

STOCHASTIC RESONANCE

From Suprathreshold Stochastic Resonance to Stochastic Signal Quantization

Stochastic resonance occurs when random noise provides a signal processing benefit, and has been observed in many physical and biological systems. Many aspects have been hotly debated by scientists for nearly 30 years, with one of the main questions being whether biological neurons utilise stochastic resonance. This book addresses in detail various theoretical aspects of stochastic resonance with a focus on its extension to suprathreshold stochastic resonance, in the context of stochastic signal quantization theory. Models in which suprathreshold stochastic resonance occur support significantly enhanced “noise benefits”, and exploitation of the effect may prove extremely useful in the design of future engineering systems such as distributed sensor networks, nano-electronics, and biomedical prosthetics.

For the first time, this book reviews and systemizes the topic in a way that brings clarity to a range of researchers from computational neuroscientists through to electronic engineers. To set the scene, the initial chapters review stochastic resonance and outline some of the controversies and debates that have surrounded it. The book then discusses the suprathreshold stochastic resonance effect as a form of stochastic quantization. Next, it considers various extensions, such as optimization and tradeoffs for stochastic quantizers. On the topic of biomedical prosthetics, the book culminates in a chapter on the application of suprathreshold stochastic resonance to the design of cochlear implants. Each chapter ends with a review summarizing the main points, and open questions to guide researchers into finding new research directions.

STOCHASTIC RESONANCE

From Suprathreshold Stochastic Resonance to Stochastic Signal Quantization

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In memory of Charles Edward Miller Pearce (1940 -2012)

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Preface

Quantization of a signal or data source refers to the division or classification of that source into a discrete number of categories or states. It occurs, for example, when analogue electronic signals are converted into digital signals, or when data are binned into histograms. By definition, quantization is a lossy process, which compresses data into a more compact representation, so that the number of states in a quantizer's output is usually far fewer than the number of possible input values.

Most existing theory on the performance and design of quantization schemes specifies only deterministic rules governing how data are quantized. By contrast, *stochastic quantization* is a term intended to pertain to quantization where the rules governing the assignment of input values to output states are stochastic rather than deterministic. One form of stochastic quantization that has already been widely studied is a signal processing technique called *dithering*. However, the stochastic aspect of dithering is usually restricted so that it is equivalent to adding random noise to a signal *prior* to quantization. The term *stochastic quantization* is intended to be far more general, and applies to the situation where the rules of the quantization process are stochastic.

The inspiration for this study comes from a phenomenon known as *stochastic resonance*, which is said to occur when the presence of noise in a system provides a better performance than the absence of noise. Specifically, this book discusses a particular form of stochastic resonance – discovered by Stocks – known as *suprathreshold stochastic resonance*, and demonstrates how and why this effect is a form of stochastic quantization.

The motivation is two-fold. First, stochastic resonance has been observed in many forms of neuron and neural systems, both in models and in real physiological experiments. The model in which suprathreshold stochastic resonance occurs – sometimes called a *pooling network* – was designed to model a population of neurons, rather than a single neuron. Unlike single neurons, the suprathreshold stochastic resonance model supports stochastic resonance for input signals that are

not entirely or predominantly subthreshold. Hence, it has been conjectured that the suprathreshold stochastic resonance effect is utilized by populations of neurons to encode noisy sensory information, for example in the cochlear nerve.

Second, although stochastic resonance has been observed in many different systems, in a wide variety of scientific fields, to date very few applications inspired by stochastic resonance have been proposed. One of the reasons for this is that in many circumstances utilizing stochastic resonance to improve a system is dismissed as suboptimal when compared with optimizing that system to operate without requiring stochastic resonance. This is because, given a system or device that is *a priori* nonlinear, a designer has the choice of (i) trying to operate it in a quasi-linear regime by locking operation to a near-linear part of the input–output transfer function, or (ii) allowing the system to be operated throughout its full nonlinear characteristic. The first alternative has historically been preferred, because linear systems are far easier to understand and analyse. However, if the system is allowed to run freely, then it is possible to utilize stochastic resonance, in a very carefully controlled manner, to enhance performance. Although adjusting certain parameters in the nonlinear system other than noise may be the preferred option, sometimes this cannot be achieved, and utilizing noise via stochastic resonance can provide a benefit. Given that stochastic resonance is so widespread in nature, and that many new technologies have been inspired by natural systems – particularly biological systems – new applications incorporating aspects of stochastic resonance may yet prove revolutionary in fields such as distributed sensor networks, nano-electronics, and electronic biomedical prosthetics.

As a necessary step towards confirming the above two hypotheses, this book addresses in detail for the first time various theoretical aspects of stochastic quantization, in the context of the suprathreshold stochastic resonance effect. The original work on suprathreshold stochastic resonance considers the effect from the point of view of an information channel. This book comprehensively reviews all such previous work. It then makes several extensions: first, it considers the suprathreshold stochastic resonance effect as a form of stochastic quantization; second, it considers stochastic quantization in a model where all threshold devices are not necessarily identical, but are still independently noisy; and, third, it considers various constraints and tradeoffs in the performance of stochastic quantizers. To set the scene, the initial chapters review stochastic resonance and outline some of the controversies and debates that have surrounded it.

Foreword

Due to the multidisciplinary nature of stochastic resonance the Foreword begins with a commentary from Bart Kosko representing the engineering field and ends with comments from Sergey M. Bezuikov representing the biophysics field. Both are distinguished researchers in the area of stochastic resonance and together they bring in a wider perspective that is demanded by the nature of the topic.

The authors have produced a breakthrough treatise with their new book *Stochastic Resonance*. The work synthesizes and extends several threads of noise-benefit research that have appeared in recent years in the growing literature on stochastic resonance. It carefully explores how a wide variety of noise types can often improve several types of nonlinear signal processing and communication. Readers from diverse backgrounds will find the book accessible because the authors have patiently argued their case for nonlinear noise benefits using only basic tools from probability and matrix algebra.

Stochastic Resonance also offers a much-needed treatment of the topic from an engineering perspective. The historical roots of stochastic resonance lie in physics and neural modelling. The authors reflect this history in their extensive discussion of stochastic resonance in neural networks. But they have gone further and now present the exposition in terms of modern information theory and statistical signal processing. This common technical language should help promote a wide range of stochastic resonance applications across engineering and scientific disciplines. The result is an important scholarly work that substantially advances the state of the art.

Professor Bart Kosko

Department of Electrical Engineering, Signal and Image Processing Institute,
University of Southern California, December 2007

A book on stochastic resonance (SR) that covers the field from suprathreshold stochastic resonance (SSR) to stochastic signal quantization is a long-anticipated major event in the world of signal processing.

Written by leading experts in the field, it starts with a didactic introduction to the counterintuitive phenomenon of stochastic resonance – the noise-induced increase of order – complete with a historical review and list of controversies and debates. The book then quickly advances to the hot areas of signal quantization, decoding, and optimal reconstruction.

The book will be indispensable for both students and established researchers who need to navigate through the modern sea of stochastic resonance literature. With the significance of the subject growing as we advance in the direction of nanotechnologies, wherein ambient fluctuations play an ever-increasing role, this book is bound to become an influential reference for many years to come.

Sergey M. Bezrukov

National Institutes of Health (NIH)

Bethesda, Washington DC, USA

July 2007

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Putting this book together was a lengthy process and there are many people to thank. The field of stochastic resonance (SR) is one that has been rapidly evolving in recent years and has often been immersed in hot debate. Therefore we must thank all our colleagues in the SR community for providing the springboard for this book.

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