Noise-Induced Transition to Bursting in Responses of Paddlefish Electroreceptor Afferents

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Neiman AB, Yakusheva TA, Russell DF. Noise-induced transition to bursting in responses of paddlefish electroreceptor afferents. J Neurophysiol 98: 2795–2806, 2007. First published September 12, 2007; doi:10.1152/jn.01289.2006. The response properties of ampullary electroreceptors of paddlefish, Polyodon spathula, were studied in vivo, as single-unit afferent responses to external electrical stimulation with varied intensities of several types of noise waveforms, all Gaussian and zero-mean. They included broadband white noise, Ornstein–Uhlenbeck noise, low- or high-frequency band-limited noise, or natural noise recorded from swarms of Daphnia zooplankton prey, or from individual prey. Normally the afferents fire spontaneously in a tonic manner, which is actually quasiperiodic due to embedded oscillators. 1) Weak noise stimuli increased the variability of afferent firing, but it remained tonic. 2) In contrast, stimulation with less-weak broadband noise led to a qualitative change of the firing patterns, to parabolic bursting, even though the mean firing rate was scarcely affected. 3) The transition to afferent bursting was marked by the development of two well-separated timescales: the fast frequency of spiking inside bursts at ≤250 spikes/s and the slow frequency of burst occurrences at about 9 (range 5–13) bursts/s. These two timescales were manifested as two regimes in afferent power spectra, bimodal interspike interval histograms, return maps, and autocorrelation functions of afferent spike trains. 4) The stochastic approximately 9-Hz bursts were not simply driven by similar-frequency components of noise stimuli because bursts could be dissociated from stimulus waveforms using high-pass filtered noise, or a 0.1-Hz sine-wave stimulus. 5) Arrhenius plots showed that the threshold noise intensity required to elicit bursting depended on the frequency content of a noise stimulus, being lowest, about 1.2 mV/cm, for stimuli matching the 1- to 20-Hz best response band of these cathodally excited ampullary electroreceptors. This is only slightly higher than previous behavioral estimates of the electrosensory threshold as 0.5 μV/cm. 6) Comparable threshold values for bursting came from an alternate analytical approach, based on correlation times of spike trains. 7) Simultaneous recordings from pairs of afferents showed that their bursting frequencies (bursts/s) always converged as the amplitude of a noise stimulus was raised. Thus the slow timescale of bursting is similar for different electroreceptors, even though their mean spiking rates can differ. In conclusion, the ampullary electroreceptors of paddlefish have two distinct modes of operation: their spontaneous tonic firing is modulated by the weakest stimuli, but they switch to bursting output for less-weak stimuli. We propose that afferent bursting may mediate close-range tracking of planktonic prey.

INTRODUCTION

Noise always plays a negative role in linear systems, by degrading any deterministic structures and patterns in a system’s dynamics. However, in nonlinear systems, noise often plays constructive counterintuitive roles that can alter the operational performance of nonlinear systems in desirable ways. For example, the phenomenon of stochastic resonance is well studied theoretically and is observed in many experimental stochastic nonlinear systems (Wiesenfeld and Moss 1995). In sensory nervous systems, a beneficial role of noise by stochastic resonance has been demonstrated for several different modalities and species, including our demonstration of noise-enhanced sensitivity of individual electroreceptors of paddlefish (Russell et al. 2001), along with noise-enhanced electro-sensory-mediated detection and capture of prey by paddlefish, in behavioral experiments (Freund et al. 2002; Russell et al. 1999, 2001).

Noise can also cause so-called noise-induced transitions (Horsthemke and Lefever 1984), whereby perturbation with noise leads to the appearance of new regimes in the operation of a system that are not observed in the corresponding noise-free system. Thus noise can be used to reveal dynamical regimes of a system that are available but are hidden normally. There are several theoretical studies of noise-induced transitions in biological systems, including noise-induced transitions in Hodgkin–Huxley models of excitable membranes (Horsthemke and Lefever 1981; Tanabe and Pakdaman 2001), and noise-induced bursting in models of mammalian thermoreceptors (Huber et al. 2000; Longtin and Hinzer 1996).

Stimulation with broadband Gaussian noise is widely used in neuroscience to estimate the general response properties of sensory systems, by means of Wiener kernels (Marmarelis and Marmarelis 1978), or various stimulus reconstruction techniques (Bialek et al. 1991; Chichilnisky 2001; Gabbiani and Metzner 1999; Warland et al. 1997). A rationale of such approaches is that white Gaussian noise contains all possible frequencies, timescales, and waveforms, and so can be considered as a universal stimulus, which contains no specific pattern information because there are no time correlations, and has equal stimulus power at all frequencies.

All real-world systems are subject to the effects of internal and/or external noise, which in many cases can be approximated by a broadband Gaussian noise (Manwani and Koch 1999; Tuckwell 1989). Examples of internal noise include Brownian motion of the endolymph around hair cells (Jaramillo and Wiesenfeld 1998), ion channel noise in cortical neurons (Chow and White 1996; White et al. 1998), and variability in the response properties of visual interneurons of flies due to noise sources intrinsic to the nervous system.
An example of a realistic external noise stimulus is the low-frequency electrical noise produced by swarms of zooplankton, such as Daphnia. Electrical noise has been recorded from Daphnia populations held in a plastic screen corral (Russell et al. 1999), as well as from a self-organized swarm in an aquarium (Freund et al. 2002). Daphnia and other zooplankton are prey of the paddlefish, Polyodon spathula, the subject of our investigations, which locates prey by means of its electrosensory nervous system. The low-frequency electrical noise from zooplankton populations is within the 0.1- to 30-Hz response band of the peripheral electroreceptors (ERs) of paddlefish (Neiman and Russell 2004; Pei et al. 1998; Wilkens et al. 1997; Wojtenek et al. 2001).

Thousands of ERs are located on the rostrum of a paddlefish, an elongated antennal structure in front of the head, as well as on the gill covers and head, and around the jaws. The paddle-shaped rostrum is flattened in the horizontal plane and constitutes about 40% of the total length of small fish. The ERs are of the ampullary cathodally excited type, like those of marine elasmobranch fishes (sharks, etc.), thought to be the most ancient type of electroreceptor (Bullock et al. 1983). Such ERs present an interesting model of a peripheral sensory system that undergoes spontaneous oscillatory dynamics resulting from nonlinear interactions of two distinct types of internal oscillators, one associated with populations of cells in the sensory epithelia and another associated with afferent terminals (Neiman and Russell 2001, 2004). As a result, the spontaneous firing of these ER afferents is quasiperiodic, with two fundamental frequencies, and the statistics of afferent firing times are non-Poissonian, and exhibit extended-range negative serial correlation of interspike intervals (Neiman and Russell 2001, 2005). The afferents can also fire in bursts (Neiman and Russell 2002, 2004). With about 20,000 integrative cells, a paddlefish ampullary electroreceptor presents a complex yet well-defined and accessible model for studying the functional roles of oscillations and bursting in information transfer through sensory networks. Oscillations and bursting are known to be integrative processes in other sensory systems.

In this study, we characterize the statistical properties of the firing patterns of single-unit afferents from the peripheral electroreceptors of paddlefish, during varied types of noise stimuli, including natural electrical noise from zooplankton prey. We show that the afferents undergo a transition from tonic firing to parabolic burst discharges, as the magnitude of a noise stimulus is increased, such that all statistical measures of afferent firing become bimodal or switch regimes, manifesting both a slow and a fast timescale. We used unbiased statistical metrics of spike trains, to avoid whenever possible the problem of defining bursts, inevitably arbitrary. The threshold stimulus amplitude to evoke bursting was estimated by two alternate analytical approaches. We demonstrated experimentally that bursts are distinct from stimulus waveforms per se. Thus there are two distinct encoding modes, for distinct and staged but overlapping ranges of stimulus strength. The ampullary electroreceptor of paddlefish is a representative of the vital hair cell–primary afferent type of sensory receptor, such as mediate the senses of hearing and balance of all vertebrates.

**METHODS**

**Experimental procedures**

Procedures for in vivo recording from paddlefish electroreceptor afferents originating from receptive fields on the rostrum were described in Neiman and Russell (2004). A protocol for these experiments was approved by the institutional animal care and use committee. Paddlefish were obtained commercially. Data were from 29 afferents from 19 paddlefish, from fresh in vivo preparations < 16 h old. The results subsequently presented are representative of the qualitative features observed in nearly all recordings. Values are stated as means ± SD.

“Uniform field” stimulation was applied between a pair of 6 × 15-cm Ag/AgCl plates, coated with agarose, that covered the interior ends of an elongated plastic experimental chamber, in front of a fish and behind it. The plate electrodes were driven by a linear constant-current stimulus isolator, commanded by a 16-bit programmable computer interface (Cambridge Electronic Devices, Cambridge, UK) operated by Spike2 software, and a manual attenuator calibrated in decibels.

**Noise stimuli**

The sources of stationary zero-mean Gaussian noise had power spectra shown in Fig. 1. Because noise waveforms fluctuated, their amplitudes are stated as root mean square (r.m.s.) amplitude, that is, the SD. Stimulus waveforms were loaded into the memory of the programmable interface and replayed from a 16-bit D/A converter, for stimulation. 1) Noise from a General Radio model 1390B vacuum tube generator was low-pass filtered by an eight-pole Bessel filter set to 50 Hz, and digitized. It was confirmed to be Gaussian. This same noise was used in previous behavioral studies on paddlefish feeding (Russell et al. 1999, 2001). 2) Computer-generated exponentially correlated Ornstein–Uhlenbeck (OU) noise had correlation time τ = 2 ms (Gardiner 2004). 3) Computer-generated Gaussian white noise was filtered in several ways. Band-limited noise was obtained by digital low-pass filtering at a cutoff frequency ranging from 10 to 200 Hz, using MatLab (The MathWorks, Natick, MA) signal processing software. White noise with 200-Hz low-pass cutoff frequency was effectively broadband for paddlefish ERs because they are sensitive only at < 50 Hz. In some experiments, to exclude the low-frequency stimulation domain, white noise was high-pass filtered at cut-off frequencies of 1–30 Hz, using MatLab. 4) Natural electrical noise was recorded from a swarm of Daphnia zooplankton prey in a large aquarium, using a Ag/AgCl ball electrode tip encased in a cube of agarose, 1 cm on a side, to reduce mechanical artifacts from Daphnia colliding with it (Freund et al. 2002). A large Ag/AgCl strip, > 20 cm distant, was the ground reference. Baseline drift was cancelled by subtracting a replica after 1-Hz low-pass digital filtering using a MatLab zero-phase shift filter. This natural electrical noise from swarms of Daphnia zooplankton prey was Gaussian and zero-mean, and can be described as a two-dimensional OU noise (Freund et al. 2002). 5) Electrical signals recorded from a single Daphnia, immobilized by gluing its dorsal shell to a fixture, was another type of natural stochastic waveform, which had several periodicities, detected as peaks in its power spectrum (Freund et al. 2002): a sharp peak at about 7 Hz corresponded to the beating frequency of the feeding appendages and a broader peak at about 5 Hz corresponded to the frequency of antennal strokes for swimming. However, the recorded signal was non-Gaussian and therefore could not be used directly to assess information coding by ER afferents. To circumvent this problem, a matched Gaussian zero-mean noise waveform was generated as in Rieke et al. (1995) using MatLab, whose power spectrum matched that of the original recording.

Two types of noise presentations were used: 1) a single 15-min stationary realization, or 2) sequences of a repeated 180-s segment, repeated in random order with different amplitude variances or with...
to 3; 2) the maximum time between the first two spikes in a burst was set to 12 ms; and 3) the maximum time between two spikes (after the first pair) for events to be in the same burst was set to 15 ms. A burst train

$$x_d(t) = \sum_{n=1}^{N} \delta(t - t_n)$$

was formed from a sequence of delta functions centered at the onsets of bursts $b_{on}$, $m = 1 \ldots M$, where $M$ is the number of bursts in a train, always $>100$ for these data. To describe the statistical properties of bursts, we calculated the mean interburst interval

$$\bar{\tau}_b = \frac{1}{N} \sum_{n=1}^{N} (b_{on+1} - b_{on})$$

the mean number of spikes inside a burst, and the mean burst duration, using MatLab routines. The mean burst rate, $\bar{\tau}_b$, was calculated as the reciprocal of $\bar{\tau}_b$.

A less-arbitrary approach to identifying bursting behavior is to use the autocorrelation function of a spike train (Metzner et al. 1998). The signature of bursting is an autocorrelation peak at short time lag, due to fast intraburst spiking. In contrast, this peak is absent in the case of spontaneous activity and is also absent from the autocorrelation function calculated from only a sequence of burst onsets. The autocorrelation of a spike train as a function of time lag $\tau$, is defined as

$$c(\tau) = \langle x(t)x(t + \tau) \rangle - \bar{r}^2$$

with units of (spikes/s$^2$), where $\langle \rangle$ represents time averaging. It always has a $\delta$ singularity at zero time lag ($\tau = 0$), the time of occurrence of each spike, which was subtracted (Gabbiani and Koch 1998). The subtracted function was denoted as

$$c^-(\tau) = c(\tau) - \bar{r}\delta(\tau)$$

Positive values of $c^-(\tau)$ correspond to an increased probability of spiking and negative values to a reduced probability, compared with the mean firing rate. The decay of autocorrelation with time $\tau$ was characterized using the correlation time $t_{cor}$ (Stratonovich 1963), defined as

$$t_{cor} = (1/\bar{r})^2 \int_0^\infty \left| c^-(\tau) \right| d\tau$$

The power spectrum density of a spike train, $G_s(f)$ as a function of frequency $f$, or the power spectrum density of a stimulus $G_s(f)$, were calculated as in Wessel et al. (1996) and Neiman and Russell (2004), using the periodogram method, fast Fourier algorithm, and Hamming windowing (procedure pwelch of MatLab). Each periodogram window was 4.096 s long.

**RESULTS**

All of the types of noise presented (see methods, Noise stimuli; Fig. 1) resulted in the same qualitative behavior of afferent firing, provided that a noise stimulus had adequate power in the frequency response band of paddlefish electroreceptors (ERs), reported as 0.1–30 Hz, peaking at 1–20 Hz (Fig. 1, green lines) (Neiman and Russell 2004; Pei et al. 1998; Wilkens et al. 1997; Wojtenek et al. 2001). Figure 2A shows representative recordings from an ER afferent stimulated by broadband OU noise. Compared with background firing (top panel), weak noise (center panel) did not qualitatively change the tonic afferent firing pattern, but did lead to enhanced variability of interspike intervals (ISIs). In contrast, the firing
Affereunt was characterized by a unimodal distribution (Fig. 2). Spontaneous firing of an electoreceptor afferent during spontaneous control activity (top), weak OU noise stimulation (center), or moderate-amplitude OU noise (bottom). Instantaneous firing rate is shown in the top trace of each panel. Note the parabolic shape of the intraburst instantaneous firing rate (bottom). B: probability densities of interspike intervals (ISIs), corresponding to recordings in A, on logarithmic scales.

Pattern changed qualitatively, from tonic to bursting, during stimulation with higher-intensity noise (bottom panel), seen as short ISIs inside bursts and long silent epochs between bursts. The noise-induced bursts possessed the characteristic structure of so-called parabolic bursts because the firing rate increased toward the center of a burst and then decreased again (Ermentrout and Kopell 1986; Izhikevich 2006). Qualitatively similar results were obtained with band-limited white noise or noise from an electronic generator. Thus, the main feature of noise-induced bursting was the appearance of two well-separated timescales: fast spiking inside bursts, and slow dynamics of burst occurrence.

Separation of two timescales

Interspike interval distributions and burst statistics. The transition to a bursting mode led to qualitative changes in the structure of probability distributions of ISIs [interspike interval histograms (ISIHs)]. Spontaneous firing of an electoreceptor afferent was characterized by a unimodal distribution (Fig. 2B, spontaneous) (Neiman and Russell 2004). In contrast, during stimulation with moderate-intensity noise, the ISIH showed a bimodal distribution (Fig. 2B, 14 µV/cm line). As the intensity of noise was increased, the single ISIH peak split into two peaks, including a progressively larger peak at progressively shorter intervals (Fig. 3A, blue circles), so that noise facilitated spiking inside bursts. The other peak, associated with burst dynamics, progressively shifted toward longer intervals (red squares). Also, bursts became longer at higher noise intensity (green dotted line). However, the overall mean ISI (black line) was scarcely affected by the transition from tonic firing to bursting.

The overall variability of afferent firing increased monotonically with noise intensity, as measured by the coefficient of variation (CV) of ISIs (Fig. 3B, black line). This was due to increased variability of the ISIs inside bursts (blue line) and of the burst durations (green line), among other parameters. In contrast, the CV of interburst intervals (red line) declined, signifying that bursting became more regular at higher noise intensities.

To verify the origin of the two ISIH peaks, and to study the statistical properties of noise-induced bursts, we separately analyzed three features at varied noise intensities. 1) ISIs inside bursts formed a narrow unimodal symmetrical distribution (blue lines in Fig. 3, C1–C3) that matched the position of the first peak in the bimodal conventional ISIH (during bursting). Also, the mean ISI inside bursts became shorter at higher noise

FIG. 2. Noise-induced afferent bursting. A: firing of an electoreceptor afferent during spontaneous control activity (top), weak OU noise stimulation (center), or moderate-amplitude OU noise (bottom). Instantaneous firing rate is shown in the top trace of each panel. Note the parabolic shape of the intraburst instantaneous firing rate (bottom). B: probability densities of interspike intervals (ISIs), corresponding to recordings in A, on logarithmic scales.

FIG. 3. Statistical properties of single-unit afferent bursts in paddlefish electoreceptors, at varied r.m.s. amplitude (SD) of OU noise stimuli. A–C: data for same afferent. A: burst parameters. Blue circles: ISI duration at the first interspike interval histogram (ISIH) maximum. Orange dashed line: mean ISI inside bursts. Red squares: ISI duration at the second ISIH maximum. Green dotted line: mean burst duration. Black line: overall mean ISI. B: coefficients of variation (= SD/mean) of ISIs inside bursts (blue), of interburst intervals (red), of burst durations (green), and of all ISIs (black), vs. noise r.m.s. amplitude. C1–C3: probability densities of ISIs inside bursts (blue), of interburst intervals (red), of burst durations (green), and of all ISIs (black), for the 3 listed r.m.s. amplitudes of OU noise. Areas under the 4 curves in a panel were made equal. D: mean number of spikes per burst vs. noise r.m.s. amplitude, for 3 different afferents. E: return map of ISIs during noise-induced bursting. Colors code the probability density of ISIs. Inset: superimposed return map for spontaneous activity, on the same axes; it obscures some low-density datapoints of the larger graph.
intervals (that is, plots of the duration of ISI) was also clearly demonstrated in return maps of interspike intervals (Fig. 3C1, red). At larger noise intensity, interburst intervals became shorter (leftward shift of red curve peak in Fig. 3, C1–C3). The distribution became narrower, giving rise to regularization of the interburst intervals, and to the lower CV already noted (Fig. 3B, red). 3) Burst durations were distributed as a narrow peak, for weak noise (Fig. 3C1, green), with only three to five spikes per burst (Fig. 3D). Longer bursts became possible at larger noise intensities, but some bursts were still short, seen as broadening and rightward shift of the distribution toward longer durations (Fig. 3, C2 and C3, green).

The maximum burst rate tended to saturate for large noise intensities and was similar for the sample of afferents in this study: 8.8 ± 2.4 bursts/s, range 5.4–13.0 (n = 19 ERs). In contrast, their mean spiking rates in the same data were more variable: 64 ± 12 spikes/s, range 52.9–86.3 (n = 19 ERs).

These data confirm that the first peak in a bimodal ISI distribution during noise stimulation corresponds to the short ISIs inside bursts. The second peak was associated with burst dynamics because it appeared when bursting began. However, it did not match the distribution of either interburst intervals or burst durations. Probably both of these, along with refractory intervals after bursts, gave rise to the second peak in a bimodal ISIH during noise stimulation.

RETURN MAPS. The timescale separation due to noise stimulation was also clearly demonstrated in return maps of interspike intervals (that is, plots of the duration of ISI|z| vs. the duration of the preceding ISI; Fig. 3E). The return map of spontaneous activity (superimposed inset) showed an inverse relation over a confined range (Neiman and Russell 2004). In contrast, the range expanded considerably during noise stimulation. The clustering of ISIs in Fig. 3 bottom left corner corresponded to fast spiking inside bursts, whereas the elongated clusters parallel to the axes refer to slow burst dynamics. Such a return map structure is typical for bursting neurons, as observed, for example, in the electrosensory lateral line lobe neurons of paddlefish, during the transition to bursting at varied noise intensities (Fig. 5). In the absence of noise, all afferents had a power spectrum showing a fundamental peak (f0) at the mean firing rate of the afferent oscillator, and another fundamental peak (f0) at approximately 26 Hz (at 22°C) corresponding to epithelial oscillators, along with sidebands at combination frequencies (f0 ± f0) (Fig. 5A, black line) (Neiman and Russell 2004). External stimulation with weak OU noise (SD <1 µV/cm) led to broadening of the afferent (f0) peak and sidebands, but the center frequency of the f0 peak was unaltered, and f0 continued to match the mean firing rate, r0, as seen in Fig. 5B, showing the evolution of the power spectrum at varied noise intensity. During larger noise intensities, and a transition to bursting, the position of the f0 peak shifted toward higher frequencies (Fig. 5A, red line; Fig. 5B), indicating the appearance of fast spiking inside bursts. This shift of the f0 peak toward higher frequencies commenced abruptly at an intermediate intensity of noise, then continued monotonically as the noise intensity was raised further (Fig. 5C, blue line). However, the mean firing rate r0 increased only slightly over the

**Figure 4.** Correlation properties of noise-stimulated afferent firing. A: autocorrelation function of afferent spike trains during control firing (black), or OU noise stimulation at a low (green) or moderate (red) SD. After subtracting the value at zero lag, correlation values were normalized to the mean firing rate squared, *e*–(r/2)2. Black arrow, red arrow: peak and trough that were characteristic of bursting during large noise. B: 3-di-dimensional (3D) plot of the autocorrelation function (ACF) vs. OU noise r.m.s. amplitude; the extended serial correlations of ISIs were abolished by large noise stimuli.
entire range of noise intensities (0–25 µV/cm) presented to this afferent (Fig. 5C, black line).

The slow bursting dynamics were reflected in a broad power spectrum peak at 5–7 Hz (b, Fig. 5A). The power in this frequency band grew monotonically as the noise intensity was raised (Fig. 5B). Even during spontaneous firing, there was elevated power in the same frequency band (asterisk, Fig. 5A, black line), suggesting some manifestation of the slow timescale of bursting normally, even in the absence of external noise stimulation. A similar peak was present in afferent power spectra from experiments of stopping the artificial ventilation of water into the mouth of an immobilized fish for a few minutes (not illustrated), excluding water motion as a possible source of low-frequency noise. However, we could not exclude a possible origin from heartbeat pulsation.

Remarkably, the peak corresponding to the epithelial oscillations \( f_e \) did not change its frequency or width over a large range of noise intensities (0–14 µV/cm) (Fig. 5, B and C), confirming that the frequencies of epithelial oscillations are invariant of external stimulation (Clusin and Bennett 1979; Lu and Fishman 1995; Neiman and Russell 2004). This was confirmed by direct simultaneous recording from an afferent and a canal in the corresponding receptive field: the power spectrum of oscillatory extracellular potentials recorded with a loose pipet in the canal did not show significant changes when the electroreceptor was stimulated with noise, even though the afferent responded as in Fig. 5 (not illustrated). For larger noise intensities (OU, r.m.s. amplitude >14 µV/cm), the epithelial peak became almost indistinguishable (Fig. 5A) due to the general elevation of spectral power.

**Dissociation of bursting from band-limited stimuli**

The manifestation of stochastic 5- to 13-Hz bursts was not simply due to low-frequency components of noise stimuli. One approach to demonstrating this was to stimulate ERs with high-pass filtered white noise, with cut-on frequencies ranging from 1 to 250 Hz, such that low-frequency components were removed (Fig. 6A; stimulus power was held constant for all panels). The bursting regime was preserved for cut-on frequencies \( \leq 20 \) Hz, as indicated by the existence of two well-separated peaks in the distributions of ISIs (Fig. 6B). Even noise with a 30-Hz cut-on frequency, at the upper extreme of the frequency sensitivity of paddlefish ERs as measured by conventional metrics (Fig. 1, green lines), elicited spike doublets and triplets (Fig. 6A), which can be considered as brief bursts, and a bimodal ISI density (Fig. 6B). Bursting disappeared for higher-frequency noise, when the cut-on frequency went beyond 30 Hz. Similar results were obtained with high-pass filtered OU noise (not illustrated). Therefore bursting did not require a low-frequency (e.g., 5–13 Hz) stimulus.

**FIG. 5.** Power spectra of electroreceptor (ER) afferent responses to broadband OU noise, calculated from the same data as Fig. 4. A: superimposed spectra for control spontaneous firing (black) and for external stimulation with low-amplitude (green) or high-amplitude (red) OU noise, for the same afferent. \( f_a, f_e \): spectrum peak of the afferent or epithelial oscillators, respectively; b: low-frequency peak due to bursting. \( f_a, f_e \) peak of the green line obscures a similar \( f_e \) peak of the black line. B: 3D plot of the afferent power spectrum vs. OU noise amplitude (SD). C: frequency values at different noise r.m.s amplitudes for the afferent (blue squares) or epithelial (red circles) spectral peaks, and the mean firing rate \( r \) (black line).

**FIG. 6.** Dissociation of bursting from the stimulus timescale. A: raw recordings, all from the same afferent, illustrating bursting during stimulation with white Gaussian noise, filtered at varied frequencies. B: probability density of ISIs for stimulation with high-pass filtered OU noise (not illustrated). Therefore bursting did not require a low-frequency (e.g., 5–13 Hz) stimulus.
Another approach to dissociating bursting from stimulation was to apply a 0.1-Hz sine-wave stimulus, at the lower extreme of the frequency sensitivity of paddlefish ERs. Each sine-wave cycle was accompanied by a brief (<1-s duration) discharge in which the afferent firing rate rose, then fell, along a parabolic time course (asterisks, Fig. 6C), and was followed by a 1- to 2-s epoch of reduced firing rate. That is, the 0.1-Hz sine-wave stimulus appeared to trigger bursts whose kinetics, once triggered, were faster than the slow stimulus.

Although not necessary to elicit bursting, low-frequency noise was nonetheless an effective stimulus for bursts, as seen in Fig. 6A (last panel), in which long bursts with fast firing were elicited by white noise that had been low-pass filtered at 10 Hz. Thus the efficacy of a Gaussian noise stimulus, to elicit bursting, depended on both its r.m.s. amplitude and also how well its power spectrum matched the frequency tuning of the electroreceptors.

**Natural noises from zooplankton prey elicit afferent bursts**

We presented two types of naturalistic noise waveforms to paddlefish ERs, reproduced from a D/A converter, that commanded a linear stimulus isolation unit (see METHODS), to study whether naturalistic noise also could evoke afferent bursts. The first type was prey swarm noise. A paddlefish such as the 35- to 50-cm fish that we studied, feeds by filtering: it swims forward, with its capacious mouth open, and filters from the water numerous 1- to 10-mm plankton, including the zooplankton *Daphnia*, a usual prey (Rosen and Hales 1981). The spatial distribution of *Daphnia* tends to be nonuniform, in patches. They can also form high-density vortex-like swarms under certain conditions (Ordemann et al. 2003). A unipolar recording electrode placed near a *Daphnia* swarm revealed low-frequency electrical noise (Fig. 7A), whose power spectrum (Fig. 1B, line 5) resembled OU noise with a correlation time of about 130 ms (Freund et al. 2002). A second type of natural noisy stimulus was the electrical signal from an individual *Daphnia*, tethered for recording purposes. It was treated as a Gaussian zero-mean stochastic stimulus waveform (METHODS) whose power spectrum had several peaks (Fig. 1B, line 6) associated with motions of the feeding legs and antennae of *Daphnia* at about 5 and 7 Hz, respectively (Freund et al. 2002).

Here, we demonstrate the efficacy of these naturalistic noises for evoking afferent bursts. Afferent bursts were evoked by *Daphnia* noise from a swarm (Fig. 7A) or from a tethered individual (Fig. 7B). Although the frequency content of the swarm noise was near the lower limit of frequency sensitivity of paddlefish ERs, afferents fired in robust bursts at stimulus intensities as low as 2.6–3.6 μV/cm r.m.s. The frequency components of signals from an individual *Daphnia* were well matched to the frequency response band of paddlefish ERs, and so weak r.m.s. amplitudes, as low as 1.6–2.0 μV/cm, evoked afferent bursts. Both types of naturalistic noise gave rise to bimodal ISI distributions (Fig. 7B).

**Threshold for bursting**

We used two approaches to estimate the noise intensities at which the onset ("threshold") of bursting occurred. The first approach was to determine an excitability threshold from the dependence of the mean interburst interval \( \tilde{t}_b \) on the r.m.s. amplitude of a noise stimulus (Fig. 8A). This required identification of bursts, estimation of the mean interburst interval \( \tilde{t}_b \) at different noise SD, and then fitting the obtained dependence. From the theory of noise-activated processes, it is known that the mean time to escape from a potential well, which involves both a potential barrier (threshold) and the noise intensity, follows an Arrhenius law (Hänggi et al. 1990). In noise-activated excitable neural systems, it has been observed (Lindner et al. 2004; Neiman and Russell 2002) that the dependence of the mean interevent interval \( \tilde{t}_e \) on the r.m.s. noise amplitude follows an Arrhenius exponential relation

\[
\tilde{t}_e = \nu \exp(\Delta/\sigma^2)
\]

where \( \nu \) is a constant, \( \Delta \) is a threshold, and \( \sigma^2 \) is the noise variance. Using this approach (Fig. 8A), the value of \( \Delta \) was 34 ± 19 μV/cm (\( n = 9 \) ERs) when using broadband white noise of 200-Hz cutoff frequency. Low-frequency noise, including natural noise from *Daphnia*, gave a lower threshold of \( \Delta = 2.5 \pm 1.2 \) μV/cm (\( n = 9 \) ERs). The lowest value of bursting threshold, at 1.2 μV/cm, was obtained for Gaussian noise with 20-Hz low-pass cutoff frequency, matching the best frequency response band of paddlefish ERs.

An alternate approach to estimating the threshold noise intensity for evoking bursts was based on monitoring structural changes in the autocorrelation function of afferent ISIs (Eq. 5, Fig. 4A), by calculating a correlation time \( t_{cor} \) (Eq. 6). A transition to bursting was expressed as a minimum in the dependence of the correlation time versus the noise variance (Fig. 8B); threshold was taken as the noise variance at which this minimum occurred. For broadband white noise (200-Hz
The following parameters: circles: show mean-square fits of an Arrhenius exponential function (Eq. 7) for 4 different afferents (different lines). A and B, circles: afferent stimulated with white noise with 20-Hz low-pass cutoff. Triangles: afferent stimulated with high-frequency OU noise. Squares: afferents stimulated with white noise, 200-Hz low-pass cutoff. Diamonds: afferent stimulated with low-frequency noise from a swarm of Daphnia. In A, lines show mean-square fits of an Arrhenius exponential function (Eq. 7), yielding the following parameters: circles: $\nu = 104$ ms, $\Delta = 1.22$ $\mu$V/cm; triangles: $\nu = 119$ ms, $\Delta = 3.21$ $\mu$V/cm; squares: $\nu = 90.2$ ms, $\Delta = 10.8$ $\mu$V/cm; diamonds: $\nu = 249$ ms, $\Delta = 2.2$ $\mu$V/cm.

cutoff), threshold was estimated in this way as $\Delta_{\text{cor}} = 37 \pm 25$ $\mu$V/cm ($n = 9$ ERs), whereas for low-frequency noise $\Delta_{\text{cor}} = 2.7 \pm 1.5$ $\mu$V/cm ($n = 9$ ERs).

**Shared slow timescale**

Simultaneous recordings from pairs of ERs presented with a common stimulus demonstrated that different ERs had similar (“shared”) slow timescales of bursting (Neiman and Russell 2002). For example, in Fig. 9A (top), the mean interburst interval of two different costimulated afferents converged to a similar value, as the amplitude of a noise stimulus was increased. The convergence was more evident when plotted as the ratio of the mean bursting rates at different noise SD, for a pair of afferents (Fig. 9B, triangles). Such convergence was observed for several types of Gaussian noise. This convergence of noise-induced bursting rates occurred even though the mean spike firing rates and burst thresholds of different afferents could be widely spread, or could be relatively invariant with stimulus amplitude (Fig. 9A, bottom; Fig. 9B, circles). For $n = 8$ pairs of afferents, the difference between converged burst rates at large noise was $0.6 \pm 0.4$ bursts/s. The same pairs showed a difference of $7.7 \pm 5.2$ spikes/s between their mean firing rates at corresponding noise intensities. Thus the slow timescale of noise-induced bursting was shared among different ER afferents, even afferents differing in other metrics of neural activity. The exponential convergence of burst rates resembled the phenomenon of frequency entrainment in coupled oscillators (Pikovsky et al. 2001).

**Discussion**

We have characterized and quantitated two distinct modes of stimulus encoding by the cathodally excited ampullary electroreceptors of North American paddlefish, for separate but overlapping ranges of stimulus strength. As stimulus strength grows, there is a transition, from tonic firing to a bursting mode of afferent firing. This transition was observed for external stimulation with various kinds of noise voltage gradients, all changing in time, all Gaussian, ranging from broadband white noise to realistic low-frequency noise produced by planktonic prey. We recognize in our findings clear similarities to what previous authors have termed “noise-induced transitions.”

A noise-induced transition is defined as a qualitative change in the structure of a steady-state probability measure of a system in response to external noise (Horsthemke and Lefever 1984). For example, a stationary probability distribution of a system parameter may change from unimodal to bimodal shape as the intensity of external noise increases. Thus noise leads to the appearance of a new structure that was not observed in the noise-free system.

This should be contrasted to situations when adding more noise leads to broadening of peaks already existing in a probability distribution to begin with. For example, in a bistable situation of coexisting tonic spiking and bursting regimes in a neuron (Shilnikov et al. 2005), the type of output can be realized by proper choice of initial conditions. Each regime may be associated with a peak in a probability distribution. External Gaussian noise stimulation may result in switching between both regimes in a random manner. Thus adding more noise may result in broadening of peaks in the probability distribution.

In our study, we have used several metrics of electroreceptor spike trains to monitor effects of external noise stimuli. Weak
stimuli (<2 μV/cm) did not qualitatively change the firing patterns of afferents, which continued to be tonic (quasiperiodic actually). The tonic firing of an individual afferent was only slightly modulated by weak stimuli, yet changes in activity were discernible in ISIHs and power spectra of afferent spike trains, such as broadening of a spectral peak at an afferent oscillator’s fundamental frequency, or peak splitting in response to weak frequency-matched periodic stimuli (Neiman and Russell 2001, 2004).

Less-weak noise stimuli, >2 μV/cm r.m.s. amplitude, drastically changed the afferent dynamics, leading to bursting. The hallmark of bursting was the separation of two timescales of afferent spiking: the fast spiking inside bursts at rates ≤250 spikes/s, and the slow frequency of burst occurrences at about 9 bursts/s. The burst infrastructure had a parabolic shape, that is, the spike rate inside a burst reached a maximum near the midpoint of the burst. The transition to bursting was accompanied by qualitative changes in the structure of ISIHs, autocorrelation functions of spike trains, and power spectra. We studied this noise-induced transition to bursting mode for different noise variances, while keeping the noise bandwidth constant. For noises with different frequency bands, we kept constant the total power of each stimulus. Thus the power at low frequencies, e.g., in the 0.1- to 30-Hz response band of paddlefish ERs, was reduced for noise stimuli of expanded bandwidth. We used nonarbitrary analytical approaches, including ISI distributions, autocorrelations, and power spectra, to characterize the transition to bursting, to avoid whenever possible having to define an algorithm to identify bursts, because any such definition would be arbitrary.

Threshold of bursting

Noise-induced transitions are detected as constituting a qualitative change in the structure of probability distributions. However, various averaged measures, devised from corresponding probability distributions, change gradually with increased noise intensity (Horsthemke and Lefever 1984). Also, they reach extremes at slightly different values of noise intensity, depending on what metric is used. This is true for probability distributions of a state variable or power spectrum. Thus it is difficult to identify a single critical or bifurcation value of a control parameter, at which the transition occurs. Rather, it is more appropriate to cite an effective bifurcation range of parameter values (Meunier and Verga 1988). In other words, the “threshold” is “soft.”

Because the transition to bursting of ER afferents was smooth, we used two independent approaches to estimate a critical noise SD that results in bursting. The first was based on Arrhenius rate theory (Hänggi et al. 1990) and the second was based on correlation time analysis. Although theory for the latter approach is known (Stratonovich 1963), we are unaware of its previous use in neuroscience. An advantage of the correlation time approach is that it did not require identification of bursts because the autocorrelation function was calculated for a complete spike train. Thus the autocorrelation approach was free from the additional parameters of Arrhenius plots, which required discrimination of bursts before threshold analysis. A disadvantage of correlation time analysis is that the threshold is calculated as the minimum of a flattened curve (Fig. 8B).

The values obtained by the two methods corresponded. The large SDs in both types of threshold estimates may have arisen from differences in the sensitivity of different ERs.

Our results show that the threshold for bursting depends on the frequency band of a noise stimulus, being lowest for noise that is band-matched to the frequency response of ERs. For example, broadband noise such as white noise with 200-Hz cutoff frequency, effectively broadband for paddlefish ERs, gave rather high values of bursting threshold (10–57 μV/cm, mean 34 μV/cm) because most of the spectral power was outside of the frequency response band of these ERs (see Fig. 1). A much lower threshold value, about 2.2 μV/cm, was obtained for Daphnia swarm noise whose spectral power was concentrated near the lower boundary of the ER frequency response band. A low threshold value (1.2–5.2 μV/cm, mean 2.5 μV/cm) was also obtained for band-limited noise resembling the stochastic oscillatory signal from an individual Daphnia, that matched well the ER frequency response band. These lower threshold values obtained using frequency-matched naturalistic stimuli are more physiologically relevant. Thus the r.m.s. amplitude of noise at which afferent bursting commences is only slightly higher than previous behavioral estimates of the electroreceptive threshold, at 0.5 μV/cm (discussed in the following text). Our data establish that the threshold for afferent bursting is sufficiently low that this signal-processing mechanism, carried out by the peripheral electroreceptors, will come into play for all but the weakest stimuli. We note, however, that somewhat higher noise intensities are required to obtain obvious bursting and bimodal ISI distributions.

Functional significance of afferent bursts

There are presently several conjectures about the general functional significance of bursting in sensory information processing (Krahe and Gabbiani 2004). Some studies have shown that bursts can serve to detect or extract specific stimulus features (Metzner et al. 1998). Another concept is that bursts and individual spikes may carry distinct information about stimuli, multiplexing two parallel information channels into a single spike train (Oswald et al. 2004). Other studies suggest that bursts may transmit similar information as tonic spikes, but at a higher signal-to-noise ratio, with increased probability of transmission through CNS sensory relays (Lisman 1997).

Bursting occurs at CNS levels of many sensory systems, but usually not at the level of peripheral receptor afferents. A famous exception is the repetitive bursting of afferents of mammalian thermoreceptors for cold (Darian-Smith et al. 1973; Huber et al. 2000; Longtin and Hinzer 1996). Another example is probability (P) type electroreceptor afferents of weakly electric fish, which can be divided into two groups of tonic and bursting spontaneous firing (Bastian 1981; Xu et al. 1996). A modeling study (Chacron et al. 2004) compared tonic and bursting afferents and revealed differences in their coding properties. Although tonic spiking afferents are good linear encoders, bursting units showed nonlinear coding properties and were efficient in detection of stimulus features.

In paddlefish, stimulus-induced afferent bursting may mediate the close-range (near-field) tracking of prey. Passive electroreception provides three-dimensional (3D) spatial information, along with relatively rapid temporal information about the environment and events in it. Such sensing is mediated by
vision in most animals, but vision is ineffective in the turbid (muddy) opaque large rivers inhabited by paddlefish. Passive electrosense has been shown to mediate the detection and 3D spatial localization of individual zooplankton prey by small paddlefish, that is, during particulate-mode feeding (Wilkens et al. 1997, 2001). However, whether electrosense mediates other behaviors, such as navigation, predator avoidance, or interactions with conspecifics, including in older larger paddlefish, remains to be demonstrated.

The sensitivity of a sensory system limits its ability to detect a novel stimulus. Stochastic resonance experiments on the particulate feeding behavior of small paddlefish have yielded a value of 0.5 \( \mu \text{V/cm} \) for the passive electrosensory threshold (Russell et al. 1999, 2001). This is similar to behavioral estimates of a passive electrosensory threshold in certain bony fresh water fish (Bullock 1982; Peters and Wijland 1974), including catfish. This value of threshold indicates that small paddlefish do make use of the weak 0.2- to 2-\( \mu \text{V/cm} \) range of stimulus amplitudes, and that their nonbursting mode of ER encoding over this “weak” stimulus range is a meaningful sensory mechanism. Indeed, using linear stimulus reconstructions, we have demonstrated statistically significant encoding of 0.1- to 1-\( \mu \text{V/cm} \) prey signals by tonically firing individual ER afferents (not illustrated). This tonic mode of ER encoding of weak stimuli is likely used for detection of distant zooplankton prey. About 95% of the \( \textit{Daphnia} \) captured by small paddlefish are at radial distances \(<4 \text{ cm} \) from the rostrum midline axis (Russell et al. 1999; Wilkens et al. 2001). This distance threshold is governed by the inverse cube falloff with distance expected for low-frequency electrical signals from a small dipole in water, as well as by ER sensitivity.

The higher stimulus amplitudes required to elicit the bursting mode of stimulus encoding suggest that the bursting mode may function to report and track sources of electric fields at closer proximity to electroreceptors. For example, during capture of an individual zooplankton, a small (<15 cm) paddlefish goes through a sequence of motor acts to approach and engulf a prey, as seen in videos of feeding in a flow tank (BA Wettring and DF Russell, unpublished observations). The earliest signs of prey detection are usually flaring of the pectoral fins and elevation of the tail fin, which absorb reaction forces as a fish rotates about its long axis, then flexes its trunk to swing the rostrum edgewise toward the prey. This style of maneuvering apparently serves to minimize water resistance when reorienting the horizontally flattened rostrum. When its long axis is lined up on the prey, the fish lunges forward and engulfs it. During the later stages of this motor sequence, the prey is near to electroreceptors. For example, after swinging sideways, the tip of the rostrum may be close to the prey. As the fish then lunges forward, the prey undergoes relative motion along the rostrum, toward the mouth, traveling parallel to the rostrum and close to it, e.g., at radial distances \(<1-2 \text{ cm} \), as required for engulfment in the mouth. Our measurements of bursting threshold indicate that at close range, the electrical signals from zooplankton will evoke ER afferent bursts. Indeed, the afferent firing evoked by holding a \( \textit{Daphnia} \) close to an ER receptive field (e.g., Fig. 3 in Wilkens et al. 1997) resembles the parabolic bursting reported herein. Thus during close-range prey tracking, ER afferents probably operate in the bursting regime.

What advantage would bursting confer? A major difference between spikes and bursts is that bursts are readily synchronized, whereas individual spikes are not, among weakly coupled neurons (Izhikevich 2006). Our data show that a slow timescale of stimulus-induced burst rates is shared among populations of ER afferents, even though their spike firing rates may be diverse, and even though different ERs are not physically coupled. As a result, the burst onsets of afferents from different ERs can be tightly synchronized, due to “stimulus-induced” virtual coupling by a shared stimulus (Neiman and Russell 2002). Our working hypothesis is that synchronization of bursts in different afferents may mediate spatial tracking of prey. Although synchronized, the burst onsets in different afferents may not be simultaneous, presumably due to the different locations of receptive fields. Such nonzero phase shifts of bursts may convey information about the spatial location of prey.

This demonstration of afferent bursting reinforces our view of paddlefish ERs as peripheral preprocessors. Sensory information transformations that in other species are carried out in the CNS, instead appear to be exteriorized to the highly accessible peripheral electroreceptors of paddlefish. Such access, along with the ability to quantitate the operation of paddlefish electrosense at multiple levels, ranging from encoding to prey detection behavior, are useful experimental advantages of this model sensory system.

\textbf{Dynamics of bursting}

Bursting is a widespread form of neural activity, which can derive from different neural mechanisms and can display different phenotypes (parabolic bursts, bistability, etc.), for which there are various classification and naming schemes. A unified mathematical classification is possible based on bifurcation mechanisms of burst initiation and termination (Izhikevich 2006). Some neurons demonstrate coexistent tonic and bursting modes, which can be switched by external stimulation. Examples include pyramidal cells in the electrosensory system of weakly electric fish (Oswald et al. 2004), LGN (lateral geniculate nucleus) cells (Lesica and Stanley 2004; Reinagel et al. 1999), and leech heart interneurons (Shilnikov et al. 2005).

For the bursting described here, the transition from tonic firing to bursting does not seem to be a case of mode switching, as cited in the previous paragraph, because we have not been able to evoke mode switching by brief stimuli, except for instances of a few (~3) bursts evoked after a strong “off” (anodal) DC step stimulus.

Although stimulus input altered the mean firing rate relatively little, much higher peak firing rates were achieved during bursting. This was reflected in structural changes in the ISIH, as a transition from unimodal to bimodal, and in power spectra of spike trains as a shift toward higher frequencies of the main peak associated with the frequency of the afferent oscillator \( f_a \). In contrast, weak stimuli did not alter the center frequency of the \( f_a \) peak, but instead altered the width of the peak or evoked sidebands (Neiman and Russell 2004). Apparently, nonweak time-varying (“AC”) stimulation activates a mechanism, presumably cellular and ionic, that drives the faster firing during bursts.
An important point is that treatments as in Fig. 6 were able to dissociate bursts from stimulus waveforms. Thus the bursts are not merely forced by stimulus waveforms. A paddlefish electroreceptor does not merely act as a low-pass filter for broadband stimuli, with the resulting filtered slow noise acting to force a conventional spiking mechanism into epochs of rapid firing or quiescence. Instead, the bursting is partly stimulus induced. There appears to be an amplification mechanism, giving rise to bursting, presumably mediated by ion channels, whose expression is raised during exposure of an ER to voltage fluctuations and transients (that is, noise) of sufficient size, in the frequency band of these ERs. Overall, low-frequency noise has a dual effect, both forcing and inducing bursts.

Statistical properties of noise-induced bursting in paddlefish ER afferents, such as exponential dependence of the mean interburst interval on the noise intensity, and the parabolic character of bursts, suggest a possible dynamical mechanism (Neiman and Russell 2002). In this model, bursting arises due to stimulus-induced slow variations of a parameter that controls fast spiking (Ermentrout and Kopell 1986). Both initiation and termination of bursts occur due to saddle-node bifurcations. A recent theoretical study (Liepelt et al. 2005) has shown that such a model describes well the basic statistical properties of noise-induced bursting, such as ISI distributions and the mean rates of spikes and bursts as functions of noise intensity.

Spontaneous parabolic bursts can be observed when the receptive field of a paddlefish ER afferent is chilled to 7–10°C (Neiman and Russell 2004). At the higher temperature in the present experiments, 22°C, which is within the normal range for paddlefish habitat in spring and fall, when electrosensomediated feeding occurs, afferents instead show tonic spiking spontaneous dynamics. The bursting described herein was not conditioned by external permissive synaptic input because ERs are not under efferent control (Bullock 1986).

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