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Exploring the Relationship Between Synaptic Dynamics Properties: Gain-Control and Temporal Filtering

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Abstract. The Gain-Control property of Synaptic Dynamics (SD) describes how the response of a neuron, mediated by short-term depression, can be sensitive to proportional changes of stochastic inputs. This has been related to the temporal filtering property of synaptic efficacy. However, the limits of the strength of Gain-Control in relationship to the efficacy have not been explored. This paper meets this gap by simulating networks using two synapses with fast- and slow-decays of efficacy. The results show that the Gain-Control effect decreases with the decay of efficacy. Formally describing this relationship can facilitate the integration of SD into Spiking Neural Networks.

1 Introduction

Computational models of Short-Term Plasticity (STP) or Synaptic Dynamics (SD - including the postsynaptic component of a neuron) are versatile tools in the fields of experimental neuroscience and also in Spiking Neural Networks (SNNs) [1, 2]: either helping to model the experimental findings from physiological recordings (and therefore extending the study of synaptic plasticity [3]) or enhancing the properties of SNNs when SD models are incorporated [4].

Synaptic responses depend on the firing activity of the presynaptic neuron and the morphological characteristics of the synapse [1]. These can lead to the expression of Short-Term Facilitation (STF) or Short-Term Depression (STD) [5], whose functional properties can be integrated into SNNs as computational properties, e.g., temporal filtering [6] or Gain-Control properties [7].

The temporal filtering property refers to the dependency of the synaptic contribution to a postsynaptic neuron given the input firing rates [6]. For STF synapses, the synaptic efficacy is increased, while it is decreased for STD. If the input comes from evenly separated spikes, the temporal filtering can be represented in a frequency response. Thus, the frequency response gives information about the nature of the temporal filtering property of SD.

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The Gain-Control property of STD describes how the postsynaptic response is sensitive to the proportional change of input at a baseline firing rate, no matter if the baseline is at low- or high-firing rate (similar to the Weber-Fechner law) [7]. Even if this sensitivity is mentioned to decrease at high-firing rates, the limits where this effect vanishes have not been fully investigated. Thus, this paper explores the high-firing rates when the Gain-Control contribution on the postsynaptic neuron is lower than the neuron activity due to random fluctuations.

We hypothesised that the effect of Gain-Control vanishes once the frequency response of efficacy reaches a steady value. To explore this, two small SNNs equipped with two different synapses (each of them with different decays of efficacy in the frequency response –one with fast- and one with low-decay–) are simulated using the Modified Stochastic Synaptic Model (MSSM) [8]. In this work, we contribute towards a deeper understanding of the relationship of Gain-Control and temporal filtering properties, which can represent an enhancement for the properties of SNNs equipped with SD models.

2 Methodology

With the aim of studying the relationship between the SD properties of Gain-Control and temporal filtering, we present the architecture of the network used to replicate the findings of Gain-Control in [7], as well as the nature of the input stimuli. After that, the MSSM is introduced, a biophysical model of SD, whose parameters are tuned for the fast- and slow-decay synapses. This is achieved by a pipeline that uses the frequency response of efficacy as reference signal [9]. Two networks are implemented, one for each studied synapse. Then, a metric is described to assess the effect of Gain-Control on the activity of the output neuron and the limit when this effect is vanished. The implementation of the networks is available in this repository [1].

2.1 Architecture and input stimuli

One of the experiments from the original work of the Gain-Control property in [7] is implemented in this paper to explore the limits of the Gain-Control effect. More specifically, the experiment of a network that connects 200 inputs to a Leaky Integrate-and-Fire (LiF) neuron using STD synapses (same parameters for all synapses). Two networks are implemented, one with fast-decay synapses, and the other with slow-decay synapses. For each network, 100 synapses receive high-firing rate inputs and the rest receive low-firing rate inputs (See figure 1). Each input follows a Poisson process at a given firing-rate. One simulation is 15 seconds long. The low-firing rate inputs fire at 10Hz, representing a background activity. The high-firing rate inputs change their rate every 30ms following a sinusoidal modulation of 50% of a baseline rate, simulating the encoding of a sinusoidal input stimulus (See figure 2).

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[1] Code available at https://github.com/kilmfer91/Synaptic_Dynamics_properties

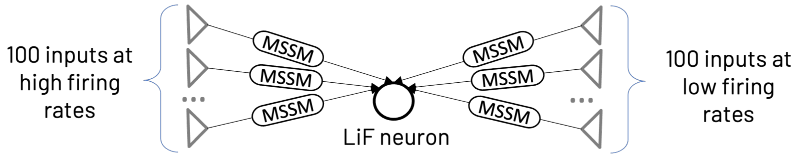

Fig. 1: Small network of 200 STD synapses connecting to a LiF neuron. The first 100 synapses receives inputs from high-firing rate spike trains, while the rest receives inputs from low-firing rates.

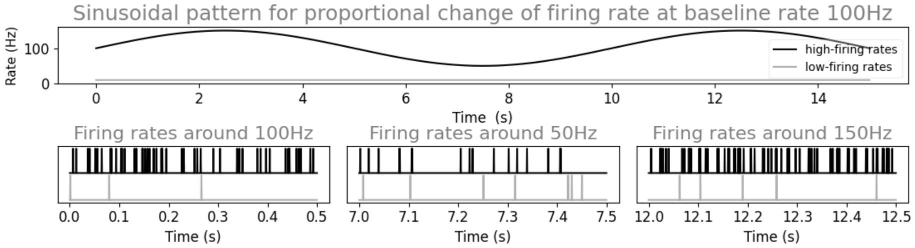

Fig. 2: Example of input stimuli: (top) 50% sinusoidal modulation of high-firing rates around 100Hz –black– while low-firing rate is 10Hz –gray–. (bottom) Corresponding spike trains in the periods $[0 - 0.5s]$, $[7 - 7.5s]$, and $[12 - 12.5s]$.

2.2 Synaptic Dynamics Models

Biophysical models of SD (e.g. the MSSM [8]) can represent the biological principles of synapses more faithfully than phenomenological models. The MSSM, which can recreate the Gain-Control property [10], is used to simulate the fast- and slow-decay synapses. The MSSM describes presynaptic dynamics (calcium buffering, vesicles cycle, release-probability of neurotransmitters), synaptic cleft (neurotransmitters) and postsynaptic contribution. The model comprises ten parameters for simulating facilitation or depression (α, τ_C, V_o, τ_V, P_0, k_{N_t}, $k_{N_t,V}$, τ_{N_t}, $\tau_{E_{psc}}$, and k_{epsc}). Detail description of the equations of the MSSM and the LiF neuron (and its parameters) can be found in the repository [1].

2.3 Tuning parameters of the MSSM for fast- and slow-decay synapses

A pipeline based on Differential Evolution is used to tune the ten parameters of the MSSM [9]. Having a reference signal to minimise the root-mean squared error, the optimisation technique finds a distribution of parameters for SD models. In this paper, the frequency response of efficacy is used as reference signal. The response of the fast-decay synapse is extracted from the Gain-Control seminal paper [7], while the response of the slow-decay is designed to have a longer decay, aiming to highlight differences on the Gain-Control effect given the frequency response of efficacy. The parameters of each synapse are found by running once the optimisation pipeline and picking the best individual (i.e. set of parameters).

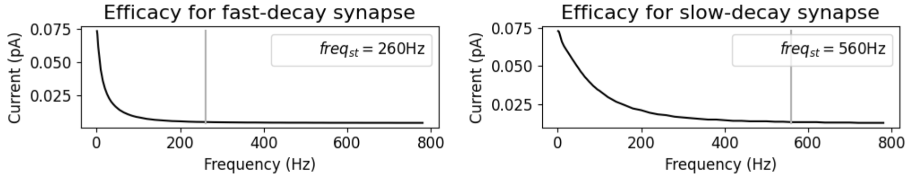

Fig. 3: Frequency responses of efficacy for the fast-decay (left) and the slow-decay (right). The $freq_{st}$, defined as the frequency where the efficacy varies by less than 1%, is 260Hz and 560Hz for the fast- and slow-decay synapses. Both responses are used as reference signals to tune the parameters of the MSSM.

The steady-state of the efficacy is reached once its response does not vary more than 1%. The frequency, at which the steady-state is reached, is referred as the $freq_{st}$ of efficacy. Figure 3 shows the frequency responses and the $freq_{st}$ of efficacy for the fast- and slow-decay synapses: 260Hz and 560Hz, respectively.

2.4 Metric of Gain-Control

In the experimental setup, the membrane potential of the LiF neuron presents a sinusoidal pattern –following the input modulation of high-firing rates– and a variance due to the stochasticity of the inputs. From the original work [7], the sinusoidal pattern is stronger than the variance for the baseline rate of 100Hz, reflecting the influence of the input pattern on the output (Figure 4 second column). In this paper, the effect of Gain-Control is defined to vanish if the amplitude of the sinusoidal pattern is lower than its variance for a given baseline rate, i.e., the influence of the input pattern is lost in the stochastic component. To test this, four simulations are run with different baseline rates: 50Hz, 100Hz, 300Hz and 500Hz. The baseline values are chosen based on the frequency responses of fast- and slow-decay synapses (Figure 3), hypothesising that the Gain-Control sensitivity vanishes in synapses when the baseline rate is higher than the $freq_{st}$ of efficacy, while it is preserved otherwise. The membrane potential of the neuron is low- and high-pass filtered to obtain the underline sinusoidal pattern and the variance (cutt-off frequency of 1Hz for both filters). The amplitude is calculated from the low-pass signal, while the variance is the difference between the 90% and 10% quartiles of the high-pass signal.

3 Results

Table 1 shows the parameters found by the pipeline to recreate the slow- and fast-decay synapses: the former has shorter time constants for the dynamics of Calcium and Vesicles (τ_c and τ_v, resp.) than the later. The slow-decay synapse recovers faster to resting values, i.e., it is more ready to release neurotransmitters for high-firing rates compared to the fast-decay one, which needs more time to recover and therefore stays longer in a depleted state for the same high rates.

Figure 4 illustrates the membrane potential of the networks (with fast- and slow-decay synapses) for the baseline input firing-rates tested. In both networks, the higher the baseline rate, the greater the mean of the membrane potential. The amplitude of the underlined sinusoidal pattern and the variance decrease with the baseline rate (as shown in table 2). In the case of the fast-decay synapse, the amplitude of the sinusoidal pattern is already lower than the variance for baseline rates 300Hz and 500Hz, showing that the Gain-Control effect has already vanished for a baseline rate higher than the $freq_{st}$ of efficacy (260Hz for this synapse). In the case of the slow-decay synapse, with 560Hz as $freq_{st}$ of efficacy, the Gain-Control effect does not vanish for the tested baseline rates (expected to vanish for higher rates). These findings suggest that the vanishing of the Gain-Control effect has a relationship to the temporal filtering property of SD: the higher the $freq_{st}$ of efficacy, the more sustain the Gain-Control effect at high-firing rates.

Synapse	τ_C	α	V_o	τ_V	P_0	$k_{N_t,V}$	k_{N_t}	τ_{N_t}	k_{epsc}	τ_{epsc}
fast-decay	**78.6ms**	0.46	1.47μM	**164ms**	0.00024	58.46μM	0.8μM	1.5ms	3.78nM	1.76ms
slow-decay	**30.4ms**	0.15	1.28μM	**83.3ms**	0.001	70.62μM	0.98μM	1ms	11.2nM	1ms

Table 1: Parameters of the MSSM found by the pipeline in [9], with the aim of recreating the slow- and fast-decay efficacies (Figure 3).

Baseline rate for synapses	50Hz		100Hz		300Hz		500Hz	
	amplitude	variance	amplitude	variance	amplitude	variance	amplitude	variance
fast-decay	1.4mV	0.97mV	0.85mV	0.78mV	**0.48mV**	**0.71mV**	**0.28mV**	**0.72mV**
slow-decay	4.56mV	1.18mV	4.54mV	1.03mV	2.68mV	0.89mV	1.93mV	0.8mV

Table 2: Amplitude and variance of membrane potential. The effect of Gain-Control vanishes when the amplitude is lower than the variance for a given baseline rate. This is evident at 300Hz and 500Hz for the fast-decay synapse.

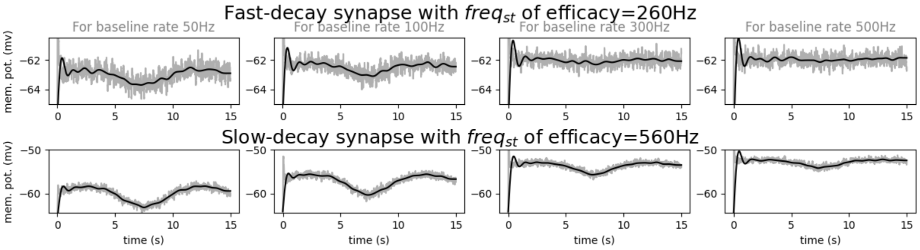

Fig. 4: Membrane potential of networks equipped with fast-decay and slow-decay synapses for different baseline rates. Once the amplitude of the underlined sinusoidal input pattern is lower than the variance of the noisy activity of the output neuron, the effect of Gain-Control vanishes. This effect remains for the slow-decay synapse but vanishes for the fast-decay synapse, which has a $freq_{st}$ of efficacy lower than the slow-decay synapse.

4 Discussion and Future Work

This paper explores the limits of the Gain-Control property of STD, highlighting that its effect vanishes once the frequency response of the efficacy (associated to the temporal filtering property of SD) reaches a steady-state value. Two synapses are recreated using the MSSM, one with fast-decay of efficacy and another with slow-decay. Each synapse is equipped in a network setup inspired by the Gain-Control seminal work. A metric to measure the strength of the Gain-Control effect is defined based on the underlined sinusoidal pattern of the output neuron and its variance, reflecting the input modulation and the stochasticity of the process. We demonstrate that the Gain-Control effect decreases with frequency and it is related to the value where the efficacy has no strong changes. Future work will focus on formal definitions of the Gain-Control vanishing frequency and its relationship with temporal filtering. Finally, our findings might guide practical decisions for embedding SD models into SNNs, such as identifying parameters ranges that preserve Gain-Control across typical firing regimes.

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