Propagation of quasi-stable activation in a chain of recurrent neural networks

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Abstract

We consider a chain of feed-forward connected recurrent networks of leaky-integrate-and-fire neurons with membrane potential bistability. It is shown that lump neural activation, lasting for several seconds at each recurrent network, is gradually relayed along the chain. The time scale of the lump activation and its propagation along the chain agrees with that characterizing mental process. These results suggest that our model will provide possible neural mechanisms underlying mental representation of episodes.

Keywords: Temporal sequence; recurrent network; chain; bistable; stochastic process.

1. Introduction

It is generally viewed in cognitive neuroscience that representation of a certain image in one's mind is caused by reverberatory activation of a population of neurons that encode this image. Computational neuroscience argues that recurrent connection among a population of neurons can generate such reverberatory activation of these neurons (Durstewitz et al., 2000), while we introspectively guess that 'mental process' evolves as consecutive generation and extinction of images in a sequence. From these observations, it is reasonable to consider that mental process is expressed as quasi-stable neural activation relayed from one population of recurrently connected neurons to another. Moreover, as we feel, the time scale of mental process is of the order ~hundred milliseconds to seconds. Therefore, quasi-stable activation and its propagation must occur at this time scale, which is much longer than the time scale of neuronal dynamics (~milliseconds).

Several lines of neurophysiological evidence consistent with this view have been reported. Simultaneous neural ensemble recordings from the frontal cortex of a monkey during a delayed GO/NO-GO task have revealed that neuronal activity goes through sequence of quasi-stationary states during the delay period; each stationary states lasts for several hundred milliseconds (Abeles et al., 1995; Seidemann et al, 1995). This temporal sequence of neuronal activity probably reflects monkey's mental processes during the delay period. It has also been demonstrated that temporal patterns of neural activation during a task performance are reactivated in the monkey neocortex during the rest period after the task (Hoffman & McNaughton, 2002) or in the rat hippocampus during the REM sleep (Louie & Wilson, 2001); in both cases, the reactivation occurs at the same time scale with the task performance.

It is therefore needed to devise mechanisms that produce slow propagation of quasi-stable reverberatory activation of populations of neurons in a sequence. We will show that stochastic dynamics of a chain of recurrent networks of bistable spiking neurons can provide such mechanisms.

2. Model

We consider M layers of excitatory neurons. In each layer, neurons are all-to-all connected. Each neuron in the layer m sends projections to all the neurons in the layer m+1, giving a chain of feed-forward connected recurrent networks (Fig. 1). A set of inhibitory interneurons is also considered. Each interneuron receives/sends projections from/to all the excitatory neurons in the chain (Constantinidis et al., 2002) (Fig. 1).

The membrane potential dynamics of each neuron is described by the leaky-integrate-and-fire neuron model. We further assume that the membrane potential is subject to background noise.

One specific assumption is posed: The membrane potential of each neuron is bistable

(Okamoto & Fukai, 2001). Several cellular mechanisms to make the membrane potential bistable have been proposed (Durstewitz, 2000). The present study adopts the mechanisms by after-depolarization current (Okamoto & Fukai, 2003).

3. Results

The time course of activation of the layer m, denoted by $F(m)$, obtained by computer simulation is shown in Fig. 2. Lump activation triggered at the layer 1 at t =0 (indicated by the grey arrow) is gradually relayed along the chain (Fig. 2). It should be noted that lump activation of each layer lasts for seconds; the time lag between activations of two adjacent layers is also more than several hundred milliseconds. The time scale characterizing the obtained phenomena thus agrees with the time scale of mental process. It can be confirmed that combination of membrane potential bistability and background noise is essential for the emergence of such a long time scale (data not shown, see Okamoto & Fukai, 2001).

In the above simulation, the strength of feed-forward connections between the layers m and m+1, say $G_{m,m+1}$, is constant irrespective of m. The duration of lump activation of each layer and its relative timing are hence uniform. When $G_{m,m+1}$ varies as a function of m, a temporal sequence of lump activations with different durations and different relative timings can be produced (Fig. 3).

4. Discussions

We have shown that the stochastic dynamics of a chain of feed-forward connected recurrent networks of spiking neurons endowed with membrane potential bistability produces lump neural activation that is gradually relayed along this chain. These phenomena occur at a long time scale, in agreement with the time scale of mental process. Our model may provide possible neural bases of mental representation of episodes.

At first glance, the network structure of our model (Fig. 1) is very similar to that of the synfire-chain model (Diesmann et al, 1999). In the synfire-chain model, however, recurrent connection in each layer is absent and membrane potential bistability is not normally assumed. These make temporal profiles of neural activation produced by both the models much different. In the synfire-chain model, synchronous spiking rapidly propagates along the chain with precise timing, which is quite contrast to the slow propagation of lump neural activation in our model. Phenomena to be accounted for by the synfire-chain model and our model may be different.

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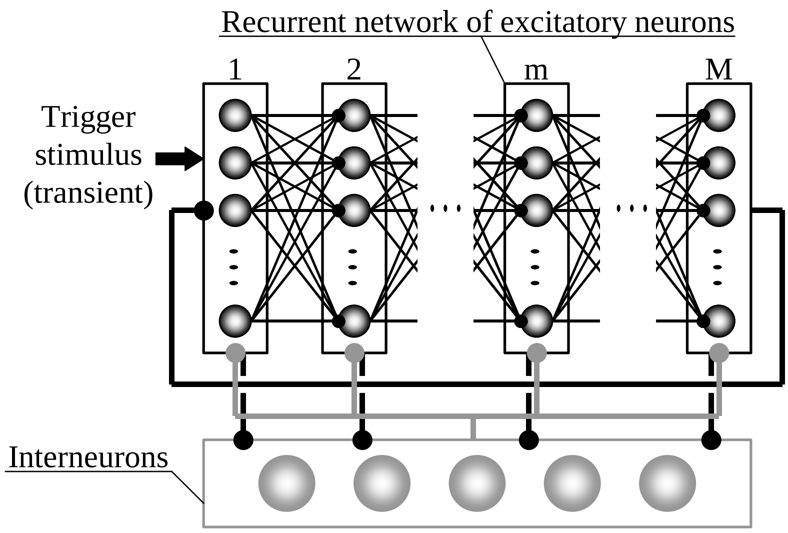

Fig. 1. Chain of feed-forward connected recurrent networks. Drawing of recurrent connections within each layer is omitted.

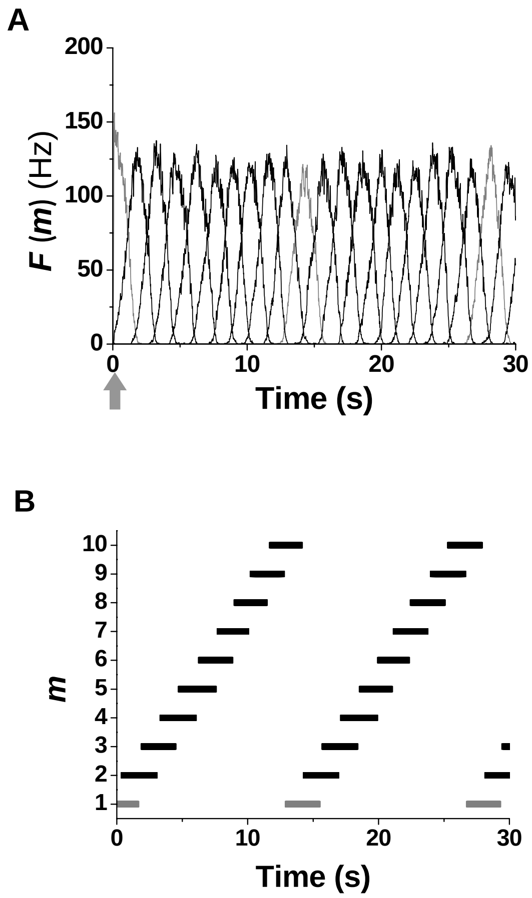

Fig. 2. A, Time course of $F(m)$ (m=1, ···, 10). Only the results for m =1 are indicated by grey line. **B,** Each bar represents the duration in which $F(m)$>30Hz. Propagation of lump neural activation along the chain is cyclic because the layer 10 sends feed-forward projections to the layer 1 (see Fig. 1).

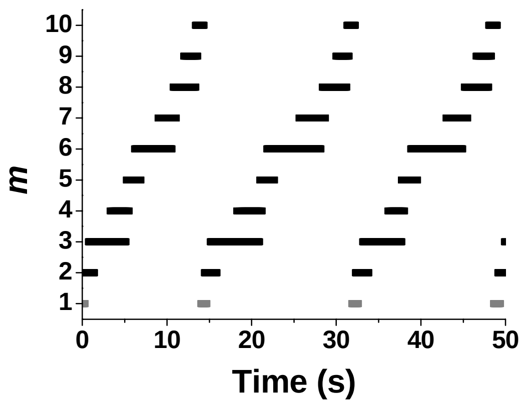

Fig. 3. Results for $G_{m,m+1}$ varying as a function of m.