Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

SaBP5.3

Enhancement of Information Transmission with Stochastic Resonance in Hippocampal CA1 Neuron Models

Hiroyuki Mino, *Senior Member IEEE*, Dominique M. Durand, *Member IEEE*,
and Minato Kawaguchi, *Student Member IEEE*

Abstract— **Stochastic resonance (SR) has been shown to enhance the signal to noise ratio or detection of signals in neurons. It is not yet clear how this effect of SR on the signal to noise ratio affects signal processing in neural networks. In this paper, we test the hypothesis that SR can improve information transmission in the hippocampus. From spike firing times recorded at the soma, the inter spike intervals were generated and then "total" and "noise" entropies were estimated to obtain the mutual information and information rate of the spike trains. The results show that the information rate reached a maximum value at a specific amplitude of the background noise, implying that the stochastic resonance can improve the information transmission in the CA1 neuron model. Furthermore, the results also show that the effect of stochastic resonance tended to decrease as the intensity of the random sub-threshold spike trains (signal) (more than 20 $1/s$) approached to that of the background noise (100 $1/s$). In conclusion, the computation results that the stochastic resonance can improve information processing in the hippocampal CA1 neuron model in which the intensity of the random sub-threshold spike trains was set at 5-20 $1/s$.**

Index Terms— **Synaptic Noise, Shot Noise, Action Potential, Stochastic Resonance, Hodgkin-Huxley model, Homogeneous Poisson Process, Numerical Method, Monte Carlo Simulation**

I. INTRODUCTION

Stochastic resonance (SR) is a phenomenon of coupling deterministic and random dynamics in non-linear systems. This phenomena can be interpreted as an increase of detecting a low-level input signal in the output of the system, which is caused by an increase of the noise level in the input signal. In neurosciences, SR has been observed in sensory nervous systems [1], [2], [3] and central nervous system [4],[5], [6]. In each investigation, it was reported that the detection of a sub-threshold input signal was improved when a certain level of noise was added. However, it is still unclear if SR would improve information processing in the nervous systems.

In the present paper, the information rate of a hippocampal CA1 neuron model in response to random sub-threshold spike trains (signal) is investigated in the presence of a homogeneous Poisson shot noise (background noise). In the computer simulation, the random sub-threshold spike trains were presented repeatedly to the mid-point of the main apical branch in the CA1 neuron model, and the background noise was applied to the mid-point of a basal dendrite, while the transmembrane potentials were recorded at the soma in the CA1 neuron model, in order to obtain the information rate estimated from the total and noise entropies of the inter-spike interval histogram (ISIH), like those in [7]

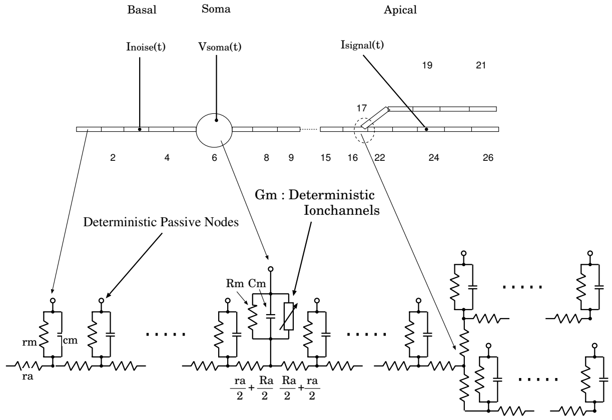

Fig. 1. Hippocampal CA1 neuron was represented as a 5 cylinder multi-compartment model possessing 26 compartments: 5 compartments in the basal, one compartment in the soma, and 20 compartments in the apical branches. The length in each segment was set at $250\mu m$ in the basal, $10\mu m$ in the soma,and $400\mu m$ in apical respectively, while the diameter was set at $4\mu m$(basal), $15\mu m$(soma), $3.5\mu m(1^\circ$ apical), $3.13\mu m(Auxiliary 2^\circ$ apical), and $1\mu m$(Main 2° apical). The equivalent electric circuit was shown in which the dendrites were composed of the passive resistances and capacitance, and in which the soma has the active ion channels. The sub-threshold "spiking signal" current, $I_{signal}(t)$, and "synaptic noise" current, $I_{noise}(t)$, were assumed to be applied to the main apical section (the 24th compartment), and the basal section (the 3rd compartment), respectively, while the transmembrane potential at the soma, $V_{soma}(t)$ was recorded.

II. METHODS

The hippocampal CA1 neuron was represented by a multi-compartment model [16] having 5 cylinders: 5 compartments in the basal, one compartment in the soma, and 20 compartments in the apical branches, as shown in Fig.1. The dendric model parameters were set as follows: the basal diameter $4\mu m$, the basal length per one segment 40 μm, the soma diameter $15\mu m$, the soma length per 50 μm, the 1° apical diameter $3.5\mu m$, the 1° apical length per one segment $40\mu m$, the auxiliary 2° apical diameter $3.13\mu m$, the auxiliary 2° apical length per one segment 80 μm, the main 2° apical diameter $1\mu m$, and the main 2° apical length per one segment 80 μm. The membrane specific resistance and capacitance in the dendrites were set at 14,000 Ωcm^2 and 2 $\mu F/cm^2$, while those in the soma were set at 28,000 Ωcm^2 and 1 $\mu F/cm^2$.

H. Mino is with Department of Electrical and Computer Engineering, Kanto Gakuin University, 1-50-1 Mutsuura E., Kanazawa-ku, Yokohama 236-8501, Japan mino@ieee.org, D. M. Durand is with Neural Engineering Center, Department of Biomedical Engineering, Case Western Reserve University, 10900 Euclid Ave., Cleveland, OH 44106-7207, U.S.A., M. Kawaguchi is with Graduate School of Engineering, Kanto Gakuin University, 1-50-1 Mutsuura E., Kanazawa-ku, Yokohama 236-8501, Japan.

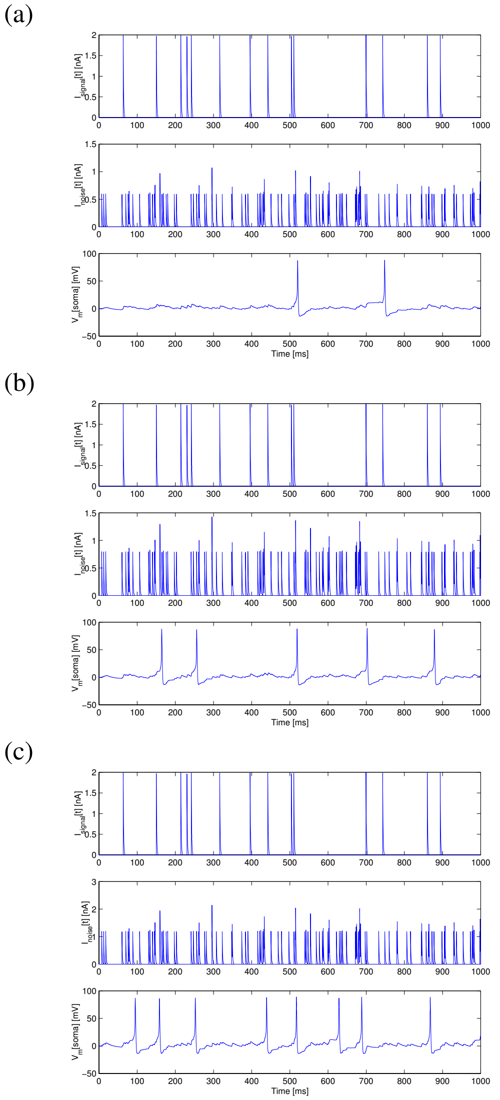

Fig. 2. Top: Input synaptic current, $I_{signal}(t)$, a homogeneous Poisson shot noise with an intensity of 10 $1/s$ and an impulse response function of $h_{signal}(t) = a_{signal}exp(-1000t)$, in which a_{signal}=2.0 nA, Middle: Background synaptic current, $I_{noise}(t)$, a homogeneous Poisson shot noise with an intensity of 100 $1/s$ and an impulse response function of $h_{noise}(t) = a_{noise}exp(-1000t)$, Bottom: Transmembrane potentials at the soma $V_{soma}(t)$ relative to the resting potential $E_{rest} = -66[mV]$. The amplitude of $h_{noise}(t)$, a_{noise}, was set at 0.6 nA in (a), 0.8 nA in (b), and 1.2 nA in (c).

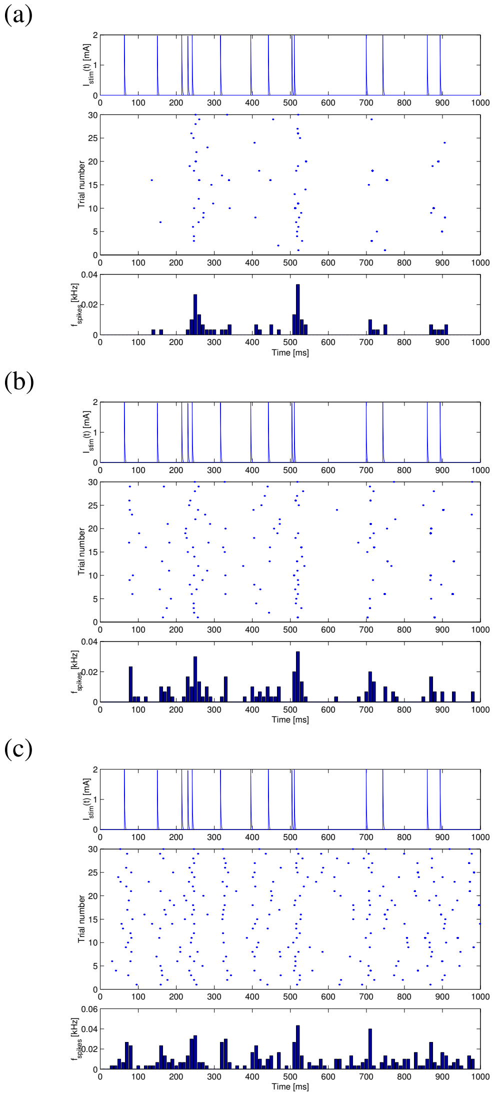

Fig. 3. Top: Input synaptic current, $I_{signal}(t)$, a homogeneous Poisson shot noise with an intensity of 10 $1/s$ and an impulse response function of $h_{signal}(t) = a_{signal}exp(-1000t)$, in which a_{signal}=2.0 nA, Middle: Raster plots of 30 trials, Bottom: Post-stimulus time histogram (PSTH). The amplitude of $h_{noise}(t)$, a_{noise}, was set at 0.6 nA in (a), 0.8 nA in (b), and 1.2 nA in (c).

All model parameters were adopted from those in [4]. The soma contained one sodium, one calcium, and five potassium channels in which conductances, and transition rates were adopted from those in [15]. The transmembrane potentials were numerically calculated by solving a diffusive partial differential equation with the Crank-Nicholson method at a sampling step of 20 μs.

In computer simulations, the sub-threshold “spiking signal” current, $I_{signal}(t)$, and “synaptic noise” current, $I_{noise}(t)$, of 30 s in time length were assumed to be applied to the main apical section, and the basal section, respectively, as shown in the top of Fig. 1, while the transmembrane potential at the soma, $V_{soma}(t)$, was recorded. The “spiking signal” was assumed to be a homogeneous Poisson process filtered by an impulse response function as follows:

$$I_{signal}(t) = \int_{-\infty}^{t} h_{signal}(\tau) dN_s(t-\tau) \qquad (1)$$

in which the intensity, λ, of the counting process $N_s(t)$ was set at 5, 10, 15, 20, 30, and 40 $1/s$, and

$$h_{signal}(t) = a_{signal} e^{-\alpha_{signal} t} \qquad (t \geq 0) \qquad (2)$$

in which a_{signal}=2 nA, and α_{signal}=1000 $1/s$. The “background noise” current was generated by a homogeneous Poisson process filtered by the impulse response function

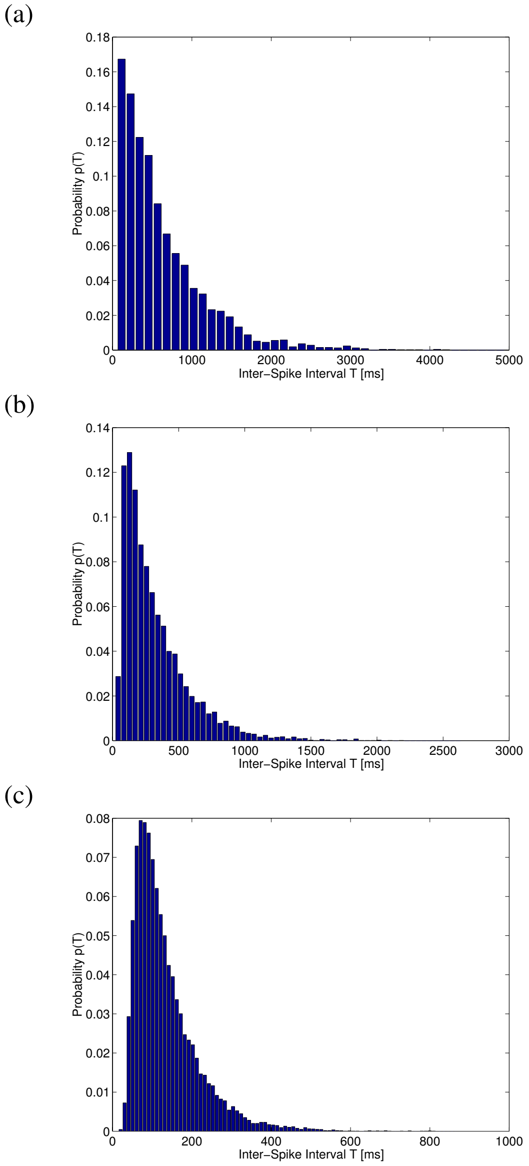

Fig. 4. Inter-spike interval histogram (ISIH) in which the amplitude of $h_{noise}(t)$, a_{noise}, was set at 0.6 nA in (a), 0.8 nA in (b), and 1.2 nA in (c). The total entropies were estimated from the ISI histograms.

as follows:

$$I_{noise}(t) = \int_{-\infty}^{t} h(\tau) dN_n(t-\tau) \tag{3}$$

in which the intensity of the counting process $N_n(t)$ was set at 100 $1/s$, and

$$h(t) = a_{noise} e^{-\alpha_{noise} t} \qquad (t \geq 0) \tag{4}$$

where α_{noise}=1000 $1/s$, and a_{noise} denotes the amplitude of the impulse response function. a_{noise} was varied between 0.3 and 1.2 to see how the background noise would improve the spike signal transmission.

The spike firing times were detected by determining when the transmembrane potential at soma, $V_{soma}(t)$, took the peak amplitude and was greater than 50% of the peak amplitude of action potentials. The inter-spike interval (ISI) histogram, the post-stimulus time (PST) histogram, and the raster plot were generated from spike firing times, where the bin width of the ISI histogram, bw, was determined by evaluating the following formula [14]:

$$bw = 3.49 \times \sigma_{ISI} \times N_{ISI} \tag{5}$$

where σ_{ISI} and N_{ISI} stand for the standard deviation and the number of the ISI data, respectively. We here note that this expression would be optimal for Gaussian distributed ISIs, however, this was utilized for determining it on the basis of observed ISI data, since the entropy estimates may be sensitive to the bin width. Then, from those histograms the information rate $bits/s$ was calculated, assuming that the ISIs were independent, i.e., renewal point process, as follows [8], [10], [13], [11], [9], [12]:

$$I_{rate}(I_{signal}(t), T) = R[H_{total}(T) - H_{noise}(T|I_{signal}(t))] \tag{6}$$

where

$$H_{total}(T) = -\sum_{i=0}^{\infty} p(T_i) log_2 p(T_i) \tag{7}$$

and

$$H_{noise}(T|I_{signal}(t)) = \\ -E[\sum_{i=0}^{\infty} p(T_i|I_{signal}(t)) log_2 p(T_i|I_{signal}(t))] \tag{8}$$

in which T and R respectively stand for the ISIs, and the spike firing rate, and E[] denotes the expectation operation.

All computer simulations were performed on an IBM compatible PC with a Pentium 4 CPU.

III. RESULTS

Figure 2 shows the input synaptic current, $I_{signal}(t)$, a homogeneous Poisson shot noise with an intensity of 10 $1/s$ and an impulse response function of $h_{signal}(t) = a_{signal} exp(-1000t)$, in which a_{signal}=2.0 nA (top), the background synaptic current, $I_{noise}(t)$, a homogeneous Poisson shot noise with an intensity of 100 $1/s$ and an impulse response function of $h_{noise}(t) = a_{noise} exp(-1000t)$ (middle), and the transmembrane potentials at the soma $V_{soma}(t)$ relative to the resting potential $E_{rest} = -66[mV]$ (bottom). The amplitude of $h_{noise}(t)$, a_{noise}, was set at 0.6 nA in (a), 0.8 nA in (b), and 1.2 nA in (c). The input spike trains tended to be encoded reliably into the spike firings (action potential occurrences) observed in the bottom trace, as a_{noise} increased (a-b). However, the noisy spike firings were observed when a_{noise} was set at 1.2 nA in (c).

Figure 3 shows the input synaptic current, $I_{signal}(t)$, a homogeneous Poisson shot noise with an intensity of 10 $1/s$ and an impulse response function of $h_{signal}(t) = a_{signal} exp(-1000t)$, in which a_{signal}=2.0 nA (top), the raster plots of 30 trials (middle), and Post-stimulus time histogram (PSTH) (bottom). The amplitude of $h_{noise}(t)$, a_{noise}, was set at 0.6 nA in (a), 0.8 nA in (b), and 1.2 nA in (c). It follows from the raster plots (middle) and the PSTH (bottom) that the input spike trains were encoded with a higher reliability

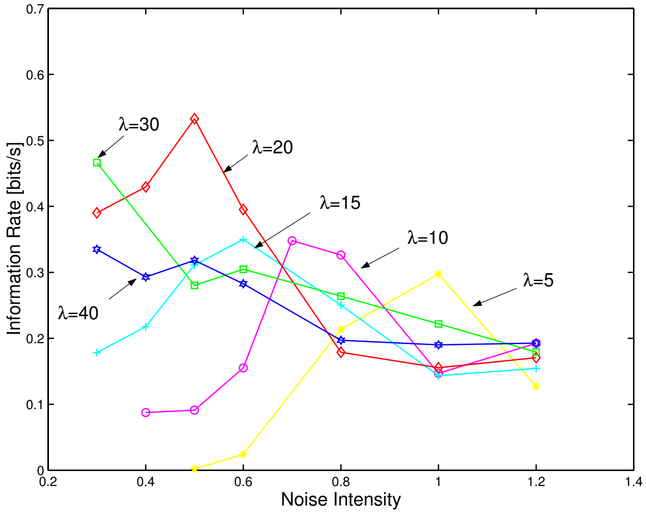

Fig. 5. The information rate as a function of a_{noise} in which the intensity λ of the homogeneous Poisson shot noise in the input synaptic current was set at 5, 10, 15, 20, 30, and 40 $1/s$.

into the spike firings, as a_{noise} increased from 0.2 to 1.0 nA, whereas the noisy spike firings were observed when a_{noise} was set at 1.2 nA.

Figure 4 shows the inter-spike interval histogram (ISIH) in which the amplitude of $h_{noise}(t)$, a_{noise}, was set at 0.6 nA in (a), 0.8 nA in (b), and 1.2 nA in (c). As a_{noise} increased, the shape of the ISIH tended to become non-exponential distributions, and the ISIs decreased. The total entropies were estimated from the ISI histograms.

Figure 5 shows the information rate as a function of a_{noise} in which the intensity λ of the homogeneous Poisson shot noise in the input synaptic current was set at 5, 10, 15, 20, 30, and 40 $1/s$. It was shown that the information rate was maximized in the cases of λ=5, 10, 15, and 20 $1/s$ due to the stochastic resonance, while the information rate was not necessarily maximized in the cases of λ=30, and 40 $1/s$.

IV. DISCUSSION AND CONCLUSION

In the present article, we have investigated the information rate of neural spike trains in which a random sub-threshold spike train was presented as stimuli into a hippocampal CA1 neuron model having the soma consisting of one sodium, one calcium, and five potassium channels in the presence of a homogeneous Poisson shot noise. We have shown that at a specific amplitude of the homogeneous Poisson shot noise, the possibility to encode the random input spike trains became greater, i.e., the information rate was found to be maximized due to the stochastic resonance, at a certain level of the intensity of the homogeneous Poisson shot noise (input signal). We have also shown that the stochastic resonance effect decreased as the intensity of the random sub-threshold spike trains (signal) was increased. It is implied that as the intensity of the “signal” gets close to the intensity of the “background noise”, the CA1 neuron model is not able to recognize the difference between the input spike signal and the background shot noise, degrading the robustness of SR, i.e., background noise does not do anything other than disturbing information transmission. Therefore information transmission in the hippocampal CA1 network can be improved by SR when the input spike intensity is set around 5-20 $1/s$. SR can clearly improve the signal to noise ratio as tested in the hippocampal slice. These simulations suggest that information transfer is also improved. Experiments have yet to be carried out to test the predictions of the model.

REFERENCES

[1] A. Bulsara, E. Jacobs, T.Zhou, F. Moss, and L. Kiss, “Stochastic Resonance in a Single Neuron Model: Theory and Analog Simulation, ” *J. Theor. Biol.*, Vol.152, pp.531-555, 1991.
[2] J. Collins, T. Imhoff, and T. Grigg, “Noise-enhanced Information Transmission in Rat SA1 Cutaneous Mechanoreceptors via Aperiodic Stochastic Resonance,” *J. Neurophysiol.*, vol. 76, pp. 642-645, 1996.
[3] J. Douglass, L. Wilkins, E. Pantazelou, and F. Moss, “Noise Enhancement of Information Transfer in Crayfish Mechanoreceptors by Stochastic Resonance,” *Nature*, vol. 365, pp. 337-340, 1993.
[4] W.C. Stacey and D.M. Durand, “Stochastic Resonance Improves Signal Detection in Hippocampal CA1 Neurons,” *J. Neurophysiol.*, vol. 83, pp. 1394-1402, 2000.
[5] W.C. Stacey and D.M. Durand, “Synaptic Noise Improves Detection of Subthreshold Signals in Hippocampal CA1 Neurons,” *J. Neurophysiol.*, vol. 86, pp. 1104-1112, 2001.
[6] W.C. Stacey and D.M. Durand, “Noise and Coupling Affect Signal Detection and Bursting in a Simulated Physiological Neural Network,” *J. Neurophysiol.*, vol. 88, pp. 2598-2611, 2002.
[7] G. Deco, and B. Schumann, “Stochastic Resonance in the Mutual Information between Input and Output Spike Trains of Noisy Central Neurons,” *Physica D*, vol. 117, pp. 276-282, 1997.
[8] R.R. de Ruyter van Steveninck, G.D. Lewen, S.P. Strong, R. Koberle, W. Bialek, “Reproducibility and variability in neural spike trains,” *Science*, 275(5307), pp.1805-1808, 1997.
[9] P. Dayan and L.F. Abbott, *Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems*, The MIT Press, Cambridge, MA, 2001.
[10] F. Rieke, D. Warland, R. de Ruyter van Steveninck, W. Bialek, *Spikes: Exploring the Neural Code*, The MIT Press, Cambridge, MA, 1997.
[11] A. Zador, “Impact of synaptic unreliability on the information transmitted by spiking neurons,” *J. Neurophysiol.*, 79, pp.1219-1229, 1998.
[12] R. Brette, and E. Guigon, “Reliability of spike timing is a general property of spiking model neurons,” *Neural Computation*, 15, pp.279-308, 2003.
[13] A.R. Bulsara, A. Zador, “Threshold detection of wideband signals: A noise-induced maximum in the mutual information,” *Phys Rev E*, 54, pp.R2185-R2188, 1996.
[14] D. W. Scott, “On optimal and data-based histograms,” *Biometrika*, 66, pp.605-610, 1979.
[15] E.N. Warman and D.M. Durand, “Reconstruction of Hippocampal CA1 Pyramidal Cell Electrophysiology by Computer Simulation,” *J. Neurophysiol.*, vol. 83, pp. 2192-2208, 1994.
[16] R. D. Traub, “ Simulation of Intrinsic Bursting in CA3 Hippocampal Neurons,” *Neurosci.*, vol. 7, pp. 1233-1242, 1982.