NONSTATIONARY STOCHASTIC RESONANCE IN A REDUCED-ORDER HODGKIN-HUXLEY NEURON

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Abstract - In this work a physiologically realistic neural system model is shown to be able to detect a weak nonstationary signal through the addition of noise. It is shown that the signal transduction performance is optimised for a nonzero value of noise intensity in a manner suggestive of stochastic resonance.

Keywords - Stochastic resonance, Hodgkin-Huxley

I. INTRODUCTION

Stochastic resonance (SR) is a nonlinear phenomenon in which a weak stimulus harnesses ambient, more energetic random noise in such a way that the stimulus component is strongly enhanced. Originally only recognised for weak periodic signals in nonlinear dynamic systems the effect has since been found in nondynamical systems and for aperiodic and recently nonstationary signals [1]. SR effects have been found for subthreshold periodic signals in neural models such as the Fitzhugh-Nagumo system [2], simple trigger systems [3] and a reduced-order Hodgkin-Huxley system (ROHH) [4].

In this work evidence for nonstationary stochastic resonance behaviour is found in a noisy ROHH system subject to a subthreshold nonstationary current input, impinging upon an afferent neural neighbour. Such evidence suggests a beneficial aspect to the presence of noise in neural systems

II. METHOD

The neural model used for the simulation consists of two parts: a reduced-order Hodgkin-Huxley system [4] which generates a sequence of action potentials \( P(t) \) in response to superthreshold current input and, a model of excitatory postsynaptic potential (EPSP) generation with impulse response \( V_s(\lambda) \) to account for the response \( R(t) \) at the soma of a neighbouring neuron with which the input neuron has synaptic contact. The input to the ROHH is a subthreshold von Koch curve \( S(t) \) [5] and gaussian noise \( \eta(t) \) characterised by a mean of zero and a variance \( \sigma^2 \). Fig. 1 summarises the experiment.

![Neural System Diagram](image)

Fig. 1. Neural system

The complete system is simulated for the duration of the input signal \( T_i (T_i \rightarrow T_r \text{, where } T_r \text{ is the absolute refractory period of the neural model}) \) and no noise. As expected \( R(t)=0 \) as no APs are produced. The experiment is repeated for \( \sigma \) increasing from 0 to 12.5 and \( R(t) \) recorded. A measure of signal similarity based on the normalised correlation at zero lag is then taken as

\[
\rho = \frac{\sum (S(n) - \overline{S}) (R(n) - \overline{R})}{\sqrt{\sum (S(n) - \overline{S})^2 \sum (R(n) - \overline{R})^2}}
\]

(1)

The procedure is then repeated for different sets of \( a \) and \( b \).

III. RESULTS

The variation of \( \rho \) with \( \sigma \) for the various sets of parameters are given in Fig. 2 below.

![Graph](image)

Fig. 2. \( \rho \) versus \( \sigma \) for various \((a,b)\)

IV. DISCUSSION

Fig. 2 shows that the subthreshold deterministic signal can only be detected by the injection of noise into the system and that the intensity of the noise required to maximise \( \rho \) is largely independent of the EPSP parameters. Moreover changes in \( b \) can vary the range over which desired levels of correlations are achieved.

V. CONCLUSION

The above results indicate beyond doubt that the presence of noise in model neurons can aid detection and coding of normally subthreshold nonstationary signals

REFERENCES