Optimal Time Scale for Spike-Time Reliability: Theory, Simulations, and Experiments

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Galán RF, Ermentrout GB, Urban NN. Optimal time scale for spike-time reliability: theory, simulations, and experiments. J Neurophysiol 99: 277–283, 2008. First published October 10, 2007; doi:10.1152/jn.00563.2007. Use of spike timing to encode information requires that neurons respond with high temporal precision and with high reliability. Fast fluctuating stimuli are known to result in highly reproducible spike times across trials, whereas constant stimuli result in variable spike times. Here, we first studied mathematically how spike-time reliability depends on the rapidness of aperiodic stimuli. Then, we tested our theoretical predictions in computer simulations of neuron models (Hodgkin-Huxley and modified quadratic integrate-and-fire), as well as in patch-clamp experiments with real neurons (mitral cells in the olfactory bulb and pyramidal cells in the neocortex). As predicted by our theory, we found that for firing frequencies in the beta/gamma range, spike-time reliability is maximal when the time scale of the input fluctuations (autocorrelation time) is in the range of a few milliseconds (2–5 ms), coinciding with the time scale of fast synapses, and decreases substantially for faster and slower inputs. Finally, we comment how these findings relate to mechanisms causing neuronal synchronization.

METHODS

Experimental

All experiments were conducted under a protocol approved by the Carnegie Mellon University Institutional Animal Care and Use Committee using procedures described previously (Urban and Sakmann 2002). Sagittal slices of the olfactory bulb and coronal slices from somatosensory, motor, and prefrontal cortex were prepared from mice aged 14–24 days. Whole cell current-clamp recordings were performed at 33°C in the presence of blockers of fast synaptic transmission (APV 25 μM, CNQX 10 μM, bicuculline 10 μM). Cells were injected with currents (duration: 2.5 s) consisting of a bias current (200–300 pA in mitral cells; 400–500 pA in pyramidal cells) plus current fluctuations of variable amplitude (from 0 to 90 pA). Aperiodic fluctuations were generated by convolving frozen white noise with an alpha function, \( t/\tau \cdot \exp(-t/\tau) \) with time-to-peak \( \tau \) and rescaling to the desired variance, so that the amplitude of the fluctuations was the same for all \( \tau \). Each stimulus was presented five times to study the reliability of the response. The mean firing rate of the neurons was between 10 and 80 Hz. Experimental estimation of the background noise level was performed by measuring the SD of the random currents recorded in voltage clamp at \(-65 \text{ mV} \). This was \(-7 \text{ pA} \).

Signal processing

The reliability of the neuronal response was calculated as the mean pairwise correlation of the spike trains obtained in different trials. Specifically, we first converted the spike trains into binary strings, where 1 represents a zero-crossing of the membrane potential and 0 represents any other value. These strings were convolved with a square function of width \( \delta = 4 \text{ ms} \), in Fig. 3) and unitary amplitude. The pairwise correlation was calculated as the dot product of these signals—without subtracting the mean—normalized by the product of their norms. This roughly corresponds to the number of reliable spikes divided by the total number of spikes fired. This measure of reliability is equivalent to other measures of reliability and synchrony previously used by several authors (Galán et al. 2006a,b; Hunter et al. 1998; Schreiber et al. 2004).

Simulations

We used the single-compartment simple neuron model proposed in Izhikevich (2004), which has two dynamical variables, the membrane potential, \( v \), and the recovery variable, \( u \), that obey the equations

\[
\begin{align*}
\frac{dv}{dt} &= 0.08 \cdot v^2 + 10v + 280 - 2u + I(t) + \eta(t) \\
\frac{du}{dt} &= a(bv - u)
\end{align*}
\]

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with $a = 0.04$ and $b = 0.2$. In addition, when $v > 30$, the membrane
potential is reset to $v = -65$ mV, and the recovery variable is reset to
$u = u + 2$. The input, $I(t)$ consisted of a bias current (8–13 × 10 pA)
plus the fluctuating stimulus (6 × 10 pA), which was 1.4 times larger
than the background noise, $\eta_i(t)$. We also used the conductance-based
single-compartment model by Hodgkin and Huxley (1952)

$$\begin{aligned}
C \cdot \frac{dV}{dt} & = g_{\text{Na}} m^3 h (E_{\text{Na}} - V) + g_{\text{K}} n^4 (E_{\text{K}} - V) + g_L (E_L - V) + I_0 + I(t) + \eta(t) \\
\frac{dm}{dt} & = \alpha_m (1 - m) - \beta_m m \\
\frac{dn}{dt} & = \alpha_n (1 - n) - \beta_n n \\
\frac{dh}{dt} & = \alpha_h (1 - h) - \beta_h h
\end{aligned}$$

where $V$ is the membrane potential and $m$, $n$, and $h$ are the gating
variables of the channels, which depend on the functions

$$\begin{aligned}
\alpha_m & = \frac{0.1 \cdot (V + 40)}{1 - \exp[-0.1 \times (V + 40)]}, \\
\beta_m & = 4 \cdot \exp[-0.0556 \times (V + 65)] \\
\alpha_n & = 0.07 \cdot \exp[-0.05 \times (V + 65)], \\
\beta_n & = 1/[1 + \exp[-0.1 \times (V + 35)]] \\
\alpha_h & = \frac{0.1 \cdot (V + 55)}{1 - \exp[-0.1 \times (V + 55)]}, \\
\beta_h & = 0.125 \cdot \exp[-0.0125 \times (V + 65)]
\end{aligned}$$

In these equations, the following parameters were used: bias current,
$I_0 = 6–9$ μA/cm²; the mean amplitude of the input fluctuations, $I$, was
5 μA/cm²; the mean amplitude of the background noise, $\eta_i(t)$, was 2
μA/cm²; $g_{\text{Na}} = 120$ mS/cm²; $g_{\text{K}} = 36$ mS/cm²; $g_L = 0.3$ mS/cm²,
$E_{\text{Na}} = 50$ mV, $E_{\text{K}} = -77$ mV, $E_L = -54.387$ mV, $C = 1$ μF/cm².
The data from simulations were analyzed in the same fashion as the
experimental data (see Signal processing).

Several studies have emphasized the importance of fast fluctuating
inputs in generating spike times that are reliable from trial to trial
(Bryant and Segundo 1976; Mainen and Sejnowski 1995). Here we
ask whether faster is always better and in particular whether there is
an optimal time scale for aperiodic fluctuating stimuli to induce
reliable firing. To this end, we have combined theoretical, computa-
tional, and experimental studies.

Mathematical theory

From a conceptual perspective, spike-time reliability is equivalent to a
limit case of noise-induced synchronization (Galán et al. 2006b; Teramae
and Tanaka 2004): In the former, the timing of spikes is preserved across
repeated trials in which the same fluctuating stimulus is delivered to a
single neuron. In the latter, a pattern of synchronous spikes is generated
during different neurons receiving similar (correlated) fluctuating inputs.
Thus the study of reliability can be reduced to the study of two identical
neurons receiving identical (perfectly correlated) fluctuating inputs in
the presence of background noise. Let $y_1(t)$ be the voltage traces of these
two neurons (outputs) and $x_i(t)$ be the respective inputs received ($i = 1, 2$).
The relationship between the inputs and the outputs is given to a first order
approximation by (Rieke et al. 1997)

$$\begin{aligned}
y_1(t) & = \int_0^t K(s) x_1(t - s) \, ds \\
y_2(t) & = \int_0^t K(s) x_2(t - s) \, ds
\end{aligned}$$

where the convolution kernel, $K(s)$ is the spike-triggered average
(STA) of the neurons reversed in time. The inputs $x_i(t)$ consist of two
components: a fluctuating signal (colored noise) common to both
neurons $l(t)$ with autocorrelation time, $\tau$, (the shorter $\tau$, the faster the
fluctuations) plus uncorrelated white noise, $\eta_i(t)$

$$x_i(t) = l(t) + \eta_i(t)$$

with

$$\langle \eta_i(t) \eta_j(t - s) \rangle = 0, \quad \langle \eta_i(t) \eta_j(t - s) \rangle = \sigma^2 \delta(t - s),$$

$$\langle l(t) l(t - s) \rangle = \sigma^2 \exp(-|s|/\tau)$$

We define reliability (or synchronization across neurons), $R$, as the
correlation coefficient of the voltage traces

$$R = \frac{\int_0^\infty y_1(t) y_2(t) \, dt}{\sqrt{\int_0^\infty y_1(t)^2 \, dt \int_0^\infty y_2(t)^2 \, dt}}$$

$$= \frac{\int_0^\infty y_1(t) y_2(t) \, dt}{\sqrt{\int_0^\infty y_1(t)^2 \, dt \int_0^\infty y_2(t)^2 \, dt}}$$

where we have used the fact that the integral of the square of $y_1(t)$ and
the integral of the square of $y_2(t)$ are equal. Substituting Eq. 1 into
Eq. 4, followed by the application of Eqs. 2 and 3, we first calculate

$$\int_0^\infty y_1(t) y_2(t) \, dt = \int_0^\infty \int_0^\infty K(s) K(s') \int_0^\infty x_1(t - s) x_2(t - s') \, ds \, ds'$$

$$= \int_0^\infty K(s) K(s') \int_0^\infty x_1(t - s) x_2(t - s') \, ds \, ds'$$

$$= \sigma^2 \int_0^\infty K(s) K(s + u) \exp(-u/\tau) \, du$$

$$= \sigma^2 \int_0^\infty K(s) K(s + u) \delta(u) \, du$$

$$= \sigma^2 \int_0^\infty \exp(-u/\tau) Q(u) \, du$$

where we have defined $Q(u) = \int_0^\infty K(s) K(s + u) \, ds$. Analogously,
we calculate

$$\int_0^\infty y_1(t) y_2(t) \, dt = \int_0^\infty \int_0^\infty K(s) K(s') \int_0^\infty x_1(t - s) x_2(t - s') \, ds \, ds'$$

$$= \int_0^\infty K(s) K(s') \int_0^\infty x_1(t - s) x_2(t - s') \, ds \, ds'$$

$$= \sigma^2 \int_0^\infty K(s) K(s + u) \delta(u) \, du$$

$$= \sigma^2 \int_0^\infty \exp(-u/\tau) Q(u) \, du + \sigma^2 Q(0)$$
Thus $R(\tau) = R$ becomes

$$R(\tau) = \frac{\sigma^2 \int_0^\infty \exp(-u/\tau)Q(u)du}{\sigma^2 \int_0^\infty \exp(-u/\tau)Q(u)du + \sigma^2 Q(0)}$$

(5)

Note that in the absence of background noise, i.e., if $\sigma_a = 0$, $R = 1$ for any $\tau$, whereas in the absence of a fluctuating signal, i.e., if $\sigma_t = 0$, $R = 0$ for any $\tau$. Figure 1A shows the curves $R$ versus $\tau$ for two neuron models [Hodgkin-Huxley’s (HH) from Hodgkin and Huxley 1952 and a simple neuron model (SM) from Izhikevich 2004] at different firing rates as predicted from their kernels, $K(t)$, shown in Fig. 1B. Clearly, in all cases, $R(\tau)$ has a maximum in the few millisecond range. Note that the HH model can fire only above ~50 Hz, whereas the SM model can fire in the beta/low gamma range as well. This is important for the explanation below. In addition, whereas the HH model contains a detailed dynamical description of realistic conductances, the SM is basically a modified quadratic integrate-and-fire model, i.e., a nonlinear device with a resetting threshold, whose kernel, $K(t)$ resembles those of real neurons and that according to Eq. 5 leads to nonmonotonic curves, $R(\tau)$.

How does the optimal time-scale for spike-time reliability, $\tau_{opt}$, depend on the average interspike interval, $T$? As neurons fire faster, $T$ decreases and the spike-triggered average is, in a first approximation, “compressed” accordingly (Fig. 1B). Thus $\tau_{opt}$ will decrease with $T$; typically, in simulations and experiments, $\tau_{opt} = 10%T$. This result can also be obtained by applying dynamical system theory as follows. Consider two identical neurons in the form of phase oscillators (Kuramoto 2003) and driven by (Eq. 2)

$$\begin{align*}
&d\theta_i/dt = 2\pi/T + Z(\theta_i) [I(t) + \eta_i(t)] \\
&d\theta_j/dt = 2\pi/T + Z(\theta_j) [I(t) + \eta_j(t)]
\end{align*}$$

(6)

where $T$ is the average natural period (mean interspike interval) of the neurons and $Z(\theta)$ is the phase-dependent sensitivity of the oscillator [phase resetting or phase response curve (PRC)], which can be determined experimentally in real neurons (Galan et al. 2005; Mancilla et al. 2007; Tateno and Robinson 2007). We now consider the relative phase of the oscillators $\phi = \theta_2 - \theta_1$. From Eq. 6, we get

$$d\phi/dt = [Z(\theta_i + \phi) - Z(\theta_i)] I(t) + [Z(\theta_2)\eta_2(t) - Z(\theta_1)\eta_1(t)]$$

(7)

Using the approximation

$$[Z(\theta_i + \phi) - Z(\theta_i)] = Z'(\theta_i)\phi$$

and averaging on time we obtain

$$d\phi/dt = -\lambda \phi + \sigma_\lambda \eta(t)$$

where $-\lambda$ is by definition the Liapunov exponent for system Eq. 6

$$\lambda = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T Z'(\theta(t)) I(t) dt$$

and $\sigma_\lambda$ is the SD of the stochastic term in Eq. 7

$$\sigma_\lambda^2 = \frac{\sigma^2}{\pi} \int_0^{2\pi} Z^2(\theta) d\theta$$

The Liapunov exponent of a dynamical system quantifies its robustness to the effect of noise: the larger its absolute value, the more robust the dynamics. Because we are assuming that the effect of the fluctuating input is small relative to the natural frequency, we can use the approximation

**FIG. 1.** Prediction of the mathematical theory. A: spike-time reliability, $R$, as a function of the time scale, $\tau$ of the stimulus fluctuations for the Hodgkin-Huxley model (HH) from Hodgkin and Huxley (1952) and for the modified simple neuron model (SM) from Izhikevich (2004). For firing rates in the beta/gamma band, the theory predicts maximal values of reliability between $\tau = 2$ and 5 ms. B: spike-triggered average reversed in time, $K(t)$ of the neuron models from which the curves in A are predicted.
METHODS that consisted of a constant current (such that the
We repetitively presented “frozen colored noise” stimuli
the following experiments with simulated and real neurons.
RESULTS observed in simulations and experiments, which is 10%
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occupation function,
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imation, this value is in the same order of magnitude as the actual
noise through different low-pass filters (see METHODS).

\lambda = \lim_{T \to \infty} \frac{1}{T} \int_0^T \left[ Z'(t)I(t) + Z''(t) \int_0^t Z(s)I(t)I(s)ds \right] dt

\approx 0 + \lim_{T \to \infty} \frac{1}{T} \int_0^T Z''(t) \int_0^t Z(s)C(t - s)ds dt \tag{8}

where \(C(t - s)\) is the autocorrelation function of the input. For a
typical phase response, \(Z(t)\) of a real neuron, the absolute value of the
Liapunov exponent is maximal for a finite \(\tau = \tau_{opt}\) of the autocorre-
lation function, \(C(s) = \sigma^2 \exp(-\omega t / \tau)\). Furthermore, since \(Z(t)\) can,
in a first approximation, be described by a sinusoidal, from Eq. 8, one
obtains \(\tau_{opt} \approx T/(2\pi) \approx 16\% T\). Despite the simplicity of the approx-
imation, this value is in the same order of magnitude as the actual \(\tau_{opt}\)
observed in simulations and experiments, which is 10\% (see below).

RESULTS
Simulations and experiments
To test the predictions of our theory, we have designed
the following experiments with simulated and real neurons.
We repetitively presented “frozen colored noise” stimuli
(see METHODS) that consisted of a constant current (such that the
neurons fired regularly in the beta/gamma band, 10–80 Hz)
plus aperiodic fluctuations, \(I(t)\), generated by passing white
noise through different low-pass filters (see Signal processing)
to generate signals with different autocorrelation times, \(\tau\) (the
shorter \(\tau\) is, the faster are the fluctuations). We performed the
experiments (Fig. 2) on mitral cells \((n = 18)\) of the olfactory
bulb and on neocortical pyramidal cells \((n = 20)\) of mice,
obtaining similar results: on average, spike-time reliability is
maximal for \(\tau = 2–5\) ms (Fig. 3A). For this time scale,
reliability monotonically increased with increasing amplitude
of the fluctuations (Fig. 3B). Interestingly, already one half of
the spikes were reliable as soon as the input fluctuations
doubled the background input noise (<10 pA). Similar curves
of reliability are followed by the HH conductance model
(Hodgkin and Huxley 1952) and even by a SM model (Izhikev-
ich 2004) lacking any conductances (Fig. 3). In the computer
simulations background, uncorrelated noise, \(\eta(t)\) was also
added (see METHODS).

Our measure of spike-time reliability for simulations and
experiments (see METHODS) differs slightly from Eq. 4: it
detects spikes that are preserved across trials within a time bin
of 2\(\delta\) ms, i.e., the tolerance to “spike jitter” is \(\pm 2\delta\) ms. In Fig.
3, we chose \(\delta = 4\) ms. Obviously, the optimal time scale for
neural reliability should not depend on this choice, and it does
not, as shown in Fig. 4A. However, the values of reliability
should increase overall as we tolerate larger spike jitter across
repetitions. This can also be observed in Fig. 4A.

Next we studied the dependence of the optimal time scale for
spike-time reliability on the average interspike interval. This
analysis was performed across the population of neurons studied
to cancel out the variability observed in single cell recordings.
In effect, although the shape of the curve \(R(\tau)\) is highly
consistent across different experiments in the same and different
cells (Fig. 3A), the exact position of the peak varies from
experiment to experiment, even in the same cell, within a range
that is comparable to the change predicted by the firing-rate
dependence. Thus we pooled all the data recorded for each
neural type and calculated a linear regression for each type. As
predicted by our theory, \(\tau_{opt}\) increases with the mean interspike

FIG. 2. Maximal reliability in real cells. Aperiodic frozen currents (top traces; \(\tau = 3\) ms) are injected 5 times into a mitral cell (4A) and
into a neocortical pyramidal cell (8B). In both neurons, virtually all spikes are preserved across all trials.
interval, \( T \), in simulations and experimental data (Fig. 4B). In all cases, however, the increase is between 8.4 and 11\% \( T \), which is lower than \( T/(2\pi) \approx 16\% T \). This is not surprising, because the relationship \( \tau_{\text{opt}} \approx T/(2\pi) \) was obtained from Eq. \( \delta \) by approximating the phase-response of the neurons with a pure sinusoidal, which is a rather crude approximation for both, mitral cells (Galán et al. 2005) and pyramidal cells (Tsabo et al. 2007) and also for the simulated neurons. We expect that a nonsinusoidal phase-response curve should shift the ratio \( \tau_{\text{opt}}/T \). Nevertheless, this simple approximation permits us to obtain the correct order of magnitude for \( \tau_{\text{opt}} \) as a function of the mean interspike interval.

**DISCUSSION**

We presented a mathematical theory that predicts a maximum of spike-time reliability for a finite value of the autocorrelation time of aperiodic stimuli and provided experimental evidence of this phenomenon in real neurons. In particular, we showed that the optimal time scale for neural reliability is in the range of 2–5 ms for neurons firing in the beta/gamma frequency band.

Previous studies showed that spike-time reliability in response to fast fluctuations can be enhanced by specific interactions between the membrane potential and the ionic currents.
(Schreiber et al. 2004). This is consistent with our finding that
the spike-triggered average of the neuron, which relies on the
activation/inactivation of intrinsic currents, determines the
function $R(\tau)$, for a fixed signal-to-noise ratio in Eq. 5. How-
ever, we showed here that even simple models lacking any
conductances, like the modified quadratic integrate-and-fire,
support high levels of spike-time reliability that is maximal at
a finite time scale. In fact, it has been suggested that reliability
is a rather general property of neurons that is facilitated by
stimuli driving the membrane potential with a large slope at
the firing threshold (Hunter et al. 1998; Rodriguez-Molina et al.
2007). In agreement with this argument, here we showed
mathematically that the trajectory of the membrane potential
not only at threshold, but also in the preceding moments, i.e.,
the spike-triggered average, determines spike-time reliability
as a function of the autocorrelation time of the inputs. Our
theory can be intuitively interpreted in the following way:
whereas the average number of spikes within a given time
window is determined by the steady-state input–output relation-
ship ($F-I$ curve), the exact times at which the spikes occur
rather depend on the input fluctuations that modulate the firing
rate. Thus if the stimulus is constant or very slow, the precise
timing will be dominated by the major source of fluctuations:
nonreproducible background noise. On the other hand, if the
stimulus fluctuations are too fast, threshold crossings will
occur when stimulus and noise add to pass threshold, so that
the neuron will sometimes fire even when at the preceding
moment it was far from threshold. As a result, the precise
timing of the spikes will be nonreproducible across trials. In
the intermediate case, when the stimulus fluctuations are nei-
ther too fast nor too slow, the neuron will most likely fire when
it is close to threshold only. This results in an optimal time
scale for spike-time reliability.

Other authors have studied the effect of intrinsic time con-
stants on spike-time reliability to periodic, multiperiodic, and
notch-filtered inputs (Hunter and Milton 2003; Schreiber et al.
2004; Thomas et al. 2003). Here, in contrast, we focused on
reliability to aperiodic inputs. The use of these inputs has the
following biological motivation: During highly active states,
when the neurons are receiving large barrages of mixed syn-
aptic excitation and inhibition, the synaptic currents approach
a random process. Some authors refer to these stochastic inputs
as “synaptic noise” (Destexhe and Rudolph 2004; Rudolph
and Destexhe 2004). In addition, the kinetics of the synapses, the
specific details of the morphology, and the electrotro properties
are going to low-pass filter those inputs, introducing a
finite autocorrelation time, $\tau$. Interestingly, the autocorrelation
time that maximizes spike-time reliability, $\tau_{\text{opt}}$, is within the
range expected for integration times of fast synapses plus
conduction delays.

In our theory, the only time scale that is directly related to
$\tau_{\text{opt}}$ is the average interspike interval, $T$. In agreement with
this, the optimal time scale of 2–5 ms reported here is
inconsistent with other time scales of the neurons: mem-
brane time constants are typically one order of magnitude
slower; subthreshold resonance, when present, is also much
slower typically occurring between 5 and 15 Hz (65–200
ms), i.e., one to two orders of magnitude slower than $\tau_{\text{opt}}$. In
fact, our theory is applicable for neural resonators (like
mitral cells) or integrators (like pyramidal cells). Moreover,
intrinsic currents in mitral cells and pyramidal cells have
different characteristics resulting in clearly distinguishable
voltage traces (Fig. 2). In fact, whereas mitral cells possess
type II excitability (Gañán et al. 2005) (neural resonators),
there is increasing evidence that at least a large fraction of
pyramidal cells possess type I excitability (Tateno and
Robinson 2006; Tsubo et al. 2007) (neural integrators).
Despite these differences the curves of reliability are very
similar and closely resemble those of neuron models
(Fig. 3).

Although fairly general, our theoretical predictions may not
be applicable for all neural types. In particular, our theory may
be inaccurate for neurons whose dynamics covers several time
scales, because the Volterra expansion used in Eq. 1 would
require additional, higher-order terms. For example, our theory
may fail in predicting reliability of some intrinsically bursting
neurons because they possess clearly separated, but coupled
time scales (slow bursts and fast spikes). The estimate that the
optimal time-scale for reliability is $\sim 16\%$ of the period follows
from the assumption that the phase-resetting curve of the
neuron is determined by the first term in its Fourier expansion.
This assumption is generally true with tonically spiking neu-
rons but not for neurons with complex waveforms like bursts.
Despite not being universal, the applicability of our theory is
broad enough to be relevant for sensory coding, like in mitral
cells, and other cognitive functions, like in pyramidal cells.

In our experiments, the input has been provided as current
injections through standard whole cell patch-clamp techniques.
The same experiments could be generalized for dynamic-clamp
techniques, in which inputs are given as conductance changes.
In this case, the driving force of the conductance is likely to increase
reliability by quickly amplifying the input at specific points of the
spike’s waveform. This would be similar to the effect that we have
seen previously with computer models in which we compared
current and conductance injection in the case of noise-induced
synchronization (Gañán et al. 2006b). In other words, our quanti-
fication of reliability may underestimate the reliability measured
with conductance clamp techniques.

Our findings on spike-time reliability and its optimal time
scale are immediately applicable to stochastic synchronization
(Gañán et al. 2006b), because both phenomena are closely
related. In the former case, the timing of the spikes is preserved
in repeated trials with the same fluctuating stimulus. In the
latter case, identical neurons receiving similar (correlated)
fluctuating stimuli trigger synchronous spikes. In particular,
barrages of spatially correlated synaptic input currents will
synchronize postsynaptic neurons quickly. Analogously, in the
case of a single neuron, a reproducible barrage of synaptic
pulses will trigger highly reliable responses.

In conclusion, we showed that neurons have a preferred time
scale in which the fidelity of the response, quantified as
spike-time reliability, is maximal. In real neurons, this time
scale is in the range of a few (2–5) milliseconds, suggesting
that neurons are adapted to optimally respond to their most
natural input signal: fast synaptic currents.

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