Neural bases of accumulator models

Hiroshi Okamoto[a, b, *], Tomoki Fukai[b, c]

[a] *Corporate Research Laboratory, Fuji Xerox Co., Ltd., 430 Sakai, Nakai-machi, Ashigarakami-gun, Kanagawa 259-0157, Japan*

[b] *CREST of JST (Japan Science and Technology Corporation), Japan*

[c] *Department of Information-Communication Engineering, Tamagawa University, Tamagawagakuen 6-1-1, Machida-shi, Tokyo 194-8610, Japan*

*Correspondence address: Corporate Research Laboratory, Fuji Xerox Co., Ltd., 430 Sakai, Nakai-machi, Ashigarakami-gun, Kanagawa 259-0157, Japan. Tel.: +81-465-80-2015; fax: +81-465-80-8971.

E-mail address: hiroshi.okamoto@fujixerox.co.jp (H. Okamoto)

Abstract

One class of cognitive models, accumulator models (AMs), is a framework to explain cognitive mechanisms of reaction timing. In AMs, an internal signal, which grows linearly with time upon the onset of an external stimulus, is postulated. Reaction time is defined by the time at which the signal reaches a predefined threshold level. Indeed, cortical neurons with activity that grows seemingly linearly with time are largely found, which is consistent with AMs. Here we show that stochastic dynamics of a recurrent network of bistable spiking neurons can produce linear growth of neuronal activity. This suggests possible neural bases of AMs.

Keywords: Accumulator model; Reaction time; Recurrent network; Stochastic dynamics; Neuronal bistability.

1. Introduction

The length of reaction time, i.e. the interval between the onset of an external stimulus (e.g. target presentation) and reaction (e.g. start of saccadic eye movement), is surprisingly long (>100 ms) [1, 11]. Obviously, this long latency cannot be accounted for only by neuronal conduction and transmission delays. This rather suggests existence of some higher-order internal processes underlying reaction timing.

Reaction timing can also be characterised by its variability. The length of reaction time largely fluctuates across trials even if the stimulation is the same in every trial [1, 11].

One class of cognitive models, accumulator models (AMs) [1, 7, 10, 11, 14], well describes the long latency and the variability of reaction timing. AMs postulate a decision signal S, which represents some internal activation level (Fig. 1A). Upon the onset of an external stimulus, S starts to grow linearly form an initial level S_0 at a rate r. When S reaches a predefined threshold level S_T, reaction (e.g. saccadic eye movement) is triggered.

AMs predict two possible sources of the variability of reaction timing [1, 7, 11]. One is that the threshold level S_T fluctuates across trials (variable-threshold model), and the other is that so does the growth rate r (variable-rate model, Fig. 1B). These models give different experimental predictions for stochastic properties of reaction timing. It has been shown that psychological experimental results are consistent with the variable-rate models [1, 7, 11].

In neurophysiology, a population of neurons with the activity resembling the decision signal postulated in AMs have been found. Upon the onset of a target stimulus, the firing rates of a saccade related neurons in the oculomotor area principally comprising the frontal eye field (FEF) and the supplementary eye field (SEF) grows seemingly linearly with time and culminate at a start of saccade [3, 4, 7, 8, 12, 13]. The growth rate appears to fluctuate across trials [3, 7, 12, 13].

In the present study, seeking for possible neural bases of AMs, we examine neural mechanisms that can produce linear growth of the neuronal firing rate. A possible origin of the fluctuation of the growth rate is also discussed.

2. Model

We consider a model for a recurrent network of excitatory leaky-integrate-and-fire neurons. The recurrent input to each neuron is described by AMPA current originating from other neurons in the network. The same gating kinetics for AMPA conductance as those used in Ref. 2 is adopted. The membrane potential of each neuron is also subject to Gaussian white noise that is uncorrelated between cells.

Specially, we assume that a neuron generates brief depolarisation after it sufficiently discharges [5, 6]. This after-depolarization (ADP) can make the membrane potential of a neuron bistable: In the off state, a neuron rarely discharges and ADP is inactive; in the on state, ADP activation and discharge of a neuron continue in a regenerative manner owing to the positive feedback between them [9].

The onset of a target stimulus is represented by the onset of a depolarizing current I_{ex}. Before the onset of I_{ex}, all the neurons are set in the off state. After the onset of I_{ex}, its amplitude is held constant.

3. Results and discussion

Let $F(t)$ be the output from the network at time t, defined by the firing rate averaged over all cells at time t. The time course of $F(t)$ was examined by computer simulation. The results obtained show that $F(t)$ grows seemingly linearly with time (Fig. 2). It is also shown that changes in I_{ex} across trials result in fluctuations of the growth rate without affecting the linearity (Fig. 2).

The above results suggest that the output from the recurrent network is the neural substrate of the decision signal postulated in AMs. The model is therefore expected to briefly describe a functional structure of the FEF or of the SEF.

The I_{ex} represents a target stimulus and its fluctuations across trials are a possible origin of those of the growth rate in the variable-rate version of AMs. It is highly probable that, although an external target appeared is the same in every trial, the visual cortex that processes a target stimulus send it to the FEF and the SEF is modified by ‘attention’ that can easily be varied across trials. It is therefore reasonable to assume that I_{ex} fluctuates across trials.

We have demonstrated that the stochastic dynamics of bistable spiking neurons provides possible neural bases of AMs. The present study thus presents a possible link between neural mechanisms and behavioural functions.

References

[1] R. H. S. Carpenter and M. L. L. Williams, Neural computation of log likehood in control of saccadic eye movements, Nature 377 (1995), 59-62.

[2] A. Destexhe, Z. F. Mainen and T. J. Sejnowski, Neural Computation 6 (1993), 14-18.

[3] S. Everling and D. P. Munoz, Neuronal correlates for preparatory set associated with pro-saccades and anti-saccades in the primate frontal eye field, J. Neurosci. 20 (2000), 387-400.

[4] N. Fujii, H. Mushiake, H. and J. Tanji, Distribution of eye- and arm-movement-related neuronal activity in the SEF and in the SMA and pre-SMA of monkeys, J. Neurophysiol. 87 (2002), 2158-2166.

[5] S. Haj-Dahmane and R. Andrade, Calcium-activated cation nonselective current contributes to the fast afterdepolarization in rat prefrontal cortex neurons, J. Neurophysiol. 78 (1997), 1983-1989.

[6] S. Haj-Dahmane and R. Andrade, Ionic mechanism of the slow afterdepolarization induced by muscariniv receptor activation in rat prefrontal cortex, J. Nuerophysiol. 80 (1998), 1197-1210.

[7] D. P. Hanes and J. D. Schall, Neural control of voluntary movement initiation, Science 274 (1996), 427-430 (1996).

[8] H. Mushiake, N. Fujii and J. Tanji, Visually guided saccade versus eye-hand reach: contrasting neuronal activity in the cortical supplementary and frontal eye fields, J. Neurophysiol. 75 (1996), 2187-2191.

[9] R. C. O'Reilly, T. S. Braver and J. D. Cohen, Mechanisms of active maintenance and executive control, in: A. Miyake and P. Shah, eds., Models of Working Memory (Cambridge Univ. Press, Cambridge, 1999) 375-411.

[10] R. Ratcliff, T. Van Zandt and G. McKoon, Connectionist and diffusion models of reaction time, Rsychol. Rev. 106 (1999), 261-300.

[11] B. A. J. Reddi and R. H. S. Carpenter, The influence of urgency on decision time, Nat. Neurosci. 3 (2000), 827-830.

[12] J. D. Schall and N. P. Bichot, Neural correlates of visual and motor decision processes, Curr. Opin. Neurobiol. 7 (1998), 211-217.

[13] J. D. Schall, Neural bases of deciding, choosing and acting, Nature Rev. Neurosci. 2 (2000), 33-42.

[14] M. Usher and J. L. McClelland, The time course of perceptual choice: the leaky, competing accumulator model, Psychol. Rev. 108 (2001), 550-592.

Figure captions

Fig. 1. A. Outline of accumulator models. B. Variable-threshold version of accumulator models.

Fig. 2. Time course of $F(t)$, the output from the recurrent network. Depolarizing current I_{ex} is set on at time 0. Different lines indicate the results for different values of I_{ex}. Exact time course of $F(t)$ is roughened with 1 ms bin.

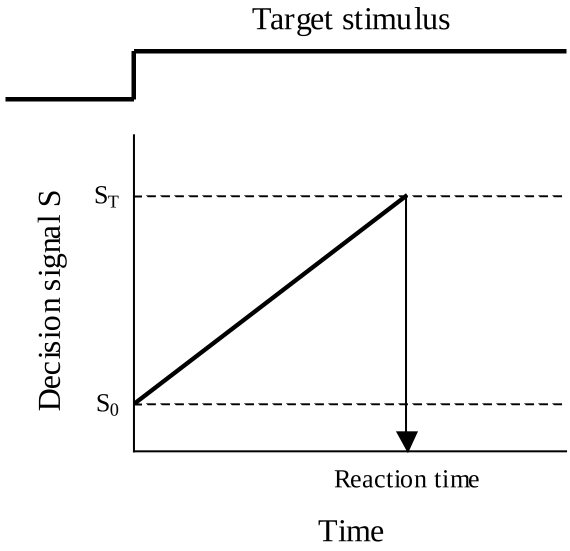

Fig. 1A

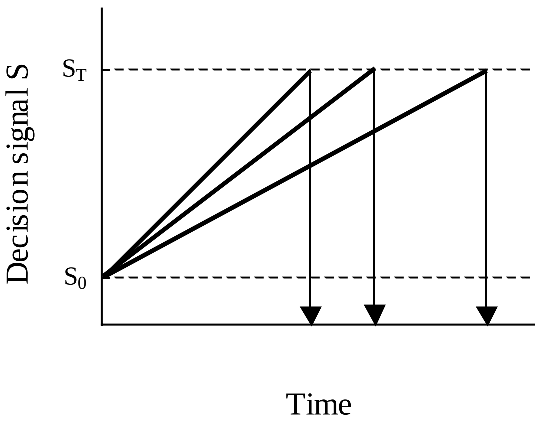

Fig. 1B

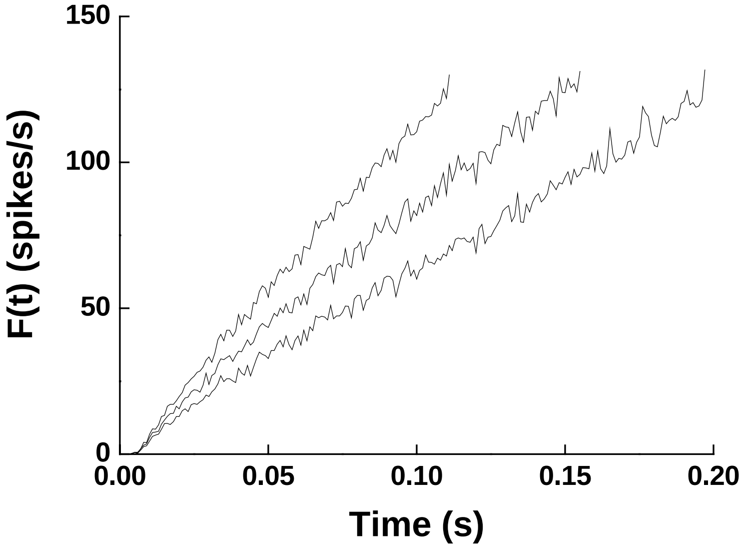

Fig. 2