Spike Synchrony Resolves Stimulus Saliency and Familiarity

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Abstract

The function of temporal coding in the brain remains controversial, with debate centering on the following question: does spike timing information, such as their temporal synchrony, play a meaningful role in neural computation which cannot be attributed to firing rate? We propose the solution to this dilemma: spike synchrony provides crucial information about stimulus familiarity under conditions when the firing rate alone is insufficient − namely, when the input stimulus is varied in saliency. Using simulations of recurrent spiking networks, we show that synchrony is particularly effective in distinguishing familiar stimuli of low saliency from novel stimuli of high saliency − an important distinction for both biological perception and artificial agents navigating dynamic environments. Synchrony is more sensitive to recurrent connectivity, that encodes prior experiences, compared to input firing rate. This highlights the relevance of synchrony for familiarity encoding in a scenario of realistic input variability.

Keywords: spiking networks; spike synchrony; temporal coding; familiarity detection; recurrent networks; associative memory.

Introduction

Spike synchrony is a highly debated form of temporal coding. Researchers view it either as a mechanism binding input features into coherent representations (Roelfsema et al., 1996; Singer, 1999) or simply as a byproduct of firing activity (Shadlen & Movshon, 1999). Others propose that synchrony functions as a mechanism for coincidence detection (Abeles et al., 1991), working memory (Szatmáry & Izhikevich, 2010), invariant input coding (Brette, 2012), or relevant stimulus selection (Fries et al. 2002). A recent perspective suggests synchrony acts as a familiarity detector (Korndörfer et al., 2017; Zemliak et al., 2024). Familiarity memory is essential for adaptive behavior in both living and artificial agents, enabling efficient decision-making based on prior experience.

Using simulations of recurrent spiking networks, we identify the conditions under which non-oscillatory, connectivity-driven synchrony carries crucial information which cannot be decoded from rate alone: it reliably detects familiar stimuli of varied saliency. Rather than replacing rate coding, synchrony complements it: rate points to the relevant neuron population, and synchrony detects familiarity from its activity.

Stimulus meta-information

Stimulus saliency and familiarity are two kinds of meta-information about incoming stimuli. They don't convey information about the specific content of perceptions, such as which objects are depicted on an image, but rather provide a higher-level context about its relevance for processing and decision making.

In our study, saliency is defined as input firing rate, reflecting bottom-up sensory characteristics of static stimuli, such as contrast and intensity. Note that in many spiking models feedforward inputs are represented as Poisson processes with constant firing rates. We argue that only in the context of variable stimulus saliency reflected in input firing rates, does spike synchrony exercise its computational potential, since it can reliably detect a different type of contextual information − input familiarity.

Following theoretical computational models, we encoded familiarity in recurrent connections (Korndörfer et al., 2017; Zemliak et al., 2024), as in the brain they reflect the acquired visual experience, and often experienced stimuli can be interpreted as familiar. At the same time, recurrent connection strength increases spike synchrony (König et al., 1993; Stettler et al., 2002). Therefore, synchrony serves as a proxy to infer stimulus familiarity from firing activity (Korndörfer et al., 2017; Zemliak et al., 2024).

Results

In our experiments, we randomly varied input saliency, and the network had to classify its familiarity. We developed two models for familiarity detection: (i) a network with V1-like connectivity (consistent with Cossel et al., 2015; Hage et al., 2022; Znamenskiy et al., 2018; Taylor et al., 2024) and (ii) an abstract associative memory model. Both models were spiking recurrent networks (SNNs) composed of LIF neurons, receiving feedforward external, recurrent excitatory and noisy background input. For familiar inputs, Poisson feedforward input was administered to strongly connected clusters of neurons, and for new ones − to weakly connected groups. Connectivity was predefined beforehand and included strongly connected ensembles, as well as cross-ensemble inhibition. For each data sample, the input rate was drawn from a uniform range of possible input firing rates, which represented saliency variability. For the V1 model, we tested different variability: 0 (fixed input rate 50 Hz), 10 (40-60 Hz), 20 (30-70 Hz), 30 (20-80 Hz), 40 Hz (10-90 Hz), and for the abstract model all experiments were performed for the range of 10-90 Hz (Fig. 1A). A single dataset included 320 stimuli: 160 familiar and 160 new.

To predict whether a stimulus was new or familiar, we used the activity of stimulated neurons in response to it. We employed binary logistic regression, using either firing rate or spike synchrony statistics as predictors. Firing rate was computed as average spike count (SC), and spike synchrony as Rsync (Eq. 1).

$$Rsync\,(S,T) = \frac{\widehat{Var}\left[\langle A_i(t)\rangle_{i\in S}\right]_{t\in T}}{\left\langle \widehat{Var}\left[A_i(t)\right]_{t\in T}\right\rangle_{i\in S}} \quad (1)$$

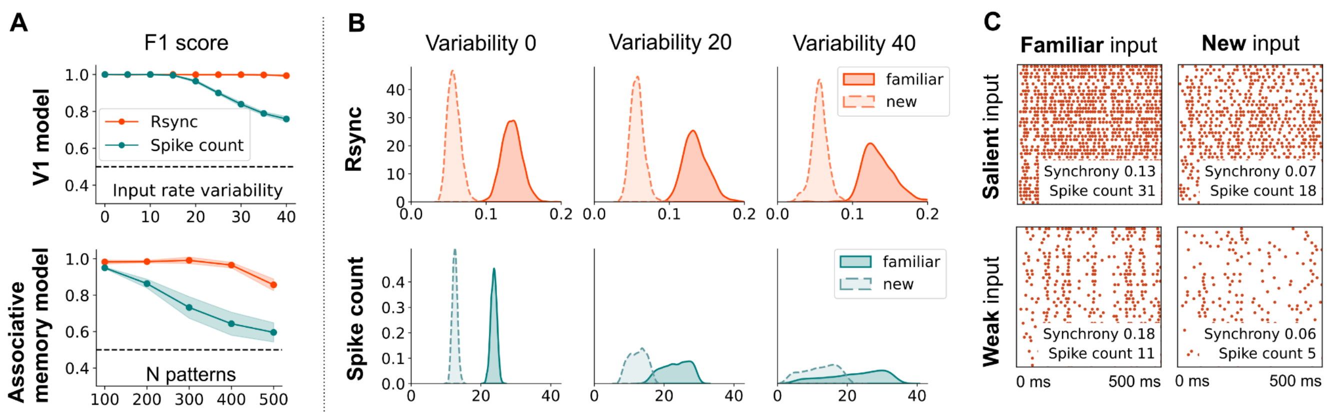

Figure 1: Familiarity detection. **A**. 10-fold cross-validation performance on familiarity detection from synchrony or spike count. Average result with standard deviations across 20 iterations, 320 samples each. Results for the V1 model are presented for various levels of saliency (input rate) variability, for the associative memory model − for highest (10-90 Hz) variability and for increasing memory load (number of pre-encoded patterns). **B**. KDE plots of synchrony and spike count of stimulated neurons in response to new and familiar stimuli in the V1 model. **C**. Spike raster plots of 500 ms of the V1 model activity in response to weak (10 Hz) and salient (90 Hz) stimuli.

In both models, synchrony outperforms spike count as a measure of stimulus familiarity when input salience varies. Thus, spike synchrony responds more to recurrent connections than input rate, while output rate fails to separate these contributions. Our findings seem to contradict Zemliak et al. (2025), who found spike count outperforms synchrony for familiarity detection in recurrent networks. However, they used Poisson input with constant firing rates, while we show synchrony's advantage emerges with varying input rates that better reflect real-world visual input. This extends Brette's (2012) theory of synchrony for invariant coding.

In the abstract model, both metrics show declining performance as the number of familiar patterns stored in the network increases. This effect aligns with Zemliak et al. (2025), who attribute it to growing overlap between clusters representing familiar patterns.

Data and code availability

All data was programmatically generated. Code for data generation, analysis and visualization can be found at https://github.com/rainsummer613/saliency-familiarity-mini.

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