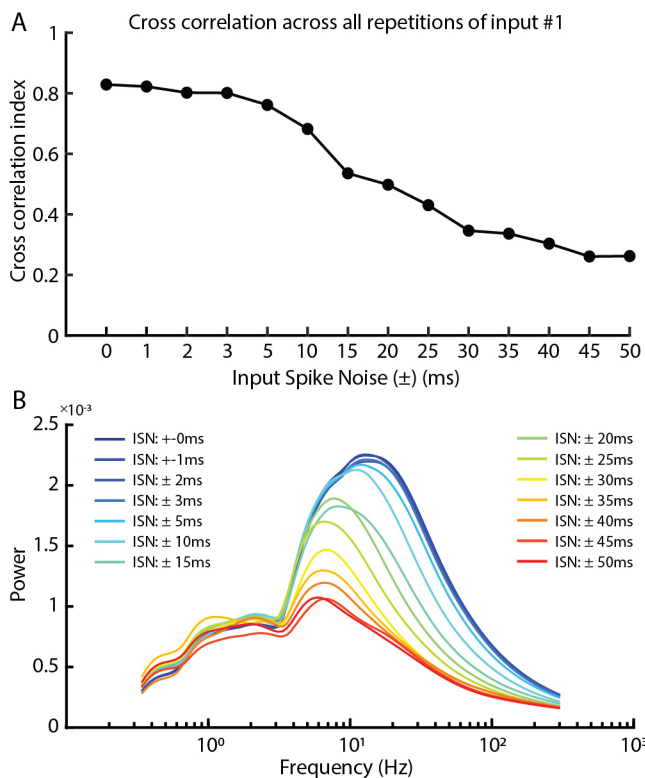


Figure 2. (A) A mean cross-correlation measure for the neuron output activity of neuron N3 using pairwise comparisons of output across 25 repetitions of Input #1 with a given input spike noise. (B) Frequency analysis on the neuron mean activity (N3) across 25 repetitions of Input #1, for a given input spike noise.

given continuous neuron activity signal is reported in Fig. 2B.

III. RESULTS

A. Effect of Noise

We first assessed the effect of input spike noise (ISN) on the variance of neuron output activity, within a densely connected neuronal network. We provided the network with Input #1 for 25 repetitions, during each of these repetitions a given amount of noise was added to the input spike times. Fig. 2A shows the mean cross-correlation measure across neuron output activity (N3) pairs, for 25 repetitions of Input #1 with a given ISN. The cross-correlation measure remained relatively high (~ 0.8) for lower amount of ISN ($\pm 0 - \pm 2$ ms), indicating that the neuron output activity had little variance for a temporal noise of 0-4 ms in the input spike trains. Further increase in the ISN led to more steep declines in the cross-correlation measure indicating a loss of temporal information within the neuron output activity. Fig. 2B shows the effect of ISN on the frequency component in the neuron activity. An increase in ISN gradually devoured the peak frequency from 50 Hz towards 0 Hz, leading to loss of activity dynamics in the neuron output activity.

Note that in Fig. 2A the cross-correlation measure for ISN = ± 0 is 0.8 instead of 1, the value that would arise in the absence of ISN. Hence, the NAN (neuron activity noise) always created an inconsistent behavior across different

repetitions of the same underlying sensor signal in the network, as measured from the output of N3 in this case.

B. Effect of Synaptic Time Constants

We further assessed the effect of synaptic time constants on the neuron activity variance, and the ability of the network to separate two different underlying inputs.

First, the time constant of the kernel function to generate the sensor signals (Fig. 1B, C) were adapted to achieve different post-synaptic responses for the same input spike trains. Fig. 3A shows the mean cross-correlation measure across neuron output activity (N3) pairs, for 25 repetitions of Input #1 with a given ISN and synaptic time constant. Fig. 3A shows that the effect of an increase in synaptic time constants results to a decrease in the effect of ISN on the neuron output activity variance. Hence, a higher synaptic time constant (bigger value) will have a low-pass filter effect on the input activity, which thereby helps in reducing the effect of ISN on the neuron output activity.

In Fig. 3B we instead report the cross-correlation measure across neuron output activity (N3) for two different inputs (Input #1 & #2). In this case, a higher correlation value indicated that the network performed worse in discriminating between the two different inputs. In Fig. 3B, an increase in the synaptic time constants led to a higher segregation of the neuron activity for different inputs, demonstrating that higher time constants could help the receiving network to separate different sensory input signals.

IV. CONCLUSION

These results (Fig. 2, 3) demonstrate that low pass filtering effect (membrane time constants, synaptic time constants) that appears in biological systems, would be advantageous in reducing the effects of noise during sensory information processing. These results also suggest that brain networks would not necessarily benefit to operate with millisecond

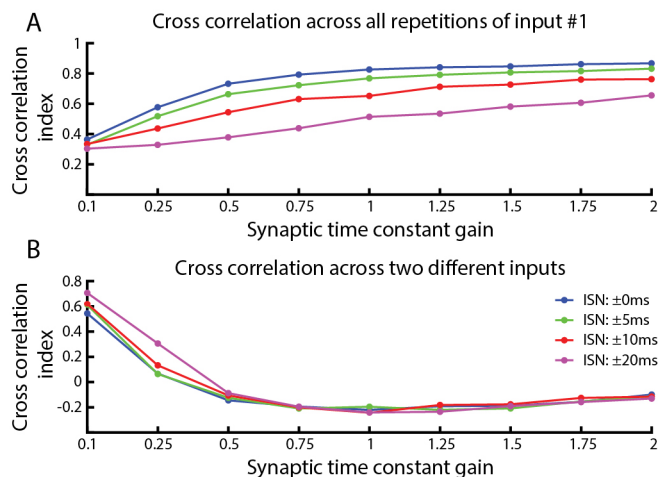


Figure 3 (A) A mean cross-correlation measure across neuron output activity (N3) pairs, for 25 repetitions of Input #1 with a given input spike noise and synaptic time constants. (B) A cross-correlation measure across neuron output activity (N3), for Input #1 and Input #2, with a given input spike noise and synaptic time constants.

precision in the representation of tactile sensory information. Instead, more benefits might arise by focusing the available system capacity on identifying the largest possible number of input sensory features (i.e. in biology the available resources of the system would equal the number of neurons in the brain of the particular species under consideration).

REFERENCES

- [1] M. Kawato, H. Hayakawa, and T. Inui, "A forward-inverse optics model of reciprocal connections between visual cortical areas," *Netw. Comput. Neural Syst.*, vol. 4, no. 4, p. 415, 1993.
- [2] A. B. Saleem, A. Ayaz, K. J. Jeffery, K. D. Harris, and M. Carandini, "Integration of visual motion and locomotion in mouse visual cortex," *Nat. Neurosci.*, vol. 16, no. 12, pp. 1864–1869, 2013.
- [3] M. Kawato, K. Furukawa, and R. Suzuki, "A hierarchical neural-network model for control and learning of voluntary movement," *Biol. Cybern.*, vol. 57, no. 3, pp. 169–185, 1987.
- [4] A. M. Bastos, W. M. Usrey, R. A. Adams, G. R. Mangun, P. Fries, and K. J. Friston, "Canonical microcircuits for predictive coding," *Neuron*, vol. 76, no. 4, pp. 695–711, 2012.
- [5] A. Clark, "Whatever next? Predictive brains, situated agents, and the future of cognitive science," *Behav. Brain Sci.*, vol. 36, no. 3, pp. 181–204, 2013.
- [6] J. Enander, A. Spanne, A. Mazzoni, F. Bengtsson, C. M. Oddo, and H. Jörntell, "Ubiquitous neocortical decoding of tactile input patterns," *Front. Cell. Neurosci.*, vol. 13, p. 140, 2019.
- [7] L. Etemadi, J. M. D. Enander, and H. M. D. Jörntell, "Remote cortical perturbation dynamically changes the network solutions to given tactile inputs in neocortical neurons," *bioRxiv*, 2021.
- [8] M. N. P. Nilsson and H. Jörntell, "Channel current fluctuations conclusively explain neuronal encoding of internal potential into spike trains," *Phys. Rev. E*, vol. 103, no. 2, p. 22407, 2021.
- [9] U. B. Rongala, J. M. D. Enander, M. Kohler, G. E. Loeb, and H. Jörntell, "A non-spiking neuron model with dynamic leak to avoid instability in recurrent networks," *Front. Comput. Neurosci.*, vol. 15, 2021.
- [10] U. B. Rongala and H. Jörntell, "Rich dynamics caused by known biological brain network features resulting in stateful networks," *arXiv Prepr. arXiv2106.01683*, 2021.