Open Questions For Suprathreshold Stochastic Resonance In Sensory Neural Models for Motion Detection Using Artificial Insect Vision

Mark D. McDonnell* and Derek Abbott*

*Centre for Biomedical Engineering (CBME) and
Department of Electrical & Electronic Engineering
The University of Adelaide, SA 5005, Australia

Abstract. Stochastic Resonance (SR) occurs when the presence of noise in a nonlinear system can induce an optimal output from that system, and has been observed in a diverse range of physical and biological systems, including neurons. Despite this widespread observation of SR, to date very few engineering applications inspired by SR have been proposed, and one of the goals of our research is to explore possible new practical applications designed to replicate the benefits of SR. In particular, since about 1991, our group has designed and implemented a number of motion detection VLSI chips based on insect vision. We are currently investigating the possibility of replicating the benefits of SR in artificial insect-vision based motion detection systems, in particular a newly described form of SR called Suprathreshold Stochastic Resonance (SSR). The current paper is intended to review and identify the key open questions and avenues for future research relating to SR and SSR in such systems.

INTRODUCTION AND MOTIVATION

There are many tasks that are performed routinely by biological organisms that either cannot be replicated at all by artificial means (that is, designed systems, whether software, electronics or mechanical systems), or cannot be replicated to anywhere near the same efficiency or with much inferior performance. Such tasks include obvious ones like abstract and creative thinking, pattern recognition, and intelligence in human beings. But there are also other seemingly lesser, more trivial tasks that are routinely performed by creatures considered much less intelligent – that is, insects. Insects such as a common house fly or honey bee, achieve motion detection tasks, for example avoiding the fly swatter, and velocity estimation and visual tracking of an object, for example a bee landing on a leaf swaying in the wind. Despite much research into robotics, artificial intelligence, Uninhabited Aerial Vehicles (UAVs) and the like no one has devised a microrobot that can do all the mechanical and visual processing tasks that a bee can do, in such a small volume.

Other examples include the other senses – artificial noses are only now starting to look possible [1], the human ear is very good at distinguishing faint signals from noise, or even listening to two conversations at once, and the entire surface area of an animal is sensitive to a wide range of heat, pressure and textures.

Hence, an important idea is to study how biology achieves these tasks, in order to

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learn from it and perhaps re-engineer systems according to this new knowledge. Such a philosophy is not uncommon – there are fields of research known as Biomimetic Engineering and Biomorphic Engineering. Although the engineering described by these terms is often at the molecular level, the concepts are just as relevant at the system level, given the fact that whole biological systems often outperform artificial systems. It is well known in the noise and fluctuation community that sensory neurons are very noisy when compared with what are acceptable levels of noise in electronic engineering [2]. Since the brain (which consists of a system of neurons) seems to function extremely well in this noise, it seems likely that either the noise is being intentionally used by the brain, or that the brain has come up with a good way around the noise.

This is a widely recognized fact, and there has been much research based around the idea, showing that the presence of noise in neurons – whether in real biological experiments, or in mathematical models of neurons, can improve some figure of merit at the output of the neuron, when compared to that figure of merit in the absence of noise. Such a phenomenon is known as Stochastic Resonance (SR).

STOCHASTIC RESONANCE

The term "Stochastic Resonance" [3, 4, 5, 6, 7] was first coined by Roberto Benzi in 1980 [8], as a name for the mechanism he suggested was behind the periodic behavior of the earth's ice ages [9]. Since this time, SR has usually been loosely defined as occurring when an increase in input noise leads to an increase in output signal to noise ratio in a nonlinear system driven by a periodic force, although, in more recent times the context of SR has been extended to include aperiodic signals, and many other measures other than SNR have been used as the figure of merit, such as cross-correlation coefficient [10] and transmitted information [11, 12]. There are many non-linear systems in which SR has been observed, such as electronic devices [13], ring lasers [14], SQUIDS (super conducting quantum interference devices) [15] and in biological sensory neurons [16, 17] and ion channels [18].

NOISE IN NEURONS

Although neurons are often modelled by complicated mathematical equations (usually coupled differential equations), for example the FitzHugh-Nagumo model and the Hodgkin-Huxley model, the essential qualitative feature of a neuron is that the output of a neuron produces a spike when the input signal increases above a threshold. Following the spike, there is a refractory period during which the neuron cannot spike again. The feature we are interested in here is the main nonlinearity involved, that is, the threshold.

SR in single threshold systems

Originally, it was thought that SR could only occur in dynamical systems obeying some differential equation. However later work showed that SR could occur in non-dynamical statistical systems, where the only components required were a threshold, noise and a subthreshold signal [19]. SR in threshold systems [20], such as a neuron, is a very simple concept to demonstrate: when noise is added to an input signal that is too small to cause the neuron to spike without noise, output spikes occur which are correlated with the amplitude of the input signal. The addition of random noise is equivalent to random changes in the values of the neuron's threshold, hence ensuring that the originally subthreshold signal becomes suprathreshold occasionally.

Although this phenomena has been extensively studied by physicists under the name of SR, the essence of it has been known to engineers for decades, by the name of dithering. Dithering has applications in the processing of noisy images and also in Analog to Digital Converters (ADCs), especially in audio systems. The addition of noise to a continuous audio signal at the input of an ADC increases the dynamic range, and decreases the output distortion, by whitening the output quantization noise, at the expense of a small increase in the output noise floor.

Some authors have recognized this fact [21, 22, 23], and either suggested that SR in threshold systems should be called "noise assisted threshold crossing" [21, 22], or that SR should be the name for naturally observed noise assisted behavior, where noise is inherently present, and dithering should be the name for artificially introduced noise, where it would not normally be present [24]. Accordingly, it seems appropriate to call the phenomenon SR in neurons, since noise seems to be unavoidable. On the other hand, perhaps evolution has evolved the brain so that the noise is there by design. Regardless of whether we call the phenomenon SR or dithering, it seems indisputable that noise in neurons causes threshold crossings and hence output spikes, that would not have occurred otherwise. Is this for the same reasons as dithering in ADC's? We believe this is worth studying. Perhaps some insights for new types of dithering may be found by the study of SR in neurons and other types of SR.

SSR – A new type of SR occurring in arrays of neurons

Recently, a series of papers by Stocks has brought to light a new form of stochastic resonance, which he has called Suprathreshold Stochastic Resonance [12]. This occurs in an array of threshold devices subject to the same input signal, but independent additive noise. The output from each device is then summed to give an overall output. Such a configuration is shown in Fig. 1. Previous work on noise in a parallel arrays of neurons [25] did not show the existence of SR in a spike timing precision measure for suprathreshold signals. Additionally, exact expressions for the correlation coefficient in parallel arrays of devices have previously been derived using linear response theory, both theoretically [26], and specifically for a parallel array of threshold devices [27]. In the latter case, however, the signal was always subthreshold, and the noise was not independent in each device.

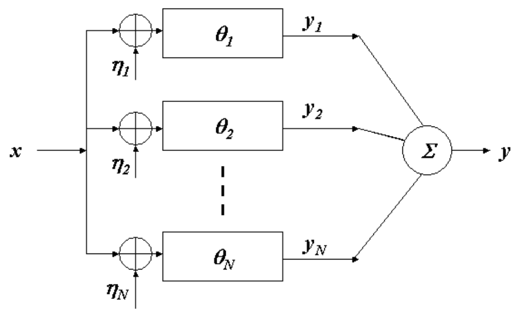

FIGURE 1. Array of N threshold devices. All devices receive the same signal, x and additive independent noise, η_i. The overall output, y, is the sum of the outputs from each device, y_i.

Stocks has used information theory to show how stochastic resonance can occur in such a system, for signals of arbitrary magnitude. If the array is considered as a semi-continuous channel [28], then the transmitted information through such a channel is given by

$$I = -\sum_{n=0}^{N} Q(n)\log_2 Q(n) - \left(-\int_{-\infty}^{\infty} P(x) \sum_{n=0}^{N} P(n|x)\log_2 P(n|x)dx \right), \qquad (1)$$

where $P(x)$ is the probability density of the input signal x, $Q(n) = \int_{-\infty}^{\infty} P(n|x)P(x)dx$ is the probability of the output signal y being equal to n ($n = 0, 1, \ldots, N$) and $P(n|x)$ the conditional probability that the output is n given the input is x [12]. $P(n|x)$ can be calculated from knowledge of the threshold settings and the noise probability density function. When all thresholds are set equal to the signal mean, Stocks has shown that the maximum transmitted information given by Eq. (1) occurs for a nonzero noise intensity for both simple Heavyside style threshold devices [12, 29, 30], as well as in an array of more realistic neuron models – FitzHugh-Nagamo neurons [31]. A typical plot of the SSR effect is shown in Fig. 2, where both the input signal, and the noise at each device are Gaussian random variables.

Analysis of SSR

The concept of threshold crossing due to noise mentioned previously is of the form such that in a single neuron a signal, which would not be otherwise detected, is detected in the presence of noise. This is a binary process – the neuron output is either a spike

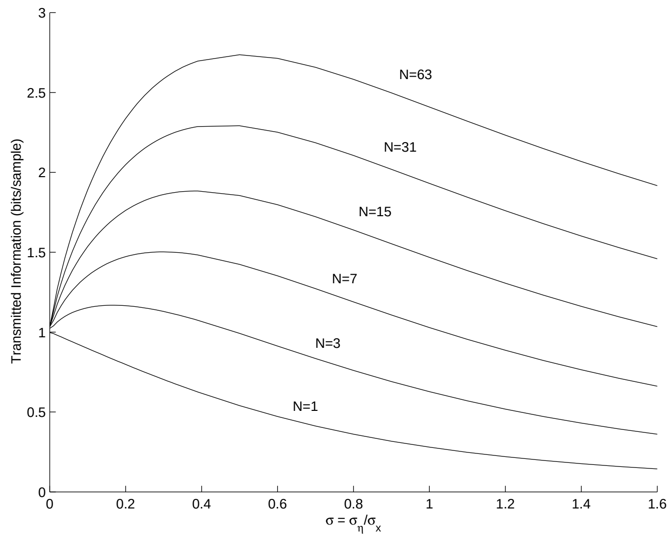

FIGURE 2. Plot of the transmitted information against the ratio of signal standard deviation to noise standard deviation, for Gaussian signal and noise, for various values of *N*

or not a spike. However if we look at an ensemble of more than one neuron, we are no longer restricted to a binary process.

Consider an array of N identical neurons (all with the same threshold value) in parallel as in Fig. 1. In the absence of noise, (or the same noise at each neuron) the overall output can only be 0 or N, indicating that the signal is either less than or greater than the threshold. However if independent noise is added to the signal at each neuron (or equivalently, each threshold varied randomly), then the output can take on any of $N+1$ values; that is, the number of neurons giving an output spike. What does this number represent? It is a scale that rates by how much the input signal exceeds or is below the threshold. Qualitatively, if the output is $N/2$, then half the thresholds have spiked and half have not spiked. If the noise is symmetrically distributed with the same mean value as the signal, then on average, if $N/2$ neurons spike, the signal must have the same value as the threshold. If N neurons spike, then on average, the signal must be much larger than the threshold, since no value of noise is negative enough to decrease the input below the threshold. If no neurons spike, then on average the signal must be much smaller than the threshold, since no value of noise is positive enough to increase the input above the threshold. All other values of the output are the intermediate values of input signal, between very large and very small compared to the threshold.

Indeed, as mentioned, Stocks showed that the transmitted information through such an array is maximized by a nonzero value of noise intensity. He has coined the term SSR to describe this effect, to differentiate it from SR in single threshold systems, where the signal must always be subthreshold for SR to occur. In the array the size of the signal is irrelevant when compared to the threshold, since the output is an indication of the magnitude of the signal.

The remarkable thing about this system is it has effectively performed an analog to digital conversion – an array of neurons can do ADC! Perhaps this is a case of engineers mimicking nature without realizing it.

Of course the distribution and power spectrum of the signal and noise affect how well the array works, but it is still effectively an ADC, which is potentially more robust to changes in the dynamic range of the input signal than conventional engineering designs.

SR IN INSECT VISION BASED MOTION DETECTION

In 1997, Moini *et al* published a paper describing the design and architecture of a VLSI motion detection chip [32]. This chip is based on the Horridge *template model* of the insect vision system [33] and is based on a (nonlinear) neuronal model. Blackwell has noted that "because of the non-linearities in the visual system, it is not unreasonable to expect that SR would be observed," [34] and indeed has "demonstrated that contrast detection thresholds of luminance sinusoids is improved when the sinusoid is embedded in low contrast noise." Therefore it is anticipated that as in real neurons, SR could be beneficially incorporated into the design of insect vision based chips.

SR in the Template Model

The reason that SR can occur in the Horridge template model is simply due to the presence of a threshold. The template model, a model based on the insect visual system [33], works by the spatio-temporal tracking of leading and trailing edges of moving objects. A large number of spatially separated parallel receivers are required. Due to this spatial separation, each receiver's input signal (the luminance) is slightly different. At each receiver, the input signal is bandpass filtered, thresholded and sampled. The input signal is then classified according to whether it is increasing in luminance, decreasing in luminance or has no change. A two by two template is then formed from this classification of the temporal rate of change of the input signal at two adjacent time samples and between each pair of adjacent receivers. This two by two template thus has 81 different possibilities. It has been shown that 8 of these are robust enough to indicate motion [33].

In the VLSI implementations of the template model designed by Moini *et al* [32], at each receiver the input signal is time differentiated and then thresholded. Note that since we require a case of no change, there are in fact two thresholds required. Since any approaching edge signal is at first subthreshold to the detector but becomes suprathreshold, the situation becomes equivalent to that of a subthreshold signal in the basic threshold systems mentioned earlier. Hence, the presence of noise in the system should presumably cause stochastic resonance to occur when signals are subthreshold.

Recent work by Harmer *et al* [35] has investigated the effects of noise in three different models of motion detection; the Reichardt correlation model [36], the directionally sensitive local inhibitory motion detector (DSLIMD) [37] and the Horridge template model [33]. For the template model, Harmer showed that under certain conditions both

SR and SSR occurred in a network of such motion detectors [38]. He concluded that SR can be of benefit by increasing the dynamic range of the system in low contrast conditions, for subthreshold signals, due to the same mechanism as SR in threshold based systems described earlier. However, by simulating an array situation within the template model, he also concluded that SSR could provide enhancement of suprathreshold signals in high contrast conditions [35].

FURTHER OPEN QUESTIONS

One of the open questions arising from Harmer's work is to investigate whether SR or SSR can occur in motion detection models other than the template model. The two other models he considered, although nonlinear, do not possess a threshold, so it is not immediately obvious whether SR could occur. Hence, further investigation into these models and others would be significant. Of particular interest is an elaborated version of the Reichardt correlator [39]. Although many physiological and behavioral experiments support the theory that Reichardt correlators form the basis for motion detection in insects, as well as in human vision [40, 41], the basic Reichardt correlator does not function as a velocity estimator, a function that both insects and humans are capable of. The elaborated Reichardt correlator has been shown by Dror *et al* to give improved velocity estimation performance in response to a variety of stimuli [40]. Our research aims to further investigate the performance of such elaborated Reichardt correlators in the presence of noise, and to search for conditions under which SR may occur.

A further investigation of SSR in the context of artificial vision is in the area of automatic gain control and logarithmic compression. It is known that both insect [42] and human visual systems [30] respond over a very wide dynamic range of light intensities without saturating. This is achieved by the adaptation of sensory neuron threshold levels to the mean value of the stimulus. Stocks *et al* noted that this phenomenon is analogous to the situation of SSR, where maximum noise-enhanced information transmission occurs precisely when neurons adapt to the mean value of the input signal [31]. Further research to explore these open questions surrounding the possible exploitation of this observation, in the design of artificial motion detectors, is of great interest.

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