Interval Coding. II. Dendrite-Dependent Mechanisms

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Doiron B, Oswald A-M, Maler L. Interval coding. II. Dendrite-dependent mechanisms. J Neurophysiol 97: 2744–2757, 2007; doi:10.1152/jn.00988.2006. The rich temporal structure of neural spike trains provides multiple dimensions to code dynamic stimuli. Popular examples are spike trains from sensory cells where bursts and isolated spikes can serve distinct coding roles. In contrast to analyses of neural coding, the cellular mechanics of burst mechanisms are typically elucidated from the neural response to static input. Bridging the mechanics of bursting with coding of dynamic stimuli is an important step in establishing theories of neural coding. Electrosensory lateral line lobe (ELL) pyramidal neurons respond to static inputs with a complex dendrite-dependent burst mechanism. Here we show that in response to dynamic broadband stimuli, these bursts lack some of the electrophysiological characteristics observed in response to static inputs. A simple leaky integrate-and-fire (LIF)-style model with a dendrite-dependent depolarizing afterpotential (DAP) is sufficient to match both the output statistics and coding performance of experimental spike trains. We use this model to investigate a simplification of interval coding where the burst interspike interval (ISI) codes for the scale of a canonical upstroke rather than a multidimensional stimulus feature. Using this stimulus reduction, we compute a quantization of the burst ISIs and the upstroke scale to show that the mutual information rate of the interval code is maximized at a moderate DAP amplitude. The combination of a reduced description of ELL pyramidal cell bursting and a simplification of the interval code increases the generality of ELL burst codes to other sensory modalities.

INTRODUCTION

A central motivation of sensory neuroscience is to identify how specific features of an input stimulus are coded by specific events of a spike train (Perkel and Bullock 1968; Rieke et al. 1997). Many studies have shown that coding schemes of single neurons can be quite complex (Koch and Segev 2000; London and Hausser 2005). This complexity can often be attributed to ensembles of voltage-gated ion channels with specific distributions over the soma and dendrites of a neuron (Reyes 2001; Stuart et al. 1997). Nonlinear dendritic processing influences the gain of spike output in response to static stimuli (Larkam et al. 2004; Mehaffy et al. 2005; Prescott and De Koninck 2003), coincidence detection tasks in auditory brain stem (Agmon-Snir et al. 1998), the capacity for burst response (Larkam et al. 2004; Mainen and Sejnowski 1996; Turner et al. 1994), as well supporting cellular based higher-order computations (Gabrianni et al. 2002; Polsky et al. 2004). Theoretical studies have discussed how passive (Tuckwell 1988) or weakly nonlinear dendrites (Maniwni and Koch 1999) shape the neural response to dynamic inputs. However, few studies have addressed how strongly nonlinear dendritic processes, such as those required for action potential backpropagation, influence neural coding schemes for time varying stimuli.

Pyramidal neurons of the electrosensory lateral line lobe (ELL) of weakly electric fish receive direct input from highly reliable receptor afferents (Berman and Maler 1999; Chacron et al. 2005; Wessel et al. 1996). ELL pyramidal cells produce spike trains that consist of isolated spikes and bursts of spikes in response to afferent signals in vivo (Gabbiani et al. 1996; Krahe and Gabbiani 2004; Oswald et al. 2004) and in response to direct somatic current injection of dynamic broadband stimuli in vitro (Oswald et al. 2004). These studies have shown how bursts encode distinct upstroke features of dynamic stimuli compared with those coded by isolated spike events (Gabbiani et al. 1996; Oswald et al. 2004). Expanding on this theme, our companion study has shown how the time interval between the spikes within a burst can code the amplitude and slope of an input upstroke (Oswald et al. 2007).

Complementary in vitro research on ELL pyramidal neurons has identified distributions of voltage-gated sodium channels along the apical dendritic tree (Turner et al. 1994). These channels support active dendritic backpropagation of action potentials resulting in a significant depolarizing afterpotential (DAP) measured at the somatic membrane after a spike; similar phenomena have been observed in a variety of neurons in a number of species (see Reyes 2001; Stuart et al. 1997 for reviews). Furthermore, voltage-gated potassium channels (Fernandez et al. 2005; Noonan et al. 2003; Rashid et al. 2001) and nonspecific leak currents (Mehaffy et al. 2005) over the ELL soma and dendrites contribute to the aforementioned ELL single neuron coding paradigms is not known.

In this study we present a reduced leaky integrate-and-fire (LIF) model of the ELL pyramidal cell that incorporates a DAP mechanism, yet none of the DAP potentiation and dendritic refractoriness that are required for the more biophysically complete ELL-burst mechanisms (Doiron et al. 2001–2003; Fernandez et al. 2005; Noonan et al. 2003). The model repre-
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produces the first- and second-order statistics of both the spike train and interspike interval (ISI) sequences observed from in vitro neurons driven with broadband inputs. Furthermore, the model outputs replicate the parallel processing code (Oswald et al. 2004) as well as the interval coding results presented in our companion paper (Oswald et al. 2007). We use this model to study a conceptually simple form of stimulus dimension reduction where the burst ISI codes the effective scale of a basis stimulus upstroke. Using this stimulus representation we compute the mutual information of a quantized ISI-scale code and show the information rate is maximized at a moderate DAP amplitude size. This provides evidence for a further computational role for dendritic excitability during electrosensory processing. The simplicity of both this pyramidal cell model and the ISI-scale code significantly broaden the applicability of ELL-burst codes both within electrosensory processing as well as in comparison with burst coding preformed in other sensory modalities (Krahe and Gabianni 2004).

METHODS

Throughout METHODS and RESULTS we use the notation introduced in our companion study Oswald et al. (2007). Where appropriate we refer the reader to that study for relevant definitions.

Experiments

Recordings from in vitro ELL pyramidal neurons were performed with identical methods detailed in our companion paper (Oswald et al. 2007).

LIF-DAP pyramidal cell model

We represent the ELL pyramidal cell membrane potential with the variable $V$. The evolution of $V$ is given by the following current balance equation

$$\frac{dV}{dt} = b - gV + I_{DAC}(t) + aI_{\text{stim}}(t) \tag{1}$$

In Eq. 1, $C$ and $g$ are the membrane capacitance and leak conductances, respectively, and $b$ is a static current that sets the equilibrium potential in the absence of dynamic inputs. The dynamics of $V$ are supplemented with the standard integrate-and-fire threshold crossing rule (Gerstner and Kistler 2002; Tuckwell 1988): when $V(t) = V_{th}$, then $V$ is immediately reset to $V_{\text{reset}}$ and forced to remain there for a refractory period $\tau_r$. After the refractory period, the subthreshold membrane evolution is again dictated by Eq. 1. The ith threshold crossing time is the spike time $t_i$.

$I_{\text{stim}}(t)$ is an applied dynamic stimulus with Gaussian statistics having zero mean and unit SD and broadband spectrum (frequencies distributed with equivalent power between 0 and 60 Hz). $\sigma$ sets the SD (contrast) of the fluctuating inputs. $I_{\text{stim}}(t)$ is identical to that used in the companion study (Oswald et al. 2007) and similar to that used in past investigations of ELL pyramidal cell coding (Bastian et al. 2002; Chacron et al. 2003; Oswald et al. 2004).

ELL pyramidal cells have a punctate distribution of Na$^+$ channels on their proximal apical dendrite (Turner et al. 1994). These channels support the active backpropagation of somatic spikes along approximately the first 200 $\mu$m of the apical dendritic tree (Fig. 1A). Rapid somatic spike repolarization ensures that for a brief window of time after a somatic spike the dendrite is more depolarized than the soma. This produces a depolarizing aftercurrent (DAC) that depolarizes the somatic membrane resulting in a DAP; see Fig. 1, A1–A3. The function $x(t) = a^2(t - t_1 - \tau_{DAC})e^{-a(t - t_1 - \tau_{DAC})}(t - t_1 - \tau_{DAC})$, low-pass filtered to mimic membrane integration, gives an acceptable fit to the time course of a typical DAP, i.e., $V(t) = A \int e^{-(t-t'\tau_{DAC})}x(t')dt'$ (see Fig. 1A3). A is the amplitude of the DAC and $\tau_{DAC}$ is a delay that models the time required for a dendritic spike to fire and the return current to source back to the soma. (Lemon and Turner 2000). Here the membrane time constant $\tau_m = C/g$.

We model dendritic activity and DAP production with a strategy that is similar to the one used in Noonan et al. (2003) and Mehaffy et al. (2005). Rather than model the dendritic tree using a cable model (Doiron et al. 2001, 2003) or a reduced two-compartment system...
(Doiron et al. 2002; Fernandez et al. 2005), we inject a current waveform \(I_{DAC}(t)\) that is representative of the DAC flow occurring after each threshold crossing. We set \(I_{DAC}(t) = Ax(t)\) where \(x(t)\) given from the fit given in the preceding text. Equivalently, we write the DAC given to the somatic membrane as the auxiliary linear nonautonomous system

\[
\frac{dx}{dt} = y
\]

\[
\frac{dy}{dt} = -\alpha^2 x - 2\alpha y + \alpha^2 \sum_i \delta(t - t_i) \theta(t - t_i - \tau_{DAC})
\]

Given a spike occurs at time \(t_i\), the solution of Eqs. 2 and 3 with the condition that \(s(t) = 0\) and \(y(t) = \alpha^2\) is the fit \(x(t)\) stated in the preceding text (shown in Fig. 1B2). The coefficient \(A\) in Eq. 1 is the amplitude of the DAC. This process is shown schematically in Fig. 1B1. The waveform \(x(t)\) and the resultant membrane excursion \(V(t)\) with \(I_{DAC}(t) = 0\) match the membrane potential fit that was obtained from the data (Fig. 1B2). This class of model replaces the need to model an independent excitatory dendritic compartment and merely models the effect of dendritic backpropagation on the somatic membrane via \(x(t)\). We compare the membrane dynamics with and without DAP dynamics during spiking activity (Fig. 1B3). As expected, the DAP brings the model cell potential closer to threshold (black trace), as compared with the case without a DAP (gray trace), and thus decreases the ISI.

The model parameters were \(V_m = 15\) mV, \(V_{reset} = 0\) mV, \(C = 150\) nF, \(g = 30\) nS, \(b = 0.387\) nA, \(\sigma = 0.18\) nA, \(\tau_s = 2\) ms, \(\tau_{DAC} = 2\) ms, and \(\alpha = 0.24\) ms\(^{-1}\) (see Meahaya et al. 2005) (see also results for parameter justification). Unless otherwise stated, the DAC amplitude \(A = 0.855\) nA and the stimulus SD \(\sigma = 0.18\) nA. We simulate Eqs. 1–3 with a fourth-order Runge-Kutta integration algorithm implemented with the simulation package in MATLAB (Mathworks). The random input current \(I_{DAC}\) was generated off-line with a fourth-order butterworth digital filter using the signal processing toolbox in MATLAB. For model spike train statistics and measures of stimulus coding, we typically computed 30,000–40,000 bursts (10 realizations each of 1,000 s in duration were performed for each data set).

Spike train statistics

From a membrane time series, we construct a point process spike train \(s(t) = \sum \delta(t - t_i)\) digitized at 2 kHz, where \(t_i\) is the time of the \(i\)th spike. To measure spike train patterning, we use the zero-mean corrected spike trains \(s_{unc}(t) = s(t) - \langle s(t) \rangle\) (where \(\langle \cdot \rangle\) is an average over time). The expectation (computed with chance) of observing a spike \(\tau\) time units after another spike is given by the normalized autocorrelation function \(Q(\tau) = \langle s_{unc}(t) s_{unc}(t+\tau) \rangle / \langle \langle s_{unc} \rangle^2 \rangle\) where \(\langle \cdot \rangle\) is the mean ISI (Gabbiani and Koch 1998). To quantify the linear transfer properties of spike or burst trains, we use the spectral coherence \(C(f) = \langle S_{\text{unc}}(f) S_{\text{unc}}^*(f) \rangle / \langle S_{\text{unc}}(f) S_{\text{unc}}(f) \rangle\) (Gabbiani and Koch 1998; Oswald et al. 2004). \(S_{\text{unc}}(f)\) is the cross-spectrum between the input \(I_{DAC}\) and the spike train \(s_{unc}\), \(S_{\text{unc}}^*(f)\) and \(S_{\text{unc}}(f)\) are the auto-spectra of the \(s_{unc}\) and \(I_{DAC}\) respectively. \(C(f)\) measures the normalized frequency dependent linear input-output correlation between \(s_{unc}\) and \(I_{DAC}\).

Pattern classification

Pattern classification analysis (Duda et al. 2001) and detection theory (Poor 1994) have been applied to a variety of neural spiking data (Brenner et al. 2000; Gabbiani et al. 1996; Kephig and Lism 2003; Metzner et al. 1998; Oswald et al. 2004, 2007). In this section, we introduce a stimulus-reduction ansatz appropriate for the interval coding performed by bursting ELL pyramidal neurons.

In principle, a response with many potential states \(R_1, \ldots, R_k\) can classify many associated stimulus patterns \(s_1, \ldots, s_k\). In our companion paper (Oswald et al. 2007), we defined a response set with a quantized burst ISI distribution; a given ISI of length \(\Delta\) is classified as a response in class \(R_i\) if \(\mu_i < \Delta < \mu_{i+1}\), where \(\mu_j\) is the threshold that separates responses state \(R_i\) and \(R_{i+1}\). Following Oswald et al. (2007), we typically considered only four response groups \(R_1, \ldots, R_4\) with \(\mu_0 = 3\) ms, \(\mu_1 = 5\) ms, \(\mu_2 = 7\) ms, \(\mu_3 = 9\) ms. We define a stimulus pattern as the mean of the conditional stimulus distribution \(P(s|R_i)\), where \(s\) is the event-triggered stimulus, i.e., \(s_i = \int sP(s|R_i)ds\) (we use a bold notation to indicate a vector). In practice, \(s\) is the \(K\)-dimensional vector \(s = [s(t_1), s(t_1 + \Delta), \ldots, s(t_1 + K\Delta) = s(t_1)]\) where \(K = L/\Delta\), with \(L = t_2 - t_1\) the time interval of the reverse correlation and \(\Delta\) the time discretization. It is difficult to compute \(P(s|R_i)\) if the dimensionality of \(s\) is large \((K \gg 1)\) as is the case with spike- or burst-triggered stimulus reverse correlations. Our companion paper (Oswald et al. 2007), as well as past studies of electrosensory coding (Gabbiani et al. 1996; Metzner et al. 1998; Oswald et al. 2004), have used feature extraction techniques to reduce stimulus dimension. In brief, the vector members \(s\) of the conditioned distributions \(P(s|R_i)\) and \(P(s|R_j)\) are projected onto a specific feature vector \(f_{ij}\) to obtain the projection length \(f_{ij}^T s\) is a low-dimensional stimulus representation permitting a reliable estimate of \(P(f_{ij}^T s|R_i)\) and \(P(f_{ij}^T s|R_j)\) to be computed from a reasonable sized data set.

In Oswald et al. (2007), \(f_{ij}\) was chosen such that it maximized the discriminability between conditioned events (assuming Gaussian response statistics) (see Metzner et al. 1998). Although this definition of \(f_{ij}\) provided a sensible algorithm for a classifier, interpreting the stimulus after projection onto the feature vector \(f_{ij}\) can be problematic. Specifically, \(f_{ij}\) was a function of both the event-triggered average and covariance (Metzner et al. 1998). Unfortunately, the spike-triggered covariance is a matrix the eigenspectrum of which typically admitted many principle components (typically >10 components were required to capture 95% of the variance). \(f_{ij}\) inherited this complexity, and thus despite feature extraction providing a certain optimality (in the sense of linear discrimination), an intuitive relationship between what the specific differences in the stimulus that event \(i\) selects but event \(j\) does not select is lacking. To this end, a visual inspection of the \(s_i\) vectors is typically required.

This difficulty of interpretation motivated us to propose a simple stimulus reduction approximation appropriate for the interval code. Consider the burst-triggered average computed from all burst events, \(s_{all} = \int sP(s)ds\), where each \(s\) is defined between the first spike of the burst doublet occurring at \(t_1 = t_1\) and the second spike occurring at \(t_2 = t_1 + \Delta_s\), being the ISI length. Our stimulus reduction is to approximate the stimulus vector during a given burst interval as

\[
s = \kappa s_{all}[1, \ldots, \text{Int}(\Delta/\Delta_s)]
\]

\(\kappa_s\) is a scalar chosen to be the scaling factor is the best fit in the least squares sense, i.e., minimizing \(\|s - \kappa s_{all}[1, \ldots, \text{Int}(\Delta/\Delta_s)]\|\) where \(\|\cdot\|\) is the Euclidian distance. Equation 4 effectively assumes that the stimulus that triggers each burst event is just a scaled version of a basis upstream \(s_{all}\). \(\text{Int}(\Delta/\Delta_s)\) is the real number \(\Delta/\Delta_s\) rounded up to the nearest integer. We restrict our comparison between \(s\) and \(s_{all}\) to the components of \(s_{all}\) that occur between the first and second spikes of the doublet. In essence, we assume that the shape of the burst-triggered stimulus is invariant with respect to the stimulus intensity, and it is merely scaled \((\kappa_s)\) in amplitude. Data presented in our companion paper (see Oswald et al. 2007; Fig. 2B) suggest that this is a reasonable approximation. The scalar representation of the reverse correlation by \(\kappa_s\) should be compared with the projection \(f_{ij}^T s\) computed with feature extraction. In Results (Fig. 5), we give empirical evidence for the validity of the approximation in Eq. 4 for bursting ELL pyramidal neuron spike trains.

To assess coding performance it is typical to employ a simple linear classifier (Duda et al. 2001).
where $\theta$ is a decision threshold. Here $g(s)$ is either $f^T_i s$ if the full-feature extraction method is used (Oswald et al. 2007) or it is simply $\kappa_i$ if the scale reduction is used. If $h_0 > 0$, then the predicted response is an event in $R_i$; if $h_0 < 0$, then the predicted response is an event in $R_c$. Given $M$ responses, there are $M(M-1)$ feature vectors and one dimensional classifiers; however, because the time separation between events in $R_i$ and $R_{i,2}$ is large, then it is sufficient to consider only adjacent stimulus-responses pairs, thereby giving only $M-1$ feature vectors/classifiers. A prediction choice between $R_i$ and $R_{i,2}$ requires a specific $\theta$, which in turn defines the probability of correct detection ($P_{\text{det}}$) and false alarm ($P_{\text{fa}}$) simply as $P_{\text{det}} = \int_{-\infty}^{\infty} P[g(s)]d[g(s)]$ and $P_{\text{fa}} = 1 - P_{\text{det}}$. The threshold $\theta$ that minimizes the error probability $e_{ui} = (P_{\text{fa}})2 + (1 - P_{\text{fa}})2$ gives the optimal linear classifier. Thus for both techniques the original high-dimensional classification problem has now become a threshold problem dependent on the representation in the relevant stimulus space. Hereafter we suppress the $s$ subscript on $\kappa_i$.

**ISI code**

The assumption of a basis upstroke allowed an intuitive scalar representation of the time-veceted stimuli. In our companion paper (Oswald et al. 2007), we used a quantized description of burst ISI by defining a finite set of burst groups ($R_i$; 3–5 ms; $R_c$; 5–7 ms; $R_e$; 7–9 ms; $R_c$; 9–11+ ms). Given this discrete partitioning of the burst output and the scale description of the burst-triggered stimulus we motivate an appropriately defined quantization of our stimuli ($S_i; \kappa > \kappa_{12}$, $S_1$; $\kappa_{23} < \kappa < \kappa_{12}$, $S_2$; $\kappa_{23} < \kappa < \kappa_{34}$, $S_3$; $\kappa < \kappa_{34}$, $S_4$; $\kappa < \kappa_{34}$), where $\kappa_{12}$, $\kappa_{23}$, and $\kappa_{34}$ are scale thresholds. We choose these thresholds by minimizing the error probability $e_{ij}$ for a detection task of a linear classifier (see Fig. 6). Given our discrete one-dimensional response $R_1$ to burst stimulus $S_t$, we can now easily compute the joint-probability density $P(S,R)$, the marginal response $P(R) = \sum P(S,R)$, the scale distributions $P(S) = \sum P(S,R)$, and the conditional response distribution $P(R|S) = P(S,R)/P(S)$. The Shannon mutual information (Cover and Thomas 1991) is given as the reduction of response entropy given the stimulus

$$I(S|R) = H(R) - H(R|S)$$ (5)

Here the response entropy $H(R)$ and the noise entropy $H(R|S)$ are given by

$$H(R) = -\sum_i P(R_i) \log_2 [P(R_i)]$$ (6)

$$H(R|S) = -\sum_i P(R_i|S) \log_2 [P(R_i|S)]$$ (7)

Finally, the frequency of burst events (of all groups) is $f_{\text{burst}}$, and we thus compute the information rate as $I_{\text{rate}}(S|R) = I(S|R)f_{\text{burst}}$.

We remark that an expected source of information loss in our putative interval code is the reduction of $\kappa$ and the subsequent quantization of $\kappa$ and the response ISI to the discrete groups $S_1$ to $S_4$ and $R_1$ to $R_4$ (Dimitrov and Miller 2001; Dimitrov et al. 2003). More to the point, we fully expect that $I(S,R) < I(s, ISI)$ where $I(s, ISI)$ is the mutual information of the original vector stimulus $s$ to ISI code. In fact, because the LIF-DAP model is deterministic, then the conditional entropy $H(ISI|s) = 0$, which gives the simple result that $I(s, ISI) = H(ISI)$. However, an appropriate stimulus-response reduction is required to motivate a conceptually simple neural code, such as $S_i \rightarrow R_i$ whereas a more detailed code relating a specific $s$ to $ISI$, although likely being more information-rich, could be overly cumbersome and require temporal specificity that is beyond the capacity of any reasonable decoder. Further, the exact quantization proposed here and in our companion paper (Oswald et al. 2007) may be suboptimal as we have not used techniques based on rate distortion theory to motivate our quantization (Cover and Thomas 1991; Dimitrov and Miller 2001; Dimitrov et al. 2003). However, the purpose of $I(S,R)$ is not to achieve optimal estimates of the information capacity of the interval code, yet to be a reasonable measure of interval coding as internal parameters, such as DAC amplitude, are varied (see Figs. 7 and 8). We expect the qualitative conclusions drawn from using our quantization, and thereby $I(R,S)$ will be consistent with those gained from other quantization schemes.

**RESULTS**

**Simple LIF-DAP bursting model**

Pyramidal cells exhibit a complex burst dynamic in response to static depolarizing inputs (Lemon and Turner 2000; Turner et al. 1994). Within a single burst, an accelerated “ping-pong” interaction between somatic and dendritic excitability culminates with a high-frequency spike doublet. The second spike of the doublet is not followed by a dendritic spike, and consequently, the absence of a somatic DAP reveals a large burst afterhyperpolarization (bAHP). The bAHP signals the termination of the burst. In vitro experiments by Lemon and Turner (2000) distilled the burst mechanism to three general electrophysiological requirements. First, an active Na+-dependent dendritic backpropagation is required to produce a DAP in the somatic membrane immediately after a somatic spike. Second, a spike frequency-dependent broadening of DAPs is needed to potentiate the DAPs thereby accelerating the burst frequency toward the spike doublet. The final requirement is a longer dendritic Na+ channel refractory period compared with somatic Na+ that leads to dendritic spike failure post the somatic spike doublet. This detailed characterization permitted the construction of several mathematical models of these cells, ranging from detailed multicompartmental models (Doiron et al. 2001, 2003) to two-compartment models (Doiron et al. 2002; Fernandez et al. 2005; Oswald et al. 2004) and phenomenological LIF-type bursting models (Noonan et al. 2003). The response of an in vitro ELL pyramidal cell to low-frequency (0–10 Hz) random inputs showed burst signatures associated with the response to static stimuli, specifically multiple spike bursts with a decreasing ISI pattern and terminating bAHP (Fig. 2A). In contrast, the response of the same cell to broadband stimulus (0–60 Hz) lacked bursts with more than three spikes, typically only showing two spike bursts (Fig. 2B)—a behavior consistent with in vivo spike bursts collected during broadband stimulation (Gabriani et al. 1996; Oswald et al. 2004). Furthermore, bAHPs marking the termination of a burst were absent in all recordings ($n = 52$). The lack of multi-spike bursts with decreasing ISIs and a terminating bAHP suggested that the ionic mechanisms responsible for these burst characteristics were not recruited during broadband stimulation.

In the appendix, we present a phenomenological LIF-style model that contains the essence of the three mechanistic requirements of the full burst response to static inputs. This model reproduced the preceding experimental scenario, namely a full burst was observed in response to low-frequency inputs and only spike doublet bursts in response to broadband stimulation. The model response showed that the variables associated with slow DAP potentiation and dendritic refractory
period play a limited role in determining the neural response to broadband stimuli. Burst termination in this case was induced by the stimulus rapidly decreasing to negative values rather than an intrinsic ionic event. This suggested that a reduced LIF model with a history-independent DAP mechanism could model the ELL pyramidal cell response to broadband stimuli.

Thus motivated, we proposed an LIF-DAP model to replicate the spike train response of ELL pyramidal neurons driven by broadband stimuli (see METHODS). Briefly, the model is an LIF neuron that receives a dendro-somatic current (DAC) 2 ms after each spike reset. The DAC elicits a DAP response in the somatic membrane. Importantly, and unlike all other ELL burst models, the DAP is invariant with respect to past spiking history, meaning that the DAP neither potentiates during a burst nor fails after a somatic spike doublet. This model thus retains the effect of dendritic backpropagation but ignores the second and third components of the classic ELL burst mechanism (Lemon and Turner 2000). The history independence of the post spike response makes this model a specific example of a broad class of spiking cell models called spike-response models (Gerstner and Kistler 2002). Similar style models have been successfully used to quantitative model spike behavior of both retinal ganglion cells (Pillow et al. 2005) as well as detailed models of cortical pyramidal neurons (Jolivet et al. 2004).

In response to broadband (0–60 Hz) Gaussian stimuli, the model neuron produced a sequence of single spikes and bursts along with a resultant DAC (Fig. 3A). With a reasonable choice of model parameters, the spike train firing rate was $\sim$24 Hz, the burst fraction was 0.46 (number of spikes within bursts divided by the total number of spikes), and the burst event fraction was 0.20 (number of bursts divided by the total number of events, i.e., isolated spikes and bursts). These values are within the experimental range reported for the stimulus contrast of 1.4 nA (Oswald et al. 2006; Table 1).

The spike train autocorrelation $Q(\tau)$ (see METHODS) was compared between experiment (Fig. 3B), a standard LIF model (Fig. 3C, gray), and the LIF-DAP model (Fig. 3C, black). Both the experiments and the LIF-DAP model showed prominent high spike likelihood between 5 and 10 ms after a spike. This tendency was greatly reduced in the LIF model spike train. Additionally, the experimental ISI distribution (Fig. 3D) was also better matched with the LIF-DAP model (Fig. 3E, black) as compared with the LIF model (Fig. 3E, gray). Both the data and the LIF-DAP model ISI distributions showed a strong bimodality, yet the standard LIF model spike train had an ISI distribution with a weak bimodality similar to the one obtained under TTX blockade of dendritic Na$^+$ during presentations of broadband stimuli (Oswald et al. 2004). There were no significant ISI serial correlations in either the data or model outputs, marking them all as renewal spike trains (Gabbiani and Koch 1998).
The quantitative fits of the LIF-DAP model to experimental results as well as the spike and burst firing rates were obtained by varying only a few model parameters. We varied the DAC amplitude \( A \), the mean input bias \( b \), and the stimulus contrast \( \sigma \). The other parameters, such as DAC time scale \( \tau_{DAC} \), and the membrane timescale \( \tau_{m} \), were fixed to fit experimentally estimated DAPs (see METHODS). With LIF-DAP parameters chosen to quantitatively match experimental data, we next compared the coding capabilities of the LIF-DAP model with those of real ELL pyramidal neurons.

**LIF-DAP coding of dynamic inputs**

In Oswald et al. (2004), a parallel processing scheme was introduced where isolated spikes and bursts respectively code the high- and low-frequency components of broadband input. Analogous to our past study we similarly analyzed the spike output of the LIF-DAP model. We computed the spectral coherence \( C(f) \) (see METHODS) between the stimulus and the full spike train (Fig. 4A, black), the isolated spike train (Fig. 4A, dashed), and the burst train (Fig. 4A, gray). Satisfyingly, a clear streaming of low-frequency coding by bursts and high-frequency coding by isolated spikes is observed, identical to the results in Oswald et al. (2004).

Gabbiani et al. (1996) have shown that in vivo ELL pyramidal cell bursts outperform isolated spikes in detecting specific stimulus features; this was later replicated in vitro (Oswald et al. 2004). With the LIF-DAP model, we computed receiver operator curves (ROCs) comparing the selectivity of bursts (Fig. 4B, gray) and isolated spikes (Fig. 4B, dashed) reverse correlations with that of null reverse correlation (see Gabbiani et al. 1996; Metzner et al. 1998; Oswald et al. 2004). Similar to experimental results, and a conductance based bursting model, the bursts demonstrated enhanced stimulus selectivity over isolated spikes (Oswald et al. 2004).

Finally our companion study Oswald et al. (2007) introduced an interval code whereby upstrokes of different amplitudes and slopes could reliability be discriminated based on two spike bursts of different ISI durations. With the LIF-DAP model, we computed both the average discriminability \( I_D \) and the interval code measure \( I_C \) for a range of ISI partition lengths \( T \) (Fig. 4, C and D). For ease of comparison, we also computed both the average response over the full data set from Oswald et al. (2006) and the LIF model \( (A = 0) \). The LIF-DAP model quantitatively matched the experimental results (Fig. 4, C and D), whereas the standard LIF model could not match \( I_C \) due to the lack of high-frequency burst intervals (see Fig. 3B).

In total, the preceding results show how the LIF-DAP model is sufficient to accomplish a wide variety of complex single neuron coding schemes that are exhibited by real in vitro and in vivo ELL pyramidal neurons. Furthermore, the fact that a basic LIF model could neither match the spike train statistics (Fig. 2) nor the spike train coding (Fig. 3) suggests that the LIF-DAP model is an appropriate minimal model of an ELL pyramidal cell in response to broadband inputs. We next used the LIF-DAP model to investigate a simplification of the interval code (Oswald et al. 2007) and describe the DAP dependence of interval coding.

**FIG. 4.** LIF-DAP model coding performance. A: spectral coherence \( C(f) \) between the stimulus and the full spike train (black), the isolated spike train (dashed), and the burst train (gray). B: receiver operator characteristic of the isolated spike train (dashed) and the burst train (gray). Both curves were computed for the respective spike trains as compared with the null event distribution. C and D: average burst ISI discriminability \( I_D \) and the interval code \( I_C \) as a function of ISI group duration \( T \) computed for the LIF-DAP model (black symbols), LIF model (open symbols), and the data set presented in Oswald et al. (2007) (gray symbols). The DAC amplitude \( A \) is as in Fig. 2.
Scale-ISI code

A major obstacle in any measure spike train coding is the reduction of stimulus dimension (Arcas and Fairhall 2003; Brenner et al. 2000; Metzner et al. 1998; Dimitrov and Miller 2001; Dimitrov et al. 2003; Rieke et al. 1997). In our companion study (Oswald et al. 2007), we projected burst triggered stimuli on suitably defined feature vectors to give a one-dimensional representation of the stimuli that elicit a specific burst. The feature vector was chosen to maximize the discriminability between two distinct interval groups. We then used a set of linear classifiers to quantify the performance of the burst interval code. The classifiers assessed both the ability of an ISI group to code a preferred feature and the difference between the features coded by distinct ISI groups. However, feature-extraction techniques do not allow for an intuitive picture of what are these actual differences and a visual inspection of the event triggered averages is required (see METHODS). In this section, we introduce a stimulus representation that significantly simplifies the interval code. This permits a computation of the mutual information between the burst intervals and the stimulus.

We considered the burst triggered average computed from all bursts, $s_{all}$, with each stimulus vector $s$ beginning at the first spike of the burst doublet and ending at the second spike. The maximal ISI over which the stimulus is defined was $\sim 11$ ms, whereas the fastest frequency component in $I_{stim}$ had a period of 16 ms. This resulted in the observation that any burst triggered $s$ (and by extension $s_{all}$) was a smooth function with at most one maxima (see Fig. 1A in Oswald et al. 2007). We proposed the following reduction: each burst triggered reverse correlation, $s$, was approximated by a scaled version of $s_{all}$, making $s_{all}$ an effective basis vector for the burst stimulus selectivity (see METHODS). To illustrate, we show four bursts from an ELL pyramidal cell, each of various interval lengths. For each burst, we show the stimulus waveforms $s$ that elicited them (Fig. 5A, colored solid traces), $s_{all}$ (black solid trace), and finally the best fit $s_{all}$ (colored dotted lines). To quantify the success of the fit, we computed the $\chi^2$ values of the one parameter fit between $s_{all}$ and $s$ for each burst in the data set (Fig. 5B). The fits were acceptable ($\chi^2 < 1$) for bursts that were less than $\sim 10$ ms, yet when the burst ISI approaches the time scales contained in the stimulus, the fit is less accurate. Satisfied with the reduction of stimulus dimension from a vector $s$ to the scalar $\kappa$ and basis upstroke $s_{all}$, we represented both the stimulus and response as one dimensional quantities, i.e., a burst ISI and a scale parameter $\kappa$.

We observed a strong correlation between the ISI and $\kappa$ in both the data (Fig. 5C) and the model (Fig. 5C). By quantizing the ISIs into four response groups ($R_1$-$R_4$, see METHODS) we defined the conditional stimulus distributions $P(\kappa|R_i)$ (colored groups in Fig. 5). For both the data and the LIF-DAP model, the distributions $P(\kappa|R_i)$ were unimodal and were easily visually discriminated (Fig. 5D, 1 and 2). The high-frequency ISI group ($R_1$) was most easily discriminated from the remaining lower frequency groups because the stimuli that elicit burst events in $R_1$ have the largest range in stimulus energy. This stimulus reduction strategy should be compared with the reduction of stimulus waveforms to either the average stimulus amplitude or rough stimulus slope estimate proposed in our companion paper (Oswald et al. 2007 Figs. 2, 3, and 5).

![FIG. 5. Burst ISI codes for the scale of stimulus upstroke. A: full burst triggered average $s_{all}$ (black) from a representative data set in Oswald et al. (2007). Representative ISI from each response group ($R_i$) with the stimulus $s$ that triggered it (solid lines; cyan: $R_2$; green: $R_3$; blue: $R_4$; red: $R_1$). Plotted with $s$ is $s_{all}$ (dotted) where $\kappa$ is the best fit scaling factor for each burst ISI and $s_{all}$ is the full burst triggered average. B: $\chi^2$ values for the best scale $\kappa$ fits for all burst ISIs of a representative data spike train. Color codes are as given in A. C: computed scale $\kappa$ as a function of burst ISI for the data set (C1) and the LIF-DAP model (C2). D: $\kappa$ probability distributions condition on the ISI response group estimated from both the data (D1) and the LIF-DAP model (D2). The distribution bin size was 0.05 for the data and 0.005 for the model; each distribution is normalized so the area is 1. Colors are as marked in A. The DAC amplitude $A$ is as in Fig. 2. A change in $\kappa$ synthesizes both a change in stimulus amplitude and slope, is an equally intuitive reduction, and is a single scalar quantity making it amenable for further analysis (see following text).

Given the conditional distributions $P(\kappa|R_i)$ and assuming a linear classifier model (see METHODS), we computed the probability of correct detection ($P_D$), the probability of false alarm ($F_{FA}$), and the classification error probability ($e$). We compared $e_{FE}$ computed using our scale reduction ($\kappa$) of spike-triggered stimuli to the error probability $e_{FE}$ computed where stimulus reduction was performed using standard feature extraction techniques (Fig. 6A). When response groups are partitioned using 2-ms ISI intervals, a good quantitative agreement between the two reductions techniques is observed for discrimination between groups $R_1/R_2$ and $R_2/R_4$, whereas the agreement is fair for $R_1/R_4$. In particular, the optimal linear classifiers as defined by the minimum of the error probability
are similar between the two stimulus reduction techniques. By locating the minimum of $\epsilon$, we computed optimal thresholds $\kappa_{12}$, $\kappa_{23}$, and $\kappa_{34}$ so as to best quantize the upstroke scale $\kappa$ into well-defined stimulus groups $S_1$–$S_4$ (Fig. 6B, see METHODS). By partitioning both the stimulus ($S_1$–$S_4$) and the response ($R_1$–$R_4$), we computed the 16 state discrete joint distribution $P(S,R)$ and overlaid the grid matrix on top of the continuum joint density $P(\kappa,ISI)$ (Fig. 6C). The tendency for $P(S,R)$ to be centered along the diagonal of the $P(S,R)$ grid is evident. With an accurate estimation of $P(S,R)$, we computed the mutual information $I(S,R)$ between $S$ and $R$ (see METHODS). For the fitted parameters, the LIF-DAP model yielded an $I(S,R) = 0.875$ bits. With an upper bound of 2 bits (4 stimulus/response states), the interval code thus performs adequately, and these results further suggest that interval coding is a viable coding option for ELL pyramidal neurons.

Equipped with a quantitative measure of interval coding, we next evaluate the influence of dendritic excitability on interval coding.

**Influence of DAP amplitude on interval coding**

Several experimental studies have shown that the DAP amplitude ($A$) can be regulated through both expression of dendritic potassium channels (Noonan et al. 2003) or shunting inhibitory input to the proximal dendritic shaft (Mehaffy et al. 2005). Motivated by the capacity for DAP regulation, we computed the response entropy $H(R)$, the noise entropy $H(R|S)$, and the mutual information $I(S,R)$ [i.e., the difference between $H(R)$ and $H(R|S)$] for the LIF-DAP model as a function of the DAP amplitude $A$ (Fig. 7A). Interestingly, both $H(R)$ and $I(S,R)$ show broad maxima, and all three measures decrease rapidly as $A$ goes beyond $\sim 1.3$ nA. To identify the cause for the maximum, we studied the full joint density $P(ISI,\kappa)$ and overlaid on top the optimal ISI-$\kappa$ partition grid and the resulting joint density $P(S,R)$ for three values of $A$ (Fig. 7, B–D). For small DAP amplitudes (Fig. 7B), the probability of observing high-frequency burst ISIs was negligible and the partitioning ranged over only $S_2$–$S_4$ and $R_2$–$R_4$, thereby limiting $H(S,R)$ and by extension $I(S,R)$. In a similar fashion, when the DAP amplitude was large (Fig. 7D), the burst response was dictated by the DAP alone and the partitioning was dominated by $S_4$ and $R_1$, severely restricting the information $I(S,R)$. Only when the DAP amplitude $A$ was moderate (Fig. 7C) could a full spanning of the response groups $R_1$–$R_4$ be achieved. This full spanning allowed the response entropy $H(R)$ to be large, yet the DAP amplitude was not so overpowering as to eliminate the stimulus dependence of the response, hence permitting a small noise entropy $H(R|S)$. This combination lead to a maximum in $I(S,R)$.

The probability of a burst ISI increases with the DAP amplitude $A$ (see Fig. 3E). This resulted in the burst frequency $f_{\text{burst}}$ (average number of bursts per second) also increasing with $A$ (Fig. 8A, thin black line). As a consequence, the information rate, $I_{\text{rate}}(S,R) = I_{\text{burst}}(S,R)$, of the interval code showed a clear maximum as a function of $A$ (Fig. 8A, thick black line). This again resulted from a moderate DAP amplitude permitting a wide range of possible responses (as in Fig. 7); indeed the maximums of the $I(S,R)$ and $I_{\text{rate}}(S,R)$ approximately coincided. The combination of these results show that although the DAP is required to elicit a burst response, the DAP enters the spike generation zone ($V$) as a current so its influence must be moderate to allow the stimulus $I_{\text{stim}}$ to effectively influence the burst response.

The preceding results were conditional on the stimulus $I_{\text{stim}}$ having a fixed contrast $\sigma$. However, it is expected in a natural environment that the contrast of electric field modulations can vary significantly. We computed the $A - I_{\text{rate}}(S,R)$ curve for five different stimulus contrasts and observed a systematic shift of the maximum information rate to lower DAP amplitudes as contrast increases (Fig. 8B). The pairing of the optimal $A$ for a given $\sigma$ was such that if $\sigma$ increased, the DAP mechanism needed to decrease. Otherwise the combination of a strong stimulus and a large DAP would evoke bursts leading to the scenario featured in Fig. 7D: the majority of bursts fall into ISI group $R_1$. In the opposite scenario, when the stimulus contrast was weak, the DAP amplitude was required to be large to
ensure burst responses, else only the scenario in Fig. 7B occurred: the majority of bursts fall into ISI groups $R_3-R_4$.

**DISCUSSION**

In this paper, we have shown that the burst response of ELL pyramidal cells to broadband dynamic inputs does not require the ionic machinery necessary to account for the burst response to static or low-frequency inputs. We introduced a simple LIF-DAP model that was successful at reproducing the output statistics of both the spike train and ISI sequences of in vitro ELL pyramidal cells stimulated with broadband inputs. The LIF-DAP model could also mimic the parallel processing code (Oswald et al. 2004), enhanced selectivity of burst responses as compared with isolated spikes (Gabbiani et al. 1996), and interval coding (Oswald et al. 2007) associated with these cells. We used the LIF-DAP model to investigate a stimulus dimension reduction assumption where the burst-triggered reverse correlation of a specific burst was approximated as a scaled version of the average burst triggered stimulus. The scale parameter ($\kappa$) is an effective one dimensional representation of the stimulus that drives a given burst ISI. Following our companion paper (Oswald et al. 2007), we used a set of linear classifiers to motivate a quantization of the stimulus and response are plotted as a function of the DAP amplitude $A$. A broad maximum is seen in $I(S,R)$. $B$: $P(k,ISI)$ and $P(S,R)$ when the DAP amplitude is 0. $C$: $P(k,ISI)$ and $P(S,R)$ when $A$ is such that $I(S,R)$ is maximized. $D$: $P(k,ISI)$ and $P(S,R)$ when $A$ is large and $I(S,R)$ is small.

**Caricature of the DAP-dependent interval code**

In this section, we use the simplicity of the LIF-DAP model to present a caricature that highlights the essence of several ELL burst coding strategies (Oswald et al. 2004, 2007) (Figs. 5–8 of this paper). To ease the analysis in what follows, we replace the Gaussian stochastic process $f_{stim}(t)$ with a sinusoidal forcing $f_{stim}(t) = A \sin(2\pi ft)$. We begin with a straightforward presentation of the parallel processing performed by burst and isolated spikes (Fig. 4).

The burst response to a low-frequency input (20 Hz, Fig. 9A, *top*) occurs due to a temporally coincident depolarizing stimulus (Fig. 9A, *middle*) and DAC from the first spike of the burst (Fig. 9A, *bottom*). The combination of these two input events elicits the second spike of the burst. In contrast, when the stimulus is high-frequency (50 Hz) then the DAC from the first spike of the burst is now coincident with the hyperpolarizing downstroke of the dynamic stimulus (Fig. 9B, *middle* and *bottom*). In this scenario, the DAC is insufficient to produce a second spike, and there is only a single isolated spike in response (Fig. 9B, *top*). Thus bursts are associated with the low-frequency components of a dynamic stimulus, whereas isolated spikes are associated with high-frequency components—facilitating a parallel processing of dynamic inputs (Oswald et al. 2004).

Using the LIF-DAP model, we can summarize the interval code proposed in our companion paper (Oswald et al. 2007). When a stimulus upstroke is both shallow in amplitude and slope or equivalently has a small-scale parameter $\kappa$ (Fig. 9C, *middle*, black curve), then the combination of the DAC of the first spike (Fig. 9C, *bottom*, black curve) and the stimulus produces a delayed second spike resulting in a long burst ISI response (Fig. 9C, *top*, black curve). On the other hand, if the upstroke has a large amplitude and steep slope, i.e., a large $\kappa$.
Fig. 9. Schematic illustration of LIF-DAP paradigm elucidated in the ELL may be operating in other brain regions.

Stimuli reduction and scale codes

The reduction of input stimuli and neural response to their essential features is an important component of any theory of neural processing. An increasingly popular representation of a spike train code is the spike/burst triggered reverse correlation (Reike et al. 1997). Principal component analysis or feature extraction techniques reduce the multi-dimensional stimuli measured with reverse correlation to a more manageable representation (Arcas and Fairhall 2003; Brenner et al. 2000; Metzner et al. 1998). However, a limitation of these techniques is that after reduction an intuitive interpretation of the stimuli associated DAP is often lacking. This makes a straightforward explanation of a specific neural code sometimes difficult to obtain. For instance, our companion study (Oswald et al. 2007) as well as past studies of burst coding (Kepecs and Lismann 2003) used these or similar reduction techniques to quantify the stimulus selectivity of bursts with different characteristics (ISI length, number of spikes, etc.). However, although these techniques give a well-defined metric the DAC amplitude can affect the burst response and hence the interval code (Fig. 9D).

Although all of these arguments for the mechanistic basis of the parallel processing and interval codes are simple, they do require a neural model that does not contain the ionic complexities of previous ELL models (Doiron et al. 2001–2003; Fernandez et al. 2005; Noonan et al. 2003). Using these more biophysically realistic models does not allow a dissection of burst response into a combination of the stimulus and a history-independent DAP; rather a far more cumbersome, and possibly intractable, treatment would be needed. The other significant advantage of motivating ELL coding strategies with the LIF-DAP model rather than more realistic models is that the ionic features of real ELL pyramidal cells that are ignored in the LIF-DAP model have not been observed in other types of neurons. Thus by framing the coding strategies employed by bursting ELL pyramidal neurons with the LIF-DAP framework, the potential applicability of these strategies to neurons in other brain regions is increased. Indeed, the basic DAP component of the LIF-DAP model has been well documented in both cortical (Larkum et al. 2004) and hippocampal (Magee and Carruth 1999) pyramidal cells as well as spinal cord motor neurons (Larkum et al. 1996), suggesting that the coding paradigms elucidated in the ELL may be operating in other brain regions.
to stimulus selectivity differences, one must visually compare the different response triggered averages to see what exactly those differences are.

The basis vector $s_{all}$ and the scale approximation $\kappa$ gave an empirically justified reduction of the large dimensional stimulus patterns (mean triggered responses) to an effective one variable representation. The scale of an “upstroke” in a dynamic electrosensory scene might represent how close the fish is to prey during its hunting scans of the environment (Chen et al. 2005; Nelson and Maclver 1999; D. Babineau, A. Longtin, and J. E. Lewis, unpublished data). Further, even though the exact shape of the basis vector $s_{all}$ is defined by the statistics of $I_{\text{stim}}$, the relation between $\kappa$ and ISI may be preserved for a wide range of $I_{\text{stim}}$ statistics, possibly even for non-Gaussian stimuli. One final advantage of the scale representation was that it permitted a partitioning of the stimulus space giving an estimate of the mutual information $I(S,R)$ of the interval code. Representing coding by the metric $I(S,R)$ allowed an analysis of how the interval code was influenced by neural biophysics, in this instance, the DAP generation mechanism.

In summary, the assumption of a basis upstroke and its scaling by $\kappa$ synthesized the stimulus selectivity differences that shaped the feature vectors $f_j$ used in Oswald et al. (2007). We expect that similar intuitive stimulus reductions in other coding scenarios may provide a role for cellular properties distinct from the ones presented here.

**Reduction of the ELL burst mechanism and natural electric fish prey capture**

Most single-cell burst models can be analyzed with a decomposition of their dynamics into fast (spiking) and slow subsystems (see Izhikevich 2007; Rinzel and Ermentrout 1998). Often the evolutions of the fast and slow systems are coupled, i.e., the slow subsystem transitions the fast subsystem between spiking and quiescence behavior, and the time-averaged spiking dynamics drive the slow system’s response. Such a fast-slow decomposition has been applied to models of bursting ELL pyramidal neurons when driven by static inputs (Doiron et al. 2002; Fernandez et al. 2005). In the APPENDIX, we show how the slow dynamics of a DAP potentiation and dynamic refractory period are effectively frozen when stimuli with fast timescales drive the cell membrane. This observation prompted the LIF-DAP model, which only has a fast system yet the response of which quantitatively matched to the output statistics and coding performance of real ELL pyramidal cells stimulated by broadband input. Despite the fact that we labeled the spike train output of the LIF-DAP model as bursting (see ISI histogram and spike autocorrelation in Fig. 3), the burst mechanism is quite distinct from those of fast-slow burst mechanisms because the burst termination could not be attributed to an ionic event but to a downstroke in the stimuli. The response of the LIF-DAP model to a static stimulus is a tonic spike discharge itself (not shown), indicating that the LIF-DAP model should not be classified as an intrinsic burst mechanism in the same category as many other intrinsic bursting models (Izhikevich 2007). The LIF-DAP model demonstrates that the temporal content of a driving stimulus can “gate” the influence of biophysical mechanisms on the spike/burst train output.

From a neuroethological perspective, the stimulus gating of burst responses described above can have intriguing electrosensory coding consequences. Nelson and Maclver (1999) illustrated the scanning motions used when, under laboratory conditions, single electric fish hunt for prey typically produce electrosensory signals with frequency components <20 Hz. However, when multiple fish (of both A. leptorhynchus and related species) are present, they will often forage in groups of several fish as well as in isolation (Tan et al. 2005; E. Fortune personal communication). Under these circumstances, the presence of conspecifics will produce beat frequencies that often exceed 30 Hz (E. Fortune, personal communication). There are therefore two scenarios for encoding the low-frequency signals that occur during prey detection and capture.

When hunting in isolation, these fish will receive only low-frequency signals that evoke the full burst mechanism as described in the preceding text (Fig. 2A). The large numbers of spikes that can occur during such a burst would presumably be a strong signal and readily decoded by higher brain centers. Although we have not specifically investigated this scenario, it is plausible that the firing rate during the long bursts evoked by such stimuli might simply code for the strength of the signal (Mehaffey et al. 2005). Modeling this scenario would require pyramidal cell models incorporating the full biophysical burst dynamics (Doiron et al. 2001, 2002; Fernandez et al. 2005; Lemon and Turner 2000).

In contrast, when foraging in groups high-frequency signals will also be present, and the full burst sequence will be disrupted by stimulus downstrokes as discussed in the preceding text. In this case, the LIF-DAP model of pyramidal cells would be appropriate, and the fish might resort to an interval code to assess the strength of the low-frequency prey signals. Clarification of these issues will require recording the responses of pyramidal cells and their midbrain targets to moving objects (simulating prey) in the absence or presence of high-frequency signals (mimicking conspecifics).

Consistent with these results is recent work in LGN where pyramidal cells were shown to significantly increase their burst probability when driven by natural scenes as compared with their response to broadband visual scenes (Lesica and Stanley 2004; Lesica et al. 2006). An analysis of the burst-triggered average indicated that the specific natural scenes had slow enough time scales so as to permit a prolonged hyperpolarization required by the burst mechanism characterized in the cells. In contrast, any high-frequency stimuli components, as found in white-noise visual scenes, removed the chance for long periods of hyperpolarization and hence disallowed burst outputs. An intriguing consequence is that a transition between tonic and burst codes may be mediated not only by the modulation of cellular processes or cortical feedback (Sherman 2001; Wang et al. 2006) but simply by the statistics of the stimuli that drive the neural response (Lesica et al. 2006).

**APPENDIX**

In this APPENDIX, we give an informal reduction of the full burst mechanism (Doiron et al. 2001–2003; Lemon and Turner 2000; Noonan et al. 2003) to the simple model introduced in METHODS. We first present a modified version of the LIF-type burst mechanism presented in Noonan et al. (2003). The model dynamics are described by the following system of differential equations

\[ \begin{align*} 
\frac{dV}{dt} & = I_s - I_{\text{leak}} - I_{\text{gating}} \\
\frac{dI_s}{dt} & = 1 \quad \text{if } V < V_{\text{reset}} \\
\frac{dI_{\text{gating}}}{dt} & = -1 \quad \text{if } V < V_{\text{reset}} \\
\end{align*} \]
The dynamic variables $V$, $x$, and $y$, as well as parameters $C$, $g$, $b$, $\alpha$, and stimulus $I_{stim}(t)$ are identical to those presented in METHODS. The term $Apx$ in the right-hand side of Eq. A1 represents the DAC flow that occurs post a somatic spike. The DAC is scaled by the factor $Ap$, $A$ is a static amplitude, and $p$ is a nonlinear dynamic DAC potentiation critical for proper burst generation in the ELL as measured from static input scenarios (Lemon and Turner 2000). Finally, $r$ is the dendritic spike refractory period that has also been shown to be dynamic (Noonan et al. 2003).

At almost every spike time $t_i$, we have that $p \rightarrow P + Bp^2$ and $r \rightarrow r + Cr$ in a discontinuous fashion. This rule was conditional on if $t - t_{i-1} > r$ or not; this was implemented by the Heaviside terms $\theta(t - t_{i-1} - r)$ in Eqs. A3–A5 where $\theta(x) = 1$ if $x > 0$, otherwise $\theta(x) = 0$. If $t - t_{i-1} < r$, the dendritic Na$^+$ channels were considered to be refractory and dendritic spiking could not be initiated. This implied that $x$ does not undergo a DAP excursion and $p$ and $r$ were not discontinuously updated. It should be mentioned that both $\tau_p$ and $\tau_r$ were slow variables that require a significant recruitment of activity that occurs with rapid and sustained spike discharge. The combination of the conditional spike updates and the dynamic refractory period gave the model described by Eqs. A1–A5 the qualitative behavior of ELL pyramidal cell spike and burst discharge (see Noonan et al. 2003 for further model analysis).

When $I_{stim}(t)$ was Gaussian with a spectrum equally distributed between 0 and 10 Hz and 0 elsewhere, the model response (Fig. A1A1) was qualitatively similar to the experimental results (Fig. 2A). The multispike burst was characterized with a potentiating DAC (Fig. A1A2) and the bursts terminated with the refractory variable $r$ surpassing the ISI value (Fig. A1A3). Indeed, a scatter plot of $r$ against the ISI ($r$ is measured at the time of the 2nd spike) shows that it is quite typical for $r$ to grow larger than the ISI (Fig. A1A4). Additionally, a scatter plot of $p$ against the ISI shows $p$ increasing from 0.4 for

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**FIG. A1.** Slow variables (DAC potentiation and dendritic refractory period) are required to reproduce the spike response to low-frequency stimulus 0–10 Hz but not broadband 0–60-Hz stimulus. A1: membrane $V$ response to low-frequency inputs. A2: DAP potentiation $p$ for the response in A1. A3: dendritic refractory period $r$ for the response in A1. A4: scatter plot of $r$ and ISI for 5,000 bursts. A5: scatter plot of $r$ and ISI for the same bursts in A4. The dashed line is the unit diagonal marking the failure region for dendritic backpropagation. B, 1–5: identical to A, 1–5, except that the stimulus $I_{stim}(t)$ is broadband.
long ISIs to >1 s for very short ISIs (Fig. A1A), indicating significant DAP potentiation during a burst. Thus for low-frequency inputs, the burst models with slow DAP potentiation and a dynamic refractory variable that were developed to match experiments with static inputs were both necessary and sufficient to explain the experimental results in Fig. 2A.

When $I_{\text{stim}}(t)$ is Gaussian with a spectrum equally distributed between 0 and 60 Hz (and 0 elsewhere), the model response (Fig. A1B) was qualitatively similar to the experimental results (Fig. 2B) and the LIF-DAP model (Fig. 3A). Critically, neither of the two slow variables $r$ and $p$ played a significant role in determining burst behavior. Specifically, the bursts were only very rarely terminated when $r$ surpassed the ISI (Fig. A1B, 3 and 5), and the DAP potentiation was not as evident as the slow input case (Fig. A1B) with $p$ being restricted near 0.4 independent of the burst ISI (Fig. A1B).4

The results show in Fig. A1B suggest that although the dynamical variables $r$ and $p$, and their associated Eqs. A4 and A5, were required to replicate the experimental activity shown in Fig. 2A, they were not required to replicate the activity in Fig. 2B. Motivated by this, we remove Eqs. A4 and A5 and clamp $p$ at 0.4 giving the simple LIF-DAP model presented in METHODS.

The model parameters were identical to those used in METHODS with the addition of $A = 2.14 \text{nA}$, $p_{\text{set}} = 0.4$, $r_{\text{set}} = 4 \text{ ms}$, $B = 0.3$, $C = 0.4 \text{ ms}$, $\tau_r = 5 \text{ ms}$, $\tau_p = 5 \text{ ms}$.

**GRANTS**

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**REFERENCES**


Rashid AJ, Morales E, Turner RW, Dunn RJ. The contribution of dendritic 


