Efficient Spike-Coding with Multiplicative Adaptation in a Spike Response Model[1]

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Abstract The ability of neurons to adapt their responses to greatly varying sensory signal statistics is central to efficient neural coding [2, 4]. With substantial spike-rate adaptation occurring on a time scale of just tens of milliseconds, adapting neurons necessarily generate at most tens of spikes in that period. From an adaptive coding perspective, this implies that for a neuron's adaptation to be computable by downstream neurons, the adaptation effects have to be derivable from just the emitted spike-train. Spike-based models of adaptation are thus central when accounting for adaptation as adaptive neural coding.

In variations of adaptive integrate-and-fire spiking neuron models, adaptation can be incorporated as a combination of two mechanisms: spike-triggered adaptation currents and a dynamical action-potential threshold [5, 6]. In such models, the adaptation mechanisms together increase the distance between the reversal potential and the threshold, effectively changing the gain of the neuron (illustrated in Figure 1(a)). The adaptive Spike Response Model (aSRM) [5, 6] in particular has been shown to be effective for modeling neural behavior in response to input currents with limited dynamic range [6]. On longer timescales, spike-triggered adaptation currents fit a power-law decay rather than an exponential decay, linking to observations of long-range power-law rate-adaptation [8, 6].

Still, in spite of its success, the additive model of adaptation in the aSRM effectively changes neural gain with at most a fixed step-size, and thus cannot respond quickly to changes in signal variance that are large compared to this step-size. In particular, Brette [3] argues that adaptation modulation has to be multiplicative for neurons to respond with the same level of neural activity to drastic changes in dynamic range, as is observed experimentally (e.g. [2]).

In this paper, we augment the aSRM with multiplicative adaptation dynamics. In particular, at each spike-generating threshold crossing t_i, a kernel $\vartheta(t_i)\eta(t-t_i)$ is added, where $\eta(t)$ captures generic threshold dynamics, which are multiplied by the current threshold size $\vartheta(t_i)$. The effective threshold dynamics, as compared to additive dynamics, are illustrated in Figure 1(b).

In [1], I show that such a multiplicative aSRM quantitatively matches neural responses in variance switching experiments and maximizes information transfer. Consistent with theoretical considerations of efficient coding and experimental findings, I demonstrate that the model's effective gain responds to changes in contrast, through either mean or variance of the filtered signal.

The adaptation model presented also suggests a straightforward interpretation of spike-trains in terms of threshold-based detection of discernible signal levels in the rectified filtered input signal: *adaptive spike-coding*. In Figure 2, it is shown how non-linear signal encoding with a multiplicative aSRM maintains a high coding efficiency for input stimuli that vary in magnitude over several orders of magnitude, unlike the additive aSRM. The coding efficiency is further comparable to the additive aSRM when the adaptation step-size in the latter is optimized for the local dynamic range. Importantly, this result shows that multiplicative adaptive spike coding is an efficient means of analog signal transmission in dynamical neural networks: only a limited number of spike events need to be communicated rather than a great many analog values.

[1] The full paper has been published in [1]: *Advances in Neural Information Processing Systems (NIPS) 25*, pages 1844–1852, 2012.

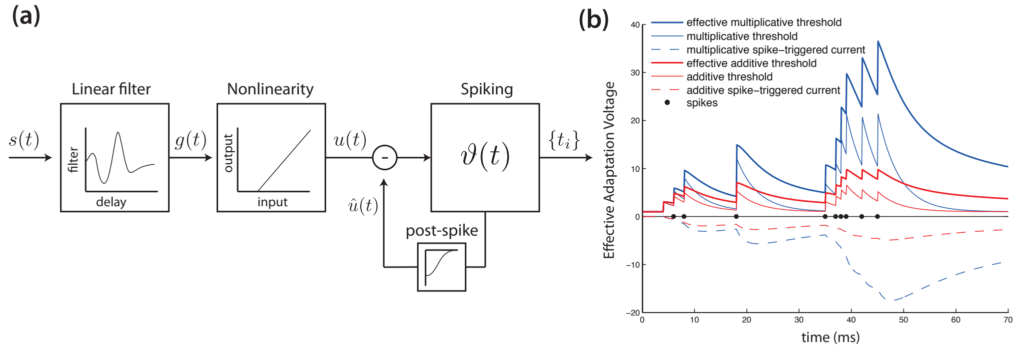

Figure 1: (a) The aSRM as a Linear-Non-Linear-Adaptive-Thresholding (LNL-AT) spiking neuron model. (b) Illustration of multiplicative and additive threshold adaptation dynamics. Effective adaptation as a sum of threshold dynamics (solid lines) and spike-triggered currents (dashed lines) given an input spike-train (black dots). Red lines correspond to additive adaptation dynamics, blue lines to multiplicative.

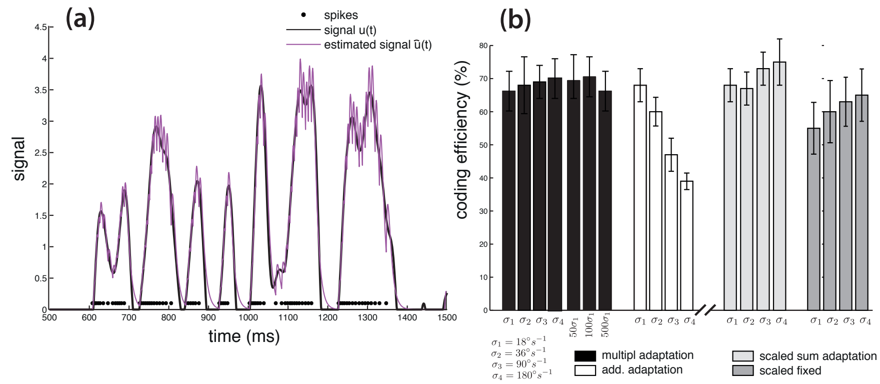

Figure 2: Multiplicative Spike-Coding: (a) illustration of stimulus encoding as a sum of shifted and weighted response kernels. Black dots denote spike-times, black solid line the signal $u(t)$, and magenta the approximated signal $\hat{u}(t)$. (b) Computed coding efficiency. Information rate R_{info} was computed, with effective signal and noise bandwidth cutoff at 50Hz (matching the original stimulus signal). Coding efficiency was computed by dividing R_{info} by the spike-train entropy rate S/T [7] for a timing precision of 1 ms.

References

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