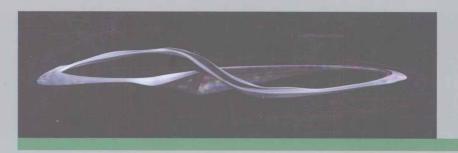
Reconstruction of Chaotic Signals with Applications to Chaos-Based Communications

混沌信号的重构及其在基于混沌的通信中的应用



Feng Jiuchao (冯久超) Tse Chi Kong (谢智刚)





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江苏工业学院图书馆 藏 书 章



内容简介

本书系统地总结了作者近年来涉及的嵌入在基于混沌的通信中的最基本问题——混沌信号的重构及其应用的研究成果,覆盖了关于混沌信号重构的基本问题和几个高层次的问题。共分为四个层次进行深入的论述:①在无噪声的信道里如何重构原始混沌信号,这是将 Takens 定理推广到时变的连续时间与离散时间系统;②如何通过噪声污染的混沌信号重构原始混沌系统的动力学;③如何通过噪声污染同时也被信道畸变的混沌信号重构原始混沌系统的动力学;④基于混沌同步的思想重构原始混沌系统的动力学。所有这些问题都是围绕基于混沌的宽带通信在实际通信环境里的实现为研究目的。

该书对于信号与信息处理、非线性电路、通信、智能信息处理和自动化等学科的大专院校高年级学生和有关研究人员具有很强的可读性和重要的参考价值,并能起到抛砖引玉的作用。

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图书在版编目(CIP)数据

混沌信号的重构及其在基于混沌的通信中的应用 = Reconstruction of Chaotic Signals with Applications to Chaos-Based Communications/冯久超,谢智刚著.—北京:清华大学出版社,2007.11

ISBN 978-7-302-12120-6

I. 混··· II. ①冯··· ②谢··· III. 混沌学 – 应用 – 信号处理 – 英文 IV. TN911.72 中国版本图书馆 CIP 数据核字(2005)第 134048 号

责任编辑:赵彤伟 张 彤

责任校对: 焦丽丽 责任印制: 王秀菊

出版发行: 清华大学出版社 地 址: 北京清华大学学研大厦 A 座

http://www.tup.com.cn 邮 编:100084

c-service@tup. tsinghua. edu. cn

社 总 机: 010-62770175 邮购热线: 010-62786544 投稿咨询: 010-62772015 客户服务: 010-62776969

印装者:北京市清华园胶印厂

经 销:全国新华书店

开 本: 152×228 印 张: 14.75 字 数: 238 千字

版 次: 2007 年 11 月第 1 版 印 次: 2007 年 11 月第 1 次印刷

භ 数:1~1000

定 价:58.00元

本书如存在文字不清、漏印、缺页、倒页、脱页等印装质量问题,请与清华大学出版社出版部 联系调换。联系电话:(010)62770177 转 3103 产品编号:018138-01

To our families
Yao Tan and Lang Feng
Belinda and Eugene

Preface

The study of time series has traditionally been within the realm of statistics. A large number of both theoretical and practical algorithms have been developed for characterizing, modeling, predicting and filtering raw data. Such techniques are widely and successfully used in a broad range of applications, e.g., signal processing and communications. However, statistical approaches use mainly linear models, and are therefore unable to take advantage of recent developments in nonlinear dynamics. In particular, it is now widely accepted that even simple nonlinear deterministic mechanisms can give rise to complex behavior (i.e., chaos) and hence to complex time series. Conventional statistical time-series approaches are unable to model or predict complex time series with a reasonable degree of accuracy. This is because they make no use of the fact that the time series has been generated by a completely deterministic process, and hence ascribe most of the complexity to random noise. Furthermore, such approaches cannot yield much useful information about the properties of the original dynamical system.

Fortunately, a remarkable result due to Takens shows that one can reconstruct the dynamics of an unknown deterministic finite-dimensional system from a scalar time series generated by that system. Takens' theorem is actually an extension of the classical Whitney's theorem. It is thus concerned with purely deterministic autonomous dynamical systems and the framework that it provides for time series analysis is unable to incorporate any notion of random behavior. This means that the process of reconstruction is outside the scope of statistical analysis because any such analysis would require a stochastic model of one kind or another as its starting point. This is reflected in common practice, where reconstruction is seen as a straightforward algorithmic procedure that aims to recover properties of an existing, but hidden, system.

The problem of reconstructing signals from noisy corrupted time series arises in many applications. For example, when measurements are taken from a physical process suspected of being chaotic, the measuring device introduces error in the recorded signal. Alternatively, the actual underlying physical phenomenon may be immersed in a noisy environment, as might be the case if one seeks to detect a low-power (chaotic) signal (possibly used for communications) that has been transmitted over a noisy and distorted channel. In both cases, we have to attempt to purify or detect a (chaotic) signal from noisy and/or distorted samples.

Separating a deterministic signal from noise or reducing noise in a noisy corrupted signal is a central problem in signal processing and communications. Conventional methods such as filtering make use of the differences between the spectra of the signal and noise to separate them, or to reduce noise. Most often the noise and the signal do not occupy distinct frequency bands, but the noise energy is distributed over a large frequency interval, while the signal energy is concentrated in a small frequency band. Therefore, applying a filter whose output retains only the signal frequency band reduces the noise considerably. When the signal and noise share the same frequency band, the conventional spectrum-based methods are no longer applicable. Indeed, chaotic signals in the time domain are neither periodic nor quasi-periodic, and appear in the frequency domain as wide "noise-like" power spectra. Conventional techniques used to process classic deterministic signals will not be applicable in this case.

Since the property of self-synchronization of chaotic systems was discovered in 1990 by Pecora and Carroll, chaos-based communications have received a great deal of attention. However, despite some inherent and claimed advantages, communicating with chaos remains, in most cases, a difficult problem. The main obstacle that prevents the use of chaotic modulation techniques in real applications is the very high sensitivity of the demodulation process. Coherent receivers which are based on synchronization suffer from high sensitivity to parameter mismatches between the transmitter and the receiver and even more from signal distortion/contamination caused by the communication channel. Non-coherent receivers which use chaotic signals for their good decorrelation properties have been shown to be more robust to channel noise; however, as

they rely mainly on (long-term) decorrelation properties of chaotic carriers, their performances are very close to those of standard non-coherent receivers using pseudo-random or random signals. In both cases, coherent and non-coherent, it has been shown that noise reduction (or signal separation) can considerably improve the performance of chaos-based communication systems.

The aforementioned problems can be conveniently tackled if signals can be reconstructed at the receiving end. Motivated by the general requirements for chaotic signal processing and chaos-based communications, this book addresses the fundamental problem of reconstruction of chaotic signals under practical communication conditions.

Recently, it has been widely recognized that artificial neural networks endow some unique attributes such as universal approximation (input-output mapping), the ability to learn from and adapt to their environments, and the ability to invoke weak assumptions about the underlying physical phenomena responsible for the generation of the input data. In this book, the technical approach to the reconstruction problem is based on the use of neural networks, and the focus is the engineering applications of signal reconstruction algorithms.

We begin in Chapter 1 by introducing some background information about the research in signal reconstruction, chaotic systems and the application of chaotic signals in communications. The main purpose is to connect chaos and communications, and show the potential benefits of using chaos for communications. In Chapter 2 we will review the state of the art in signal reconstruction, with special emphasis laid on deterministic chaotic signals. The Takens' embedding theory will be reviewed in detail, covering the salient concepts of reconstructing the dynamics of a deterministic system from a higher-dimensional reconstruction space. The concepts of embedding dimension, embedding lag (time lag), reconstruction function, etc., will be discussed. Two basic embedding methods, namely topological and differential embeddings, will be described. Some unsolved practical issues will be discussed. A thorough review of the use of neural networks will be given in Chapter 3. Two main types of neural networks will be described in detail, namely, the radial-basis-function neural networks and the recurrent neural networks. The background theory,

network configurations, learning algorithms, etc., will be covered. These networks will be shown suitable for realizing the reconstruction tasks in Chapters 7 and 8. In Chapter 4 we will describe the reconstruction problem when signals are transmitted under ideal channel conditions. The purpose is to extend the Takens' embedding theory to time-varying continuous-time and discrete-time systems, i.e., nonautonomous systems. This prepares the readers for the more advanced discussions given in the next two chapters. In Chapter 5, we will review the Kalman filter (KF) and the extended Kalman filter (EKF) algorithms. In particular, we will study a new filter, i.e., the unscented Kalman filter (UKF). The issue for filtering a chaotic system from noisy observation by using the UKF algorithm will be investigated. A lot of new finding of the UKF algorithm will be demonstrated in this chapter. In Chapter 6, we will apply the UKF algorithm to realize the reconstruction of chaotic signals from noisy and distorted observation signals, respectively. Combining the modeling technique for signal with the UKF algorithm, the original UKF algorithm will be expanded to filter timevarying chaotic signals. We will also address the issues of blind equalization for chaos-based communication systems. Our start point is to make use of the UKF algorithm and the modeling technique for signal, and to realize a blind equalization algorithm. In Chapter 7 we will present novel concepts of using a radial-basisfunction neural network for reconstructing chaotic dynamics under noisy condition. A specific adaptive training algorithm for realizing the reconstruction task will be presented. Results in terms of the mean-squared-error versus the signal-to-noise ratio will be given and compared with those obtained from conventional reconstruction approaches. Also, as a by-product, a non-coherent detection method used in chaos-based digital communication systems will be realized based on the proposed strategy. In Chapter 8 we will continue our discussion of signal reconstruction techniques. Here, we will discuss the use of a recurrent neural network for reconstructing chaotic dynamics when the signals are transmitted through distorting and noisy channels. A special training algorithm for realizing the reconstruction task will be presented. This problem will also be discussed under the conventional viewpoint of channel equalization. In Chapter 9, the reconstruction of chaotic signals will be considered in terms of chaos

synchronization approaches. In particular, the problem of multiple-access spread-spectrum synchronization for single point to multiple point communication is considered in the light of a chaotic network synchronization scheme, which combines the Pecora-Carroll synchronization scheme and the OGY control method. The results indicate that such a network synchronization scheme is applicable to fast synchronization of multiple chaotic systems, which is an essential condition for realizing single point to multiple point spread-spectrum communications. Simulation results indicate that such a network synchronization-based communication system is effective and reliable for noisy and multi-path channels. The final chapter summarizes the key results in this research.

In closing this preface, we hope that this book has provided a readable exposition of the related theories for signal reconstructions as well as some detailed descriptions of specific applications in communications. We further hope that the materials covered in this book will serve as useful references and starting points for researchers and graduate students who wish to probe further into the general theory of signal reconstruction and applications.

Jiuchao Feng, Guangzhou Chi K. Tse, Hong Kong

Acknowledgements

The completion of this book would have been impossible without the help and support of several people and institutions. We wish to express our most grateful thanks to Prof. Ah-Chung Tsoi from University of Wollongong, Australia, and Prof. Michael Wong from Hong Kong University of Science and Technology, Hong Kong, who have read an early version of this book (which was in the form of a Ph.D. thesis) and have offered countless suggestions and comments for improving the technical contents of the book.

We also wish to thank Dr. Francis Lau and Dr. Peter Tam from Hong Kong Polytechnic University, Hong Kong, for many useful and stimulating discussions throughout the course of our research.

The first author gratefully acknowledges the Hong Kong Polytechnic University for providing financial support during his Ph.D. study. He also thanks the following institutes and departments for their financial support in the course of preparing this book and in its production: The Natural Science Foundation of Guangdong Province, China (Grant Number 05006506); The Research Foundation of Southwest China Normal University, China (Grant Number 413604); The Natural Science Foundation of Guangdong Province, China, for Team Research (Grant Number 04205783); The Program Foundation for New Century Excellent Talents in Chinese University (Grant Number NCET-04-0813); The Key Project Foundation of the Education Ministry of China (Grant Number 105137); The National Natural Science Foundation of China (Grant Number 60572025); The publishing Foundation for Postgraduate's Textbook in South China University of Technology, China. He is also grateful to his graduate student Shiyuan Wang and Hongjuan Fan for their simulation work in partial chapters.

Last, but not least, we wish to thank our families for their patience, understanding and encouragement throughout the years.

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Chapter 1 Chaos and Communications

Traditionally, signals (encompassing desired signals as well as interfering signals) have been partitioned into two broadly defined classes, i.e., stochastic and deterministic. Stochastic signals are compositions of random waveforms with each component being defined by an underlying probability distribution, whereas deterministic signals are resulted from deterministic dynamical systems which can produce a number of different steady state behaviors including DC, periodic, and chaotic solutions. Deterministic signals may be described mathematically by differential or difference equations, depending on whether they evolve in continuous or discrete-time.

DC is a nonoscillatory state. Periodic behavior is the simplest type of steady state oscillatory motion. Sinusoidal signals, which are universally used as carriers in analog and digital communication systems, are periodic solutions of continuous-time deterministic dynamical systems.

Deterministic dynamical systems also admit a class of nonperiodic signals, which are characterized by a continuous "noiselike" broad power spectrum. This is called chaos.

Historically, at least three achievements were fundamental to the acceptance of communication using chaos as a field worthy of attention and exploitation.

The first was the implementation and characterization of several electronic circuits exhibiting chaotic behavior in early 1980's. This brought chaotic systems from mathematical abstraction into application in electronic engineering.

The second historical event in the path leading to exploitation for chaosbased communication was the observation make by Pecora and Carroll in 1990 that two chaotic systems can synchronize under suitable coupling or driving conditions. This suggested that chaotic signals could be used for

1.1 Historical Account

communication, where their noiselike broadband nature could improve disturbance rejection as well as security.

A third, and fundamental, step was the awareness of the nonlinear (chaos) community that chaotic systems enjoy a mixed deterministic / stochastic nature [1-4]. This had been known to mathematicians since at least the early 1970's, and advanced methods from that theory have been recently incorporated in the tools of chaos-based communication engineering. These tools were also of paramount importance in developing the quantitative models needed to design chaotic systems that comply with the usual engineering specifications.

The aim of this chapter is to give a brief review of the background theory for chaos-based communications. Based on several dynamical invariants, we will quantitatively describe the chaotic systems, and summarize the fundamental properties of chaos that make it useful in serving as a spread-spectrum carrier for communication applications. Furthermore, chaotic synchronization makes it possible for chaos-based communication using the conventional coherent approach. In the remaining part of this chapter, several fundamental chaotic synchronization schemes, and several chaos-based communication schemes will be reviewed. Finally, some open issues for chaos-based communications will be discussed.

1.1 Historical Account

In 1831, Faraday studied shallow water waves in a container vibrating vertically with a given frequency ω . In the experiment, he observed the sudden appearance of subharmonic motion at half the vibrating frequency $(\omega/2)$ under certain conditions. This experiment was later repeated by Lord Rayleigh who discussed this experiment in the classic paper *Theory of Sound*, published in 1877. This experiment has been repeatedly studied since 1960's. The reason why researchers have returned to this experiment is that the sudden appearance of subharmonic motion often prophesies the prelude to chaos.

Poincaré discovered what is today known as homoclinic trajectories in the state space. In 1892, this was published in his three-volume work on Celestial Mechanics. Only in 1962 did Smale prove that Poincaré's homoclinic trajectories are chaotic limit sets [5].

In 1927, Van der Pol and Van der Mark studied the behavior of a neon bulb RC oscillator driven by a sinusoidal voltage source [6]. They discovered that by increasing the capacitance in the circuit, sudden jumps from the drive frequency, say ω to $\omega/2$, then to $\omega/3$, etc., occurred in the response. These frequency jumps were observed, or more accurately heard, with a telephone receiver. They found that this process of frequency demultiplication (as they called it) eventually led to irregular noise. In fact, what they observed, in today's language, turned out to be caused by bifurcations and chaos. In 1944, Levinson conjectured that Birkhoff's remarkable curves might occur in the behavior of some third-order systems. This conjecture was answered affirmatively in 1949 by Levinson [7].

Birkhoff proved his famous Ergodic Theorem in 1931 [8]. He also discovered what he termed remarkable curves or thick curves, which were also studied by Charpentier in 1935 [9]. Later, these turned out to be a chaotic attractor of a discrete-time system. These curves have also been found to be fractal with dimension between 1 and 2.

In 1936, Chaundy and Phillips [10] studied the convergence of sequences defined by quadratic recurrence formulae. Essentially, they investigated the logistic map. They introduced the terminology that a sequence oscillates irrationally. Today this is known as chaotic oscillation.

Inspired by the discovery made by Van der Pol and Van der Mark, two mathematicians, Cartwright and Littlewood [11] embarked on a theoretical study of the system studied earlier by Van der Pol and Van der Mark. In 1945, they published a proof of the result that the driven Van der Pol system can exhibit nonperiodic solutions. Later, Levinson [7] referred to these solutions as singular behavior.

Melnikov [12] introduced his perturbation method for chaotic systems in 1963. This method is mainly applied to driven dynamical systems.