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MODELING BISTABLE PERCEPTION WITH A NETWORK OF CHAOTIC NEURONS

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Abstract
When an ambiguous stimulus is observed, our perception undergoes dynamical changes between two states, a situation extensively explored in association with *the Necker cube*. Such phenomenon refers to bistable perception. Here, we present a model neural network composed of forced FitzHugh-Nagumo neurons, implemented also experimentally in an electronic circuit. We show, that under a particular coupling configuration, the neural network exhibit bistability between two configurations of clusters. Each cluster composed of two neurons undergoes independent chaotic spiking dynamics. As an appropriate external perturbation is applied to the system, the network undergoes changes in the clusters configuration, involving different neurons at each time. We hypothesize that the winning cluster of neurons, responsible for perception, is that exhibiting higher mean frequency. The clusters features may contribute to an increase of local field potential in the neural network.

Key words
Bistable perception, electronic circuits, FitzHugh-Nagumo neurons, cluster formation, LFP.

1 Introduction

The well-known FitzHugh-Nagumo model (FHN) [FitzHugh, 1961], derived from the Hudgkin-Huxley equations describing the ionic dynamics of the giant squid neuron, has been the subject of intensive studies [Scott, 2002]. The model is two-dimensional and may exhibit excitable, bistable or oscillatory behaviour. More complex dynamics on the single neuron level including chaotic spiking, has been theoretically investigated in FHN by introducing a third dimension [Doi and Kumagai, 2005; Marino et al, 2007]. The chaotic behaviour was also observed in the case where the periodic forcing was considered [Pankratova, Polovinkin and Spagnolo, 2005]. The chaotic mixed-mode oscillations (chaotic small amplitude oscillations interrupted by large spikes) were observed in chemical [Petrov et al, 1992], biological [Iglesias et al, 2011] and physical [Marino et al, 2011] systems.

The FHN, as well as many other systems, have been widely used to model the information processing by the brain, like the synchronization processes or the spontaneous emergence of the brain rhythms. These phenomena are accessed experimentally mainly by the measurements of electric activity of the brain. However, there are also indirect ways of observation how the brains work, namely, the psychophysical experiments. As an example, the observers who are presented a stimulus that has two distinct interpretations alternate their perception over time between two possible percepts in an irregular manner. This phenomenon, known as perceptual bistability, appears in response to exposure to ambiguous figures like *Necker cube* [Necker, 1832] or to non-stationary ambiguous motion displays [Hupé and Rubin, 2003]. The question which arises is about the mechanism of the irregular alternations appearance. Many models have been proposed to explain this phenomenon. The most current models consider competing neuronal populations in which the alternations are generated with perfect periodicity [Lago-Fernandez and Deco, 2002]. However, the experimental data show that the ensemble of irregular durations of one percept form a Gaussian-like distribution [Rubin and Hupé, 2004]. The first proposal that these bistable transitions may be mediated by noise was provided by Haken [Haken, 1994]. The detailed models implementing the idea have been analyzed through considering the switching processes between the attractors of a network under the effect of noise [Moreno-Bote, Rinzel and Rubin, 2007]. These approaches reproduce well all the characteristics found in experimental data. However, the existence of a high complexity in neural responses gives a cue about the deterministic rather than stochastic functioning of the brain units. This of course does not exclude the existence of noisy fluctuations but restricts its action on decision making processes which are not random but deterministic. There are many experimental data which confirm the existence of chaos in the brain [Korn and Faure, 2003].

Here, we propose an alternative model for perceptual bistability based on chaos generating systems. We consider coupled FHN systems driven by an external forcing in a network that includes electrical couplings, both inhibitory and excitatory. We show that in a certain range of the coupling parameters, such a network undergoes bistable behaviour. Considering four interacting neurons we observe the emergence of two clusters with independent chaotic dynamics. The crucial difference between the clusters is the frequency of chaotic spiking. One cluster dominates over the other through the higher mean frequency and thus it contributes to higher Local Field Potential (LFP). This may be a possible mechanism of effective competition between the two perceptual choices. In fact, many physical models describe the synchronization of high frequency neuronal activity as the coordinating mechanism for feature binding [Singer, 2004], whereby spatially segregated processing areas are bounded together to provide a coherent percept [Arecchi, 2004].

2 Model of a Network

Each driven FHN system is ruled by the following equations:

$$\begin{aligned} \dot{x}_i &= x_i - x_i^3/3 - y_i + F + \alpha\Delta x_i + S \\ \dot{y}_i &= \gamma(a - by_i + x_i) \end{aligned} \tag{1}$$

where x_i is the fast variable, y_i is the recovery variable and $F = A\sin(2\pi\nu t)$ is an external driving term with amplitude A and frequency $\nu = 1/T$. We consider fixed parameters $\gamma = 0.08$, $a = 0.7$ and $b = 0.8$. Parameter α is the coupling strength. Equation 1 may be transformed to a three-variable set of equations by introducing a new variable $z_i = 2\pi\nu t = \omega t$. The bistable perception of the *Necker cube* (see Fig. 1 (a)) is modeled with the neural network shown in Fig. 1 (b). The coupling term Δx_i is defined as follows:

$$\begin{aligned} \Delta x_{1,3} &= x_4 - x_2 \\ \Delta x_{2,4} &= x_1 - x_3. \end{aligned} \tag{2}$$

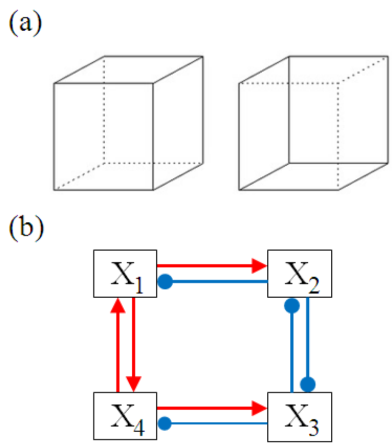

Figure 1. (a) Bistable perception of the *Necker cube*. (b) Scheme of the neural network with inhibitory (circles) and excitatory (arrows) connections that produces bistable patterns.

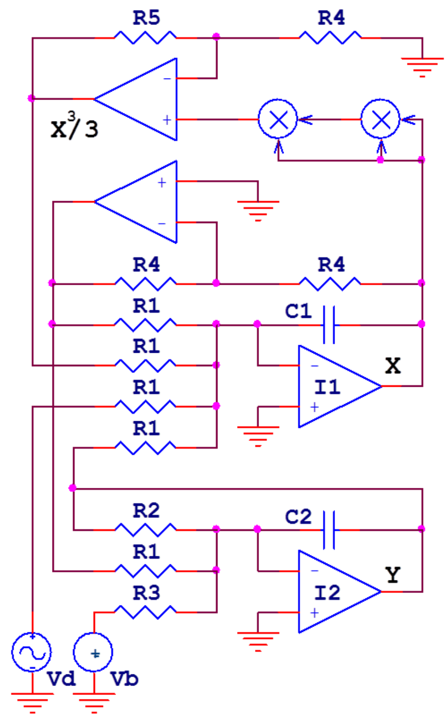

Figure 2. Electronic implementation of each FitzHugh-Nagumo system that composes a network.

The cube ambiguity may be manipulated by darkening one of the cube faces (cue) to provide a unique cube interpretation. When the position of the cue is stationary the cube perceived perspective is steady and driven by the cue position. It has been shown in [Arrighi et al, 2009], that when the position of a cue is alternated in time, two different perceptual phenomena are observed. On one hand, at low frequencies the cube perspective alternates in line with the position of the cue. On the other hand, at high frequencies the cue is no longer able to bias the perception and the cube perspective returns to be bistable as in the conventional, bias-free, case.

The obtained results show the importance of a cue in the processes of perception. In our study, we hypothesize that in the absence of external cues the visual system generates its own cues through the mechanism of ocular movement [Buswell, 1935]. The slight changes S in the visual area (spatial gradient) due to ocular movement may act as the stimulus for the switching from one perspective to the other. In the model network the external perturbation S is active only for neurons x_1 and x_4 and has a form of a short rectangular pulse of amplitude B and duration Δt.

3 Experimental Realization of a Network

The electronic circuit implementing the FitzHugh-Nagumo equations is shown in Fig. 2. It consists of an electronic analog simulator implemented by commercial semiconductor devices. We set the systems in the spiking regime consisting of chaotic small amplitude oscillations interrupted by large spikes (see [Ciszak *et al.*, 2012] for details). A small amplitude chaotic regime is reached approximately at $A = 0.57$ V (for the experiment) and $A = 0.4$ (for the model). The coupling is realized by means of differential amplifiers which allow to summate the signals coming from the neighboring nodes.

4 Results

The formation of synchronized clusters is observed when the proper coupling configuration is implemented. It is determined by asymmetric inhibitory and excitatory connections in the network. More precisely, the network is composed of two excitatory and two inhibitory neurons. The bistable switching occurs for the pairs of exhibitory-inhibitory neurons. The crucial difference between the two formed clusters is the frequency of chaotic spiking. In Fig. 3 (a) we report the raster plot that shows spiking times of each node in the experimentally implemented network. The formation of two clusters is observed, each characterized by different inter-spike interval (ISI) distributions as seen in Fig. 3 (b). One cluster dominates over the other through the higher mean frequency and thus contributes to higher LFP.

The alternation between the dominant clusters may be induced by changing of initial conditions, or equivalently, by the external perturbation, that induces the transitions from one state to the other. We consider rectangular stimulus S applied to the excitatory neurons in each pair of excitatory-inhibitory neurons. Here we assume that the recorded changes in the visual field induced by the ocular movements act as external stimulation. The ocular movements may be stochastic or may undergo deterministic trajectories defined by unknown dynamical processes. In Fig. 4 (a) the raster plot for the coupled network obtained through the numerical simulations is shown. At time $t = 250$ the external perturbation S has been applied to excitatory neurons x_1 and x_4. The network reacts in switching its state, the dominating cluster $x_1 - x_3$ leaves place to the new leader $x_2 - x_4$. In order to describe the collective neurons' dynamics and their rates of firing we consider LFP. It represents the electric potential of a group of neurons recorded with limited temporal resolution. We calculate it as follows:

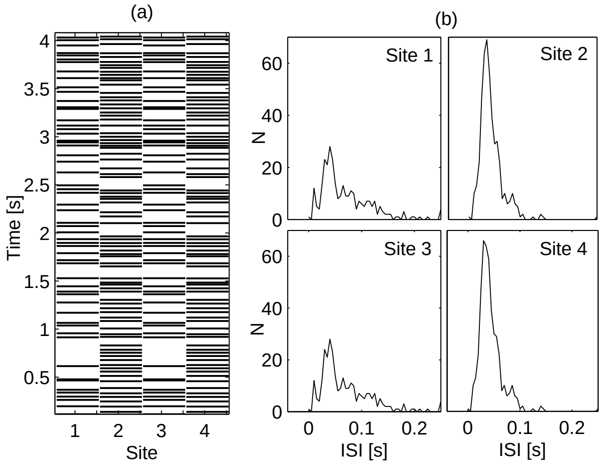

Figure 3. (a) The raster plot for four coupled FHN systems obtained from the experiment. Each horizontal line marks the appearance of a spike in time at each site. (b) Distribution of ISI calculated from the time series corresponding to the raster plot shown in (a).

$$LFP(t_m) = \sum_{i=1}^{M} \sum_{n=1}^{N} x_n(t_m + i\Delta t) \tag{3}$$

where $x_n(t_m + i\Delta t)$ denotes the nth neuron state at time $t = t_m + i\Delta t$, M is the number of summed temporal points, N is the number of neurons, Δt is the integration time step and t_m is the effective time at which the LFP is measured. As shown in Fig. 4 (b), the higher firing rate contributes to an increase in LFP. This may lead to temporal perception of an object encoded in a given column of neurons. Indeed we see the abrupt transition from one state to the other at the moment when the external perturbation is applied.

5 Conclusions

We proposed a simple network composed of chaos generating systems to model perceptual bistability. We considered four chaotic FHN systems coupled through the inhibitory and excitatory connections. We observed the emergence of two synchronized clusters that undergo independent chaotic dynamics characterized by different mean frequency of spiking. Due to these differences one cluster dominates over the other and contributes stronger to LFP leading consequently to the strengthening of a given perceptual state. This may be

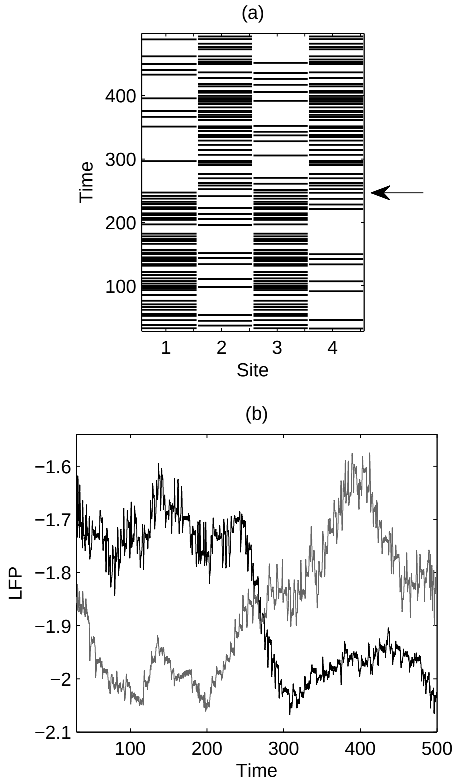

Figure 4. (a) The raster plot for four coupled FHN systems, obtained through numerical simulations, with $\alpha = 0.05$. Each horizontal line marks the appearance of a spike in time at each site. At time $t = 250$ the external perturbation S of amplitude $B = 0.3$ and duration $\Delta t = 0.01$ has been applied to neurons x_1 and x_4. (b) LFP calculated from the time series corresponding to the raster plot shown in (a). Black curve corresponds to the LFP of the cluster $x_1 - x_3$ and grey curve to the cluster $x_2 - x_4$.

a possible mechanism of effective competition between the two perceptual choices.

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