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CNS*2010 will celebrate the 20 year history of the CNS meeting, with events and presentations celebrating where we have been, and where we are going.

SCHEDULE:

Tutorials July 24

Meeting July 25–28

Workshops July 29–30

ABSTRACT SUBMISSION:

http://www.cnsorg.org/2010/submission.shtml

INVITED SPEAKERS:

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Vivian Mushahwar (University of Alberta, Canada)
Jonathan Wolpaw (Wadsworth Center & SUNY, USA)

SPECIAL SYMPOSIUM:

What have we learned in 20 years and what do we still need to know?

John Miller (Montana State University, USA)
Ron Calabrese (Emory University, USA)
Alain Destexhe (CNRS, France)
Upinder Bhalla (NCBS, Bangalore, India)
John Rinzel (NYU, USA)
Bruno Olshausen (UC - Berkeley, USA)
Sharon Crook (Arizona State University, USA)
Avrama Blackwell (George Mason University, USA)
Christiane Linster (Cornell University, USA)
Michael Hasselmo (Boston University, USA)

IMPORTANT DATES:

Abstract Submission Deadline: Feb. 14th
Advanced Registration Deadline: May 15th

Tetzlaff *et al. BMC Neuroscience* 2010, **11**(Suppl 1):O11
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ORAL PRESENTATION Open Access

Decorrelation of low-frequency neural activity by inhibitory feedback

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From Nineteenth Annual Computational Neuroscience Meeting: CNS*2010
San Antonio, TX, USA. 24-30 July 2010

To correctly judge the functional role of cooperative neural activity it is essential to understand how neural correlations are determined by the structure and dynamics of neural networks. Shared presynaptic input is one of the major sources of correlated synaptic activity in such systems. In the asynchronous state of recurrent neural network models, however, spike correlations are considerably smaller than what one would expect based on the amount of shared presynaptic sources [1,2]. A similar lack of correlations in the spiking activity of neighbouring cortical neurons has been observed experimentally [3]. Recently, it has been pointed out that shared-input correlations can be actively suppressed by the dynamics of recurrent networks [4]. Here, we show that both in networks with purely inhibitory coupling (Fig. 1A) and in those with mixed excitatory-inhibitory coupling (Fig. 1B) this active decorrelation affects mainly the activity at low frequencies (<20 Hz). High-frequency activity, in contrast, is rather unaffected. Simulations rule out that this phenomenon is the result of refractoriness. By means of a simple linear population-rate model we demonstrate that the effect is essentially explained by inhibitory feedback.

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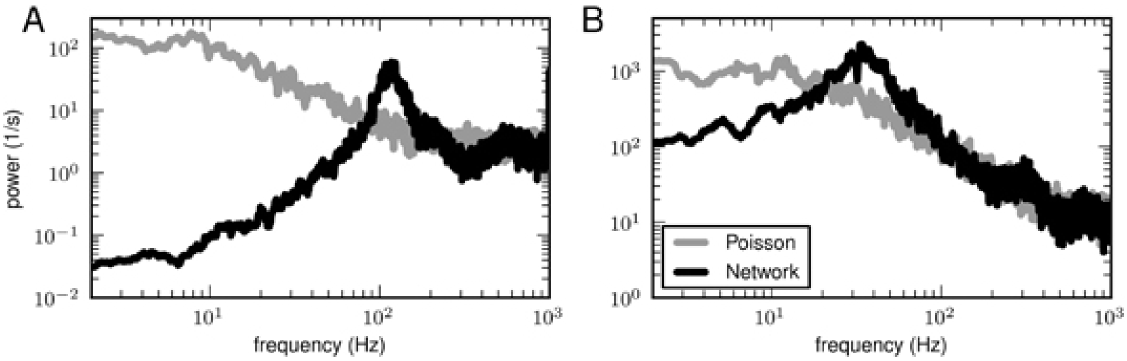

Figure 1 Population-rate power spectra for an inhibitory (**A**) and a balanced recurrent network (**B**) of leaky integrate-and-fire model neurons (black curves). Grey curves represent population-rate spectra of ensembles of unconnected neurons receiving stationary Poisson input spike trains with the same shared-input structure as in the respective recurrent cases (black curves).

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BMC
Neuroscience

POSTER PRESENTATION **Open Access**

Random wiring limits the development of functional structure in large recurrent neuronal networks

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From Nineteenth Annual Computational Neuroscience Meeting: CNS*2010
San Antonio, TX, USA. 24-30 July 2010

Spike-timing dependent plasticity (STDP) has traditionally been of great interest to theoreticians, as it seems to provide an answer to the question of how the brain can develop functional structure in response to repeated stimuli. However, despite this high level of interest, convincing demonstrations of this capacity in large, initially random networks have not been forthcoming. Such demonstrations as there are typically rely on constraining the problem artificially. Techniques include employing additional pruning mechanisms or STDP rules that enhance symmetry breaking, simulating networks with low connectivity that magnify competition between synapses, or combinations of the above (see, e.g. [1-3]).

Here, we describe a theory for the stimulus-driven development of feed-forward structures in random networks. The theory explains why the emergence of such structures does not take place in unconstrained systems [4] and enables us to identify candidate biologically motivated adaptations to the balanced random network model that might facilitate it. Finally, we investigate these candidate adaptations in large-scale simulations.

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BMC Neuroscience

POSTER PRESENTATION **Open Access**

A reafferent model of song syntax generation in the Bengalese finch

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From Nineteenth Annual Computational Neuroscience Meeting: CNS*2010
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The Bengalese finch produces a set of ordered sequences of syllables. After deafening this song syntax is disrupted, i.e. within days the sequence become randomized and unstable [1]. Interestingly, the normal song syntax is recovered when hearing is restored [2]. Studies have shown that the vocal motor control system of the Bengalese finch rely on real time auditory feedback [3] and that activity in the high vocal center (HVC) is affected by feedback perturbations [4]. This suggests a reafferent model [3] of song syntax generation in which the perception of the bird's own song (BOS) cues the motor system.

Here, we present a functional network model of the song syntax generation based on realistic spiking neurons. Neurons are connected in feed-forward structures (synfire chains, SFCs) that can reproduce the neural activity observed in the HVC of the songbird [5]. Individual syllables are represented by the activity propagation throughout distinct SFCs. The auditory perception of the syllables is modeled by activity changes in an auditory network which in turn primes specific subsets of the HVC neurons to obtain the desired song syntax. If the auditory feedback is suppressed random syllable sequences are generated due to the 'winner takes all' competition of individual syllables [6].

Conclusion

Our model can reproduce the experimentally observed song syntax of the Bengalese finch and its disruption when auditory feedback is interrupted. It provides a framework for theoretical investigations of HVC activity and changes in the song syntax in response to specific feedback disturbances. Additionally, the model predicts priming of HVC neurons at the transition between individual syllables that could be tested in further experimental studies.

From a theoretical point of view the individual syllables can be regarded as primitives of the song which are combined following a given syntax. Hence, our reafferent model demonstrates how compositionality of a system can be realized given neurobiologically realistic assumptions.

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POSTER PRESENTATION **Open Access**

Modeling persistent temporal patterns in dissociated cortical cultures using reservoir computing

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From Nineteenth Annual Computational Neuroscience Meeting: CNS*2010
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Persistent spatiotemporal patterns have been observed extensively in various neural systems including cortical cultures [1]. Activity in cortical cultures is composed of network-wide bursts of spikes, during which global firing rate increases dramatically. Previously, it has been shown that cultures display persistent temporal patterns that are hierarchically organized and stable over several hours. Fluctuations in the culture activity persistently converge to stable precise temporal patterns, for which these patterns are called dynamic attractors. Temporal structure in network bursts can be clustered into several groups, each of which can be seen as a separate burst type.

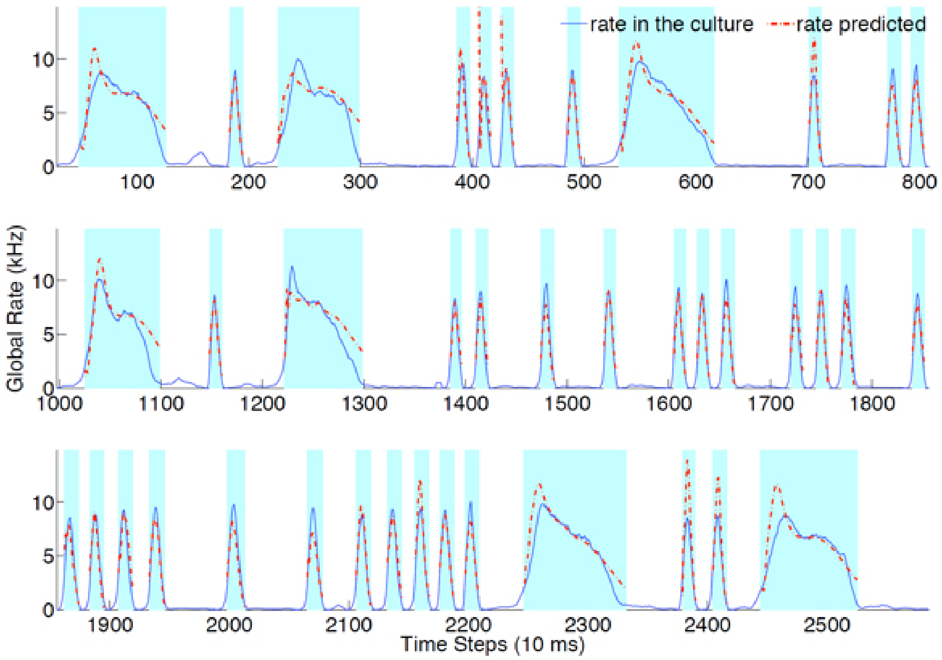

Figure 1 Comparison of the observed firing rate (solid, blue) and the predicted firing rate (dashed, red) in a selected culture. Light blue shaded regions in the background indicate the intervals, where prediction is done based on the cue signal. The cue signal is the spatial pattern containing the firing rates of all electrodes just 1 time step before the shaded region. The overall correlation coefficient between the predicted and the observed signal is 0.88.

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A model of a neural system should be able to reproduce the temporal patterns under the same input and/or initial state, which is a minimal requirement for a network-level model to reveal the information encoded in such patterns. Our approach taken here is to employ a generic model (a reservoir network) that displays a rich repertoire of complex spatiotemporal patterns to be matched with the observed biological patterns by parameter tuning. More specifically, we employ an Echo State Network (ESN) [2] with leaky integrator neurons as a modeling tool. Here, we consider cultures of dissociated cortical tissue recorded with microelectrode arrays (MEA) as an example of biological neural networks without specific connectivity and simulate the corresponding burst types based on a cue signal. The cue signal is composed of a snapshot (10 ms) of the individual firing rates recorded at each electrode at burst onset and serves as an indicator of the current dynamic state of the network. A simple readout training of the ESN yields a predictive model of the temporal activity pattern in the global firing rate. The simulated pattern displays a high correlation with the actual one observed in the culture (Figure 1). The model can also be used to visualize the underlying structure in the recorded signals.

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BMC Neuroscience

POSTER PRESENTATION **Open Access**

Neurons hear their echo

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From Nineteenth Annual Computational Neuroscience Meeting: CNS*2010
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The functional implications of correlations in cortical networks are still highly debated [1] and theoreticians are intensely searching for a self-consistent solution of the correlation structure in recurrent networks. Feed-forward descriptions have been presented as approximations [2] and different aspects of correlation functions in the asynchronous irregular state have been accurately predicted, such as the zero time lag correlation [3] and its scaling with network size on a coarse time scale [1]. Previous approaches do, however, not explain the differences between the correlation functions for excitatory and inhibitory neurons and they do not describe their temporal structure, an experimentally observable feature that has important functional consequences for synaptic plasticity [4].

The approximation of neural dynamics by a linear response kernel is a powerful technique in the analysis of recurrent networks. Here we use Hawkes processes [4,5] to model the spiking activity of a neuron as a rate-modulated Poisson process, where incoming synaptic events cause exponentially decaying deflections of the instantaneous firing rate that superimpose linearly. We analytically determine the correlation structure of recurrent random networks of these excitatory and inhibitory linear neurons with delayed pulse-coupling. We show that this minimal linear model is sufficient to explain generic features of correlations: The origin of troughs near the center peak, the asymmetry between excitatory and inhibitory neurons, and the emergence of damped oscillatory correlation functions (Fig. 1A). In our derivation we employ a novel series expansion of the correlation function in terms of resonance frequencies of the delayed feedback system, that is valid in the whole parameter regime of inhibition dominated networks. Previous expansions were limited to a feedback gain below 1 [4]. Our results identify two distinct contributions to the correlation: a feed-forward term due to correlated inputs (Fig. 1B, black) and a self-feedback term due to the activity of the neurons under consideration (Fig. 1B, gray). This self-feedback explains the asymmetry of correlations between excitatory and inhibitory neurons (Fig. 1A, black: simulation, gray: theory).

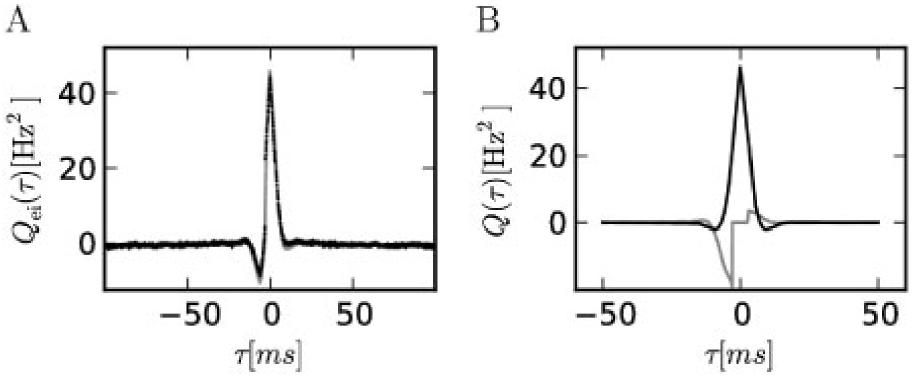

Figure 1

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