Neural Networks 82 (2016) 76–83

Contents lists available at ScienceDirect

Neural Networks

journal homepage: www.elsevier.com/locate/neunet

Global oscillation regime change by gated inhibition

August Romeo[a,*], Hans Supèr[a,b,c]

[a] Department of Cognition, Development and Educational Psychology, Faculty of Psychology, University of Barcelona, Spain
[b] Institute of Neurosciences, Faculty of Psychology, University of Barcelona, Spain
[c] Catalan Institution for Research and Advanced Studies (ICREA), Spain

ARTICLE INFO

Article history:
Received 23 November 2015
Received in revised form 6 June 2016
Accepted 26 June 2016
Available online 18 July 2016

Keywords:
Attention
Global oscillation
Gated feedback

ABSTRACT

The role of sensory inputs in the modelling of synchrony regimes is exhibited by means of networks of spiking cells where the relative strength of the inhibitory interaction is controlled by the activation of a linear unit working as a gating variable. Adaptation to stimulus size is determined by the value of a changing length scale, modelled by the time-varying radius of a circular receptive field. In this set-up, 'consolidation' time intervals relevant to attentional effects are shown to depend on the dynamics governing the evolution of the introduced length scale.

1. Introduction

Attention can be regarded as a process to reduce variability in the coincidence between expected and actual sensory input. The review offered by Ghajar and Ivry (2009) explains that individuals 'pay attention' by predicting and successfully synchronizing with selective inputs. A network involving prefrontal cortex (PFC), inferior parietal lobe (IPL) and cerebellum can be the key to predictive neural activity. This idea was favoured by the results of works like (Mantini, Perrucci, Del Gratta, Romani, & Corbetta, 2007), where EEG and fMRI were combined to study the dynamic baseline functional architecture of the human brain, focusing on the resting-state. Rather than stabilizing at an uniform level, brain activity fluctuates within definite spatiotemporal patterns, and this spontaneous ongoing oscillatory activity depends on the dynamic interplay between distinct functional networks.

As remarked, attention also engages the cerebellum, which seems to be playing a crucial role for achieving the necessary synchronization. Using coherence analysis methods, the degree of cerebellar activation has been found to correlate with that observed in dorsolateral prefrontal and inferior parietal cortices (Allen et al., 2005). The capabilities of the cerebellum may extend beyond the synchronization of actions and sensory consequences, including the category of abstract predictions (Schmahmann & Sherman, 1998). At the same time, there is an alternative framework where attention is viewed as an effect rather than a causal agent (Krauzlis, Bollimunta, Arcizet, & Wang, 2014; Krauzlis, Lovejoy, & Zénon, 2013). In that context, attention arises as a functional consequence of circuits centred on the basal ganglia involved in decision making.

Oscillatory neural activity is induced when sensory signals are properly processed in the sensory system. Therefore, attention has to be deeply related to oscillation modes. Global oscillations of finite coherent time may exist in a number of situations. Particularly, recurrent inhibition plays an important role in the generation of synchronized oscillations (see e.g. MacLeod & Laurent, 1996 and Whittington, Traub, & Jefferys, 1995). In fact, oscillation periods depend on the synaptic times and on the characteristics of the internal inputs. Isolated neurons receive a large amount of background synaptic noise and generate Poisson-like spike trains. Brunel and Hakim (1999) considered populations of such neurons randomly connected by delayed synaptic interactions, and illustrated the working of sparsely connected inhibitory cells for a network made of integrate-and-fire units. Instead, for our neurons we shall be using Izhikevich's 'simple model' (Izhikevich, 2007). Rhythmogenesis is often based on coupled inhibitory neurons capable of rebound excitations (see e.g. Selverston & Moulins, 1985) and one of the advantages of Izhikevich's model is its power to reproduce rebound effects. Fast global oscillation takes place when all neurons fire irregularly with an average individual frequency lower than the population (global) frequency. The stability analysis for that phenomenon was provided in Brunel and Hakim (1999) (see also Brunel & Hakim, 2008).

---

* Correspondence to: Department of Cognition, Development and Educational Psychology, Faculty of Psychology, University of Barcelona, Pg. Vall d'Hebron 171, 08035 Barcelona, Spain.
E-mail address: hans.super@icrea.cat (H. Supèr).

http://dx.doi.org/10.1016/j.neunet.2016.06.007
0893-6080/

Attentive states typically involve oscillatory regimes trying to anticipate some magnitude of the expected stimulus. Extensive reviews of the oscillations occurring in the cerebral cortex during cognition were offered by Buzsáki (2006), Wang (2010) and, from the viewpoint of synchrony, many computational issues connected to the binding problem were discussed in Wang (2005) (see also Quiles, Wang, Zhao, Romero, & Huang, 2011 and Terman & Wang, 1995). Reviews about other aspects of attention were given by Carrasco (2011), Desimone and Duncan (1995) and Itti and Koch (2001). Particularly, on the subject of attention, synchrony and coherence, see Börgers, Epstein, and Kopell (2008), Fries (2005) and Fries, Reynolds, Rorie, and Desimone (2001), or the experimental evidence – e.g. Bosman et al. (2012) – indicating that selective synchronization renders the behaviourally relevant input effective.

In the present work we are making an attempt to model the degree of readiness in an attentional task depending on a changing length scale, i.e., a single variable with dimension of length which evolves in time. Our considered stimuli are circles and the internal states of the system are represented by the radius of a visual receptive field (RF), which is also circular and evolves in time. Next, going on to the inner processing units (neurons), time oscillation and synchrony properties provide pictures of their global states, and may reflect the variations which take place during a cognitive task, including the case of stimulus detection.

The behaviour of our presented network is, to a good extent, consistent with existing models, like the ones based on pyramidal-interneuron interactions (see e.g. Bibbig, Traub, & Whittington, 2002, Traub, Whittington, Stanford, & Jefferys, 1996 and refs therein), which have proved to be remarkably successful. A further feature in our scheme is the modelling of interareal inhibitory connections with incidence on the properties of the gamma rhythm. Unfortunately, we cannot resort to known data for supporting the existence of these connections (although, in other contexts, interareal inhibition appears to be more widespread than initially guessed Iurilli et al., 2012). At any rate, the question is not so critical, as it can be argued that our two nominal areas simply stand for different cell classes in a common region (see alternative version in Section 2.5).

Among the proposed theories, Ardid, Wang, and Compte (2007) offered an encompassing scheme about attentional processing and coherent oscillation (which partly draws on Compte, Brunel, Goldman-Rakic, & Wang, 2000). In particular, it explained how suppressed activity can be an indirect effect of biased competition. Moreover, Ardid, Wang, Gomez-Cabrero, and Compte (2010) examined sparsely synchronized oscillation regimes and went further by reconciling rate and synchronization effects, studying interareal coherence and showing how it gives rise to modest enhancements of rate modulations as well as attention-specific enhancements of synchrony. There are a few ways in which our scheme resembles theirs. The principle of sparse synchronization is the main point. Regarding structures, our first model basically consists of two layers with nonsymmetrical two-way connections between them, but – unlike what happens in their set-up – lateral (recurrent) connections are not considered. Thus, the essential ingredient is the combination of feed-forward and feedback interactions between two areas, say ‘temporal’ and ‘frontal’. However, the aforementioned ‘alternative’ version consists of a single layer with two cell-types and recurrent interactions. Unlike in Ardid et al. (2007), our sensory inputs are not orientation-coded, as we are not dealing with feature-coded signals. Rather than that, we wish to study the effect of raw size differences depending on some suitably chosen parameter.

Our oscillating network and its dependence on a length scale determined by the sensory input are described in Section 2. Results of numerical simulations showing the different effects on consolidation times are commented in Section 3. Section 4 includes our discussion and ending remarks.

2. Model description

2.1. Receptive fields

As a convenient abstraction, we employ a pillbox-style RF – call it f_r –, which is a 2D object of the type

$$\begin{aligned} P_r(x,y) &= \begin{cases} 1, & \text{for } x^2+y^2 \le r^2 \\ 0, & \text{elsewhere,} \end{cases} \\ f_r &= \mathcal{N}_{\mathrm{RF}}(P_r), \end{aligned} \tag{1}$$

where x, y are rectangular coordinates and r is the circle radius. The $\mathcal{N}_{\mathrm{RF}}$ operation removes the mean and divides by the sum of squares afterwards, so that the resulting function can work as a valid RF, i.e.,

$$\begin{aligned} \Pi_r(x,y) &= P_r(x,y) - \frac{1}{N_x N_y} \sum_{x',y'} P_r(x',y') \\ f_r(x,y) &= \frac{\Pi_r(x,y)}{\sum\limits_{x',y'} \Pi_r^2(x',y')}. \end{aligned} \tag{2}$$

The particular shape is unlikely to be very decisive, and we have adopted the circular geometry for definiteness and simplicity. If the current number of pixels ($N_x N_y$) allowed for sufficient space resolution, the negative contribution in the first line of (2) should tend to πr^2 divided by the total area.

As our system requires variable r's, RF radii will change according to their own ‘dynamics’. Instead of single r, for every region we set a different radius $r_j(t)$, $1 \le j \le N_r$, with an evolution equation of the form

$$\begin{aligned} r_j' &= -\eta\, \Theta(m(r_j))\,(1 - m(r_j)), \\ &\quad 1 \le j \le N_r, \\ m(r_j) &= \max_{(x,y)} \left[\left(\mathrm{im}_j * f_{r_j} \right)(x,y) \right], \\ (S * T)(x,y) &\equiv \sum_{x',y'} S(x+x', y+y')\, T(x',y'). \end{aligned} \tag{3}$$

Θ denotes the Heaviside step function. im_j is the jth region of the stimulus image Im and N_r indicates the number of regions. We shall be dealing with $N_r = 2$ regions, namely, the left half and the right half of the image. The η parameter can be regarded as an adaptation rate. The larger the η value the quicker the adaptation; thus, η may be related to attention or eye vergence (Solé Puig, Pérez Zapata, Aznar-Casanova, & Supèr, 2013). Typical values are of the order of $\Delta r / t_{\text{cue off}}$, with $\Delta r \equiv r_{\text{init}} - r_{\text{final}}$. The $*$ symbol stands for the two-dimensional correlation product which is a two-dimensional function of arguments (x, y) generically defined in the third line of (3) (the sign changes $x + x'$, $y + y' \longrightarrow x - x'$, $y - y'$ turn it into the usual convolution product). By the application of $\mathcal{N}_{\mathrm{RF}}$ in (1), our RF's are already in ‘normalized’ form when evaluating these products. Taking a ‘max’ means to select the maximum of the obtained function when comparing all the possible results in the considered region. Thus, although this pooling takes place inside a specific domain, the outcome within the region in question is actually nonlocal. When the current RF circle has the same size as the stimulus, the m variable in its region will equal one and, therefore, the radius will no longer change. Note that, by construction, the r_j evolution law (3) implies feedback from hypothetical units evaluating m to the part updating r.

In the envisaged scenario the r_j's essentially decrease in time. Thus, we start from a moderately large value, bigger than the typical size of the expected stimuli, but not so large as to fill up the region in question. Initially every r_j amounts to $n/4$, being n the layer side length in pixels, while the presented stimuli have a radius of $n/8$ pixels. For the stimulated region $r_j(t)$ has a moderate decay and asymptotically approaches the length yielding