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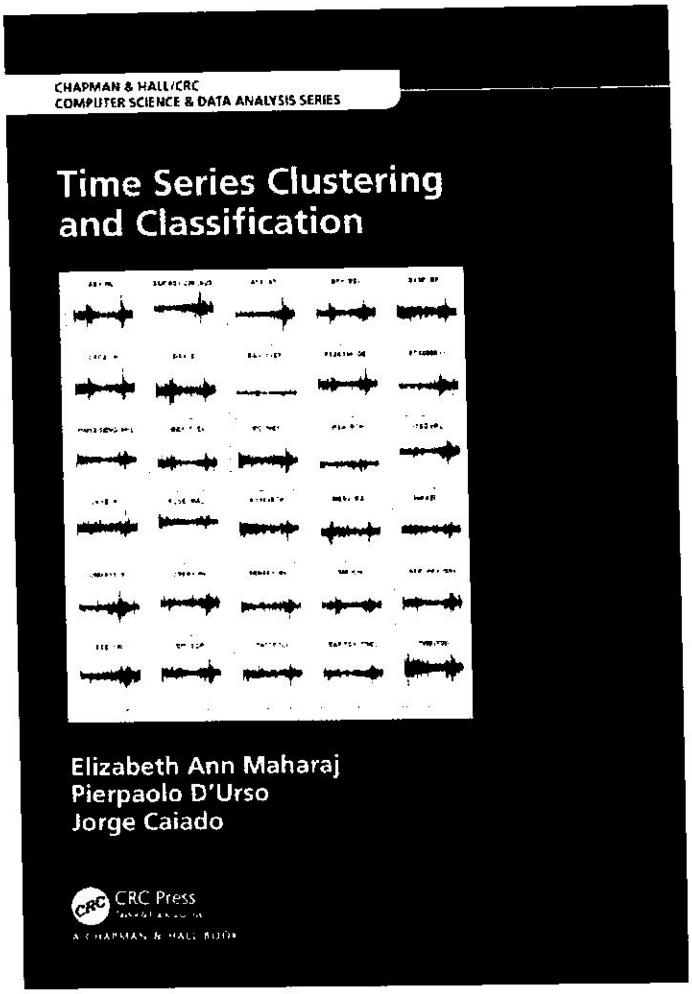

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Time Series Clustering and Classification

1st Edition

Elizabeth Ann Maharaj, Pierpaolo D'Urso, Jorge Caiado

Chapman and Hall/CRC
Published April 12, 2019
Reference - 228 Pages - 46 B/W Illustrations
ISBN 9781498773218 - CAT# K29548
Series: Chapman & Hall/CRC Computer Science & Data Analysis

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Summary

The beginning of the age of artificial intelligence and machine learning has created new challenges and opportunities for data analysts, statisticians, mathematicians, econometricians, computer scientists and many others. At the root of these techniques are algorithms and methods for clustering and classifying different types of large datasets, including time series data.

Time Series Clustering and Classification includes relevant developments on observation-based, feature-based and model-based traditional and fuzzy clustering methods, feature-based and model-based classification methods, and machine learning methods. It presents a broad and self-contained overview of techniques for both researchers and students.

Features

- Provides an overview of the methods and applications of pattern recognition of time series
- Covers a wide range of techniques, including unsupervised and supervised approaches
- Includes a range of real examples from medicine, finance, environmental science, and more
- R and MATLAB code, and relevant data sets are available on a supplementary **website**

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Time Series Clustering and Classification

Elizabeth Ann Maharaj
Department of Econometrics and Business Statistics, Monash University, Australia

Pierpaolo D'Urso
Department of Social and Economic Sciences, Sapienza – University of Rome, Italy

Jorge Caiado
Department of Mathematics, ISEG, Lisbon School of Economics & Management, University of Lisbon, Portugal

CRC Press
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CRC Press
Taylor & Francis Group
6000 Broken Sound Parkway NW, Suite 300
Boca Raton, FL 33487-2742

Printed on acid-free paper

International Standard Book Number-13: 978-1-4987-7321-8 (Hardback)

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We dedicate this book to:

Paul and Claudia

Giordana

Dina, Maria, and Martim

Contents

Preface

The beginning of the age of artificial intelligence and machine learning has created new challenges and opportunities for data analysts, statisticians, mathematicians, econometricians, computer scientists and many others. At the root of these techniques, we find algorithms and methods for clustering and classifying different types of large datasets, including time series data, spatial data, panel data, categorical data, functional data and digital data. The emphasis of this book is on the clustering and classification of time series data, and it can be regarded as a reference manual on this topic.

The subject of clustering and classification of time series with applications in fields such as geology, medicine, environmental science, astronomy, finance and economics, has attracted substantial attention over the last two to three decades. Our goal in publishing this book is to provide research students and other researchers with a broad spectrum of techniques, all of which are located in one place. It provides the relevant developments in observation-based, feature-based and model-based traditional and fuzzy clustering methods, feature-based and model-based classification methods, and machine learning methods, in a concise manner using applied and simulated studies. Presently, these techniques can be found scattered in articles in many different journals and book chapters.

In truth, we have been researching these topics for more than 20 years. Our research has led to numerous publications in scientific journals in several fields, such as economics, business, management, finance, statistics, data analysis, marketing, medicine, physics, biology, hydrology and many others. We have included our work as well as works of several other authors, thus collecting as many methods on the clustering and classifying time series as we could. However, it should be noted that the book contains as many methods as we were aware of at the time of writing, and clearly new methods have since been proposed and published in journals.

We have divided the book into three parts and eleven chapters. Chapter 1 begins with a very brief overview of the contents of the book. Chapter 2 introduces some fundamental concepts in time series, spectral and wavelet analyses that are necessary for understanding the classification and clustering methods discussed in the book. Part I is about unsupervised clustering techniques for time series and consists of five chapters. Chapter 3 outlines the basic concepts of traditional cluster analysis. Chapter 4 discusses fuzzy clustering methods. Chapter 5 considers observation-based clustering methods. Chapter 6 deals with feature-based methods in the time, frequency and wavelet domains. Chapter 7 discusses model-based clustering methods, while Chapter 8 discusses other time series clustering approaches. Part II, which deals with supervised classification techniques for time series, consists of two chapters. Chapter 9 discusses discriminant analysis and classification methods based on time series features and models. Chapter 10 explores machine learning methods, such as classification trees, support vector machines and nearest neighbour algorithms. Finally, Part III, which consists of Chapter 11, presents links to computer programs in Matlab and R, data sets and real examples through demonstration.

It would not have been possible to complete this project successfully without the unconditional support of several people. Firstly, we are greatly indebted to our families for their constant support and patience. Secondly, we would like to thank Nuno Crato, Daniel Peña, João Bastos, Andrés Alonso, Livia De Giovanni, José Vilar and the Taylor & Francis's team for their helpful suggestions and contributions. Finally, we would like to thank some of our colleagues in our departments at Monash University, Sapienza - University of Rome and University of Lisbon for their support and encouragement.

A comprehensive webpage providing additional material to support this book can be found at http://www.tsclustering.homepage.pt/

Elizabeth Ann Maharaj, Melbourne, Australia
Pierpaolo D'Urso, Rome, Italy
Jorge Caiado, Lisbon, Portugal
February 2019

Authors

Elizabeth Ann Maharaj is an Associate Professor in the Department of Econometrics and Business Statistics at Monash University, Australia. She has a Ph.D. from Monash University on the Pattern Recognition of Time Series. Ann is an elected member of the International Statistical Institute (ISI), a member of the International Association of Statistical Computing (IASC) and of the Statistical Society of Australia (SSA). She is also an accredited statistician with the SSA. Ann's main research interests are in time series classification, wavelets analysis, fuzzy classification and interval time series analysis. She has also worked on research projects in climatology, environmental science, labour markets, human mobility and finance.

Pierpaolo D'Urso is a full professor of Statistics at Sapienza - University of Rome. He is the chair of the Department of Social and Economic Sciences, Sapienza - University of Rome. He received his Ph.D. in Statistics and his bachelor's degree in Statistics both from Sapienza. He is associate editor and member of the editorial board of several journals. He has been member of several program committees of international conferences and guest editor of special issues. His recent research activity is focussed on fuzzy clustering, clustering and classification of time series, clustering of complex structures of data, and statistical methods for marketing, local labour systems, electoral studies and environmental monitoring.

Jorge Caiado has a Ph.D. in Applied Mathematics to Economics and Management. He is a Professor of Econometrics and Forecasting Methods at the Lisbon School of Economics and Management (ISEG) and Researcher at the Centre for Applied Mathematics and Economics. His research in econometrics, finance, time series analysis, forecasting methods and statistical software has led to numerous publications in scientific journals and books. He is serving as econometric and statistical consultant and trainer for numerous companies and organizations including central banks, commercial and investment banks, bureau of statistics, bureau of economic analysis, transportation and logistics companies, health companies and insurance companies. He is also a co-founder and partner of GlobalSolver.

1

Introduction

CONTENTS

1.1 Overview

Time series clustering and classification has relevance in a diverse range of fields which include geology, medicine, environmental science, finance and economics. Clustering is an unsupervised approach to grouping together similar items of interest and was initially applied to cross-sectional data. However, clustering time series data has become a popular research topic over the past three to four decades and a rich literature exists on this topic. A set of time series can be clustered using conventional hierarchical and non-hierarchical methods, fuzzy clustering methods, machine learning methods and model-based methods.

Actual time series observations can be clustered (e.g., D'Urso, 2000; Coppi and D'Urso, 2001; D'Urso, 2005), or features extracted from the time series can be clustered. Features are extracted in the time, frequency and wavelets domains. Clustering using time domain features such as autocorrelations, partial autocorrelations, and cross-correlations have been proposed by several authors including Goutte et al. (1999), Galeano and Peña (2000), Dose and Cincotti (2005), Singhal and Seborg (2005), Caiado et al. (2006), Basalto et al. (2007), Wang et al. (2007), Takayuki et al. (2006), Ausloos and Lambiotte (2007), Miskiewicz and Ausloos (2008), and D'Urso and Maharaj (2009).

In the frequency domain, features such as the periodogram and spectral and cepstral ordinates are extracted; included in the literature are studies by Kakizawa et al. (1998), Shumway (2003), Caiado et al. (2006), Maharaj and D'Urso (2010, 2011).

The features extracted in the wavelets domain are discreet wavelet transforms (DWT), wavelet variances and wavelet correlations and methods have been proposed by authors such as Zhang et al. (2005), Maharaj et al. (2010), D'Urso and Maharaj (2012) and D'Urso et al. (2014). As well, time series can be modelled and the parameters estimates used as the clustering variables. Studies on the model-based clustering method include those by Piccolo (1990), Tong and Dabas (1990), Maharaj (1996, 2000), Kalpakis et al. (2001), Ramoni et al.(2002), Xiong and Yeung (2002), Boets (2005), Singhal and Seborg (2005), Savvides et al. (2008), Otranto (2008), Caiado and Crato (2010), D'Urso et al. (2013), Maharaj et al. (2016) and D'Urso et al. (2016).

Classification is a supervised approach to grouping together items of interest and discriminant analysis and machine learning methods are amongst the approaches that have been used. Initially classification was applied to cross-sectional data but a large literature now exists on the classification of time series which includes many very useful applications. These time series classification methods include the use of feature-based, model-based and machine learning techniques. The features are extracted in the time domain (Chandler and Polonok, 2006; Maharaj, 2014), the frequency domain (Kakizawa et al., 1998; Maharaj, 2002; Shumway, 2003) and the wavelets domain (Maharaj, 2005; Maharaj and Alonso, 2007, 2014; Fryzlewicz and Omboa, 2012). Model-based approaches for time series classification include ARIMA models, Gaussian mixture models and Bayesian approaches (Maharaj, 1999, 2000; Sykacek and Roberts, 2002; Liu and Maharaj, 2013; Liu et al., 2014; Kotsifakos and Panagiotis, 2014), while machine learning approaches include classification trees, nearest neighbour methods and support vector machines (Douzal-Chouakria and Amblard, 2000; Do et al., 2017; Gudmundsson et al., 2008; Zhang et al., 2010).

It should be noted that clustering and classifying data evolving in time is substantially different from classifying static data. Hence, the volume of work on these topics focuses on extracting time series features or considering specific time series models and also understanding the risks of directly extending the common-use metric for static data to time series data.

1.2 Examples

We discuss three examples to illustrate time series clustering and classification before going into detail about these and other approaches in subsequent chapters. The first example illustrates clustering using time domain features, the second is observation-based and the third illustrates classification using wavelet features.

Example 1.1 D'Urso and Maharaj (2009) illustrate through simulated data, crisp clustering (traditional hierarchical and non-hierarchical) and fuzzy clustering of time series using the time domain features of autocorrelations. The aim here is to bring together series generated from the same process in order to understand the classification success. Fig. 1.1 shows the autocorrelation

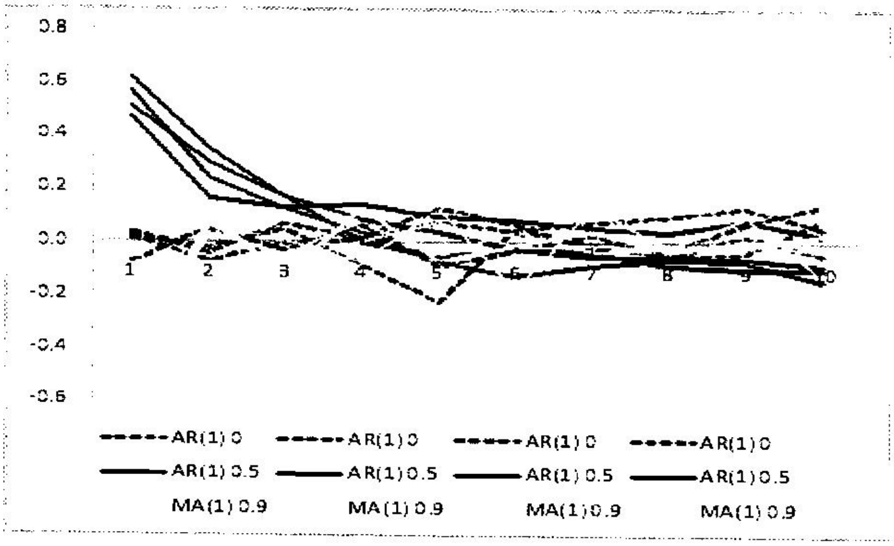

FIGURE 1.1: Autocorrelation function of series generated from three processes.

TABLE 1.1: Percentage of correct classifications using autocorrelation.

	Percentage of correct classifications
k-means	83.5
Single Linkage	85.5
Complete Linkage	93.0
Average Linkage	92.5
Ward's Method	97.8
Fuzzy c-means	87.9 - 99.5

functions (ACFs) over 10 lags for 12 simulated series, 4 of each generated from an AR(1) process with $\phi = 0$ (a white noise process), an AR(1) process with $\phi = 0.5$ and an MA(1) process with $\theta = 0.9$. The patterns of the ACFs associated with each process are clearly distinguishable at the early lags. Table 1.1 show a summary of results of clustering the 12 series, 4 from each process over 1000 simulations. The fuzzy c-means results are subject to specific choices of parameter values. It is clear from the results in Table 1.1 that the autocorrelations provide good separation features.

Example 1.2 D'Urso (2005) illustrates the application of a fuzzy clustering model to a set of short synthetic series consisting of three well-separated clusters of time series with 4, 2, and 2 time series each, respectively, and one switching time series (the 7th time series). This illustration is presented in

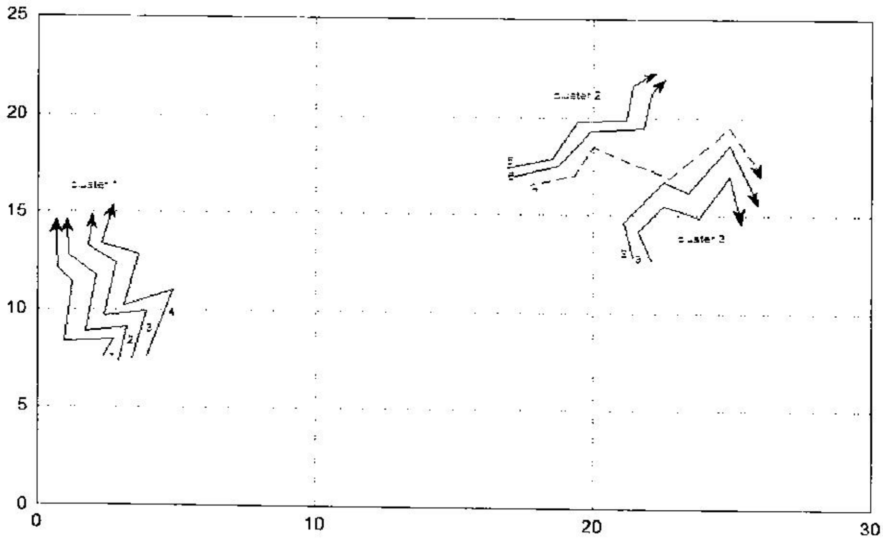

FIGURE 1.2: A set of short time series including a switching time series.

Fig.1.2 from where it can be observed that the switching time series, for the initial time period, presents an instantaneous position and slope similar to the time series belonging to Cluster 2 (series 5 and 6), while at a later time, it has an instantaneous position and slope similar to the time series belonging to Cluster 3 (series 8 and 9). Table 1.2 shows the membership degrees of each time series in each cluster and it is clear that series 1-4, 5-6 and 8-9 have crisp memberships in Clusters 1, 2 and 3 respectively, while series 7 has fuzzy membership in Clusters 2 and 3.

TABLE 1.2: Membership degrees of each time series in each cluster.

	Cluster 1	Cluster 2	Cluster 3
1	0.973	0.013	0.014
2	0.991	0.005	0.004
3	0.995	0.003	0.002
4	0.961	0.024	0.015
5	0.003	0.977	0.002
6	0.001	0.997	0.002
7	0.084	0.497	0.419
8	0.004	0.027	0.969
9	0.001	0.002	0.997

Example 1.3 Maharaj and Alonso (2014) illustrate the classification of multivariate synthetic time series using the wavelet features of variances and correlations with both linear and quadratic discriminant functions. Fig. 1.3 shows

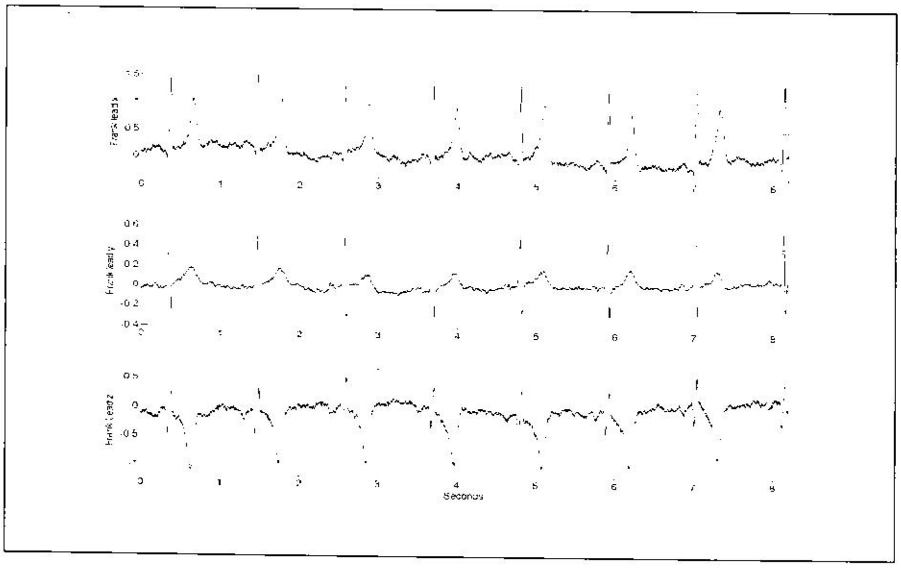

FIGURE 1.3: Synthetic ECG signals.

synthetic electrocardiogram (ECG) signals for three leads based on a three-dimensional formulation of a single dipole of the heart. Refer to Sameni et al. (2007) and Clifford et al. (2010) for more details on the development of these synthetic signals. The signals shown in Fig. 1.3 could represent those of an individual with normal heart beats. One of the parameters, λ, can be varied to simulate signals of an individual with the heart condition, acute myocardial infarction (AMI). This is done by setting $\lambda > 1$. Fig. 1.4 shows a single beat of a synthetic ECG that is normal with four scenarios of AMI when λ is varied.

For each population (Normal and AMI), 100 ECGs, each of length T=4096 were simulated and linear and quadratic discriminant analysis applied to the wavelet variances and wavelet correlations extracted from the signals. Fig. 1.5 and 1.6 show the classification rates (from hold-out-one cross-validation) using several wavelet filters with linear and quadratic discriminant functions, respectively. The results reveal with the exception of the scenario where λ was set to the smallest value greater than one, the wavelet variances and the combination of wavelet variance and correlations appear to be reasonably good features for discriminating between normal beats and those associated with AMI.

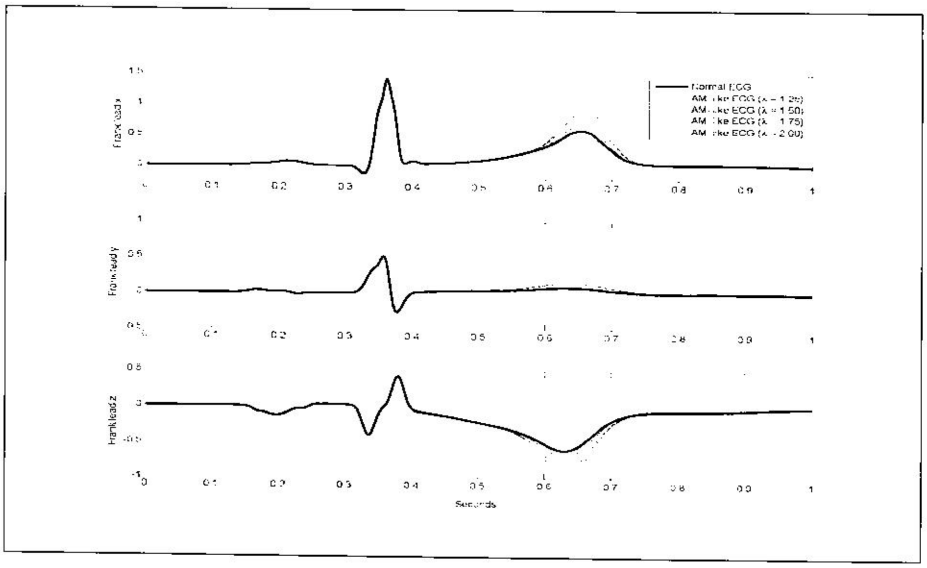

FIGURE 1.4: Single beat of a synthetic ECG signal: normal and acute myocardial infarction.

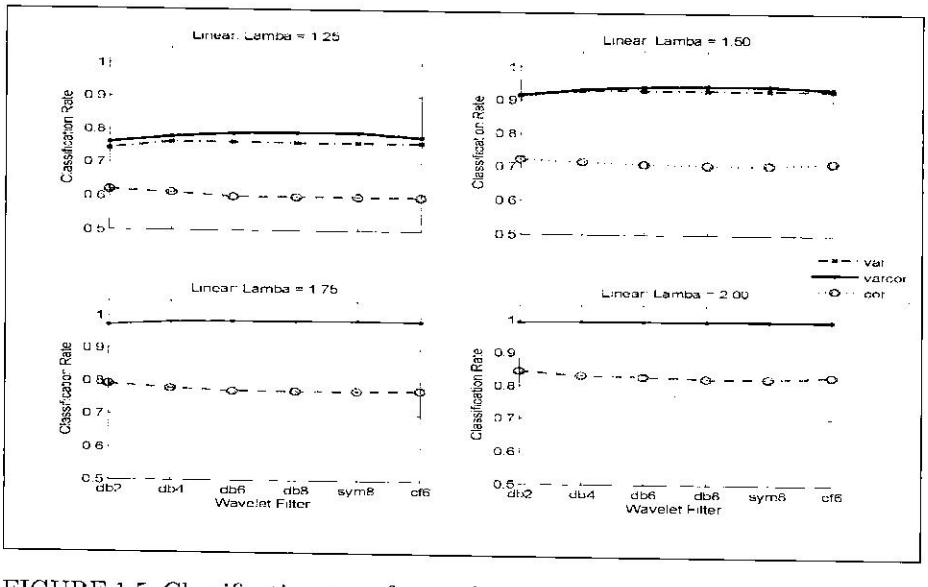

FIGURE 1.5: Classification rates for synthetic ECGs using linear discriminant functions.

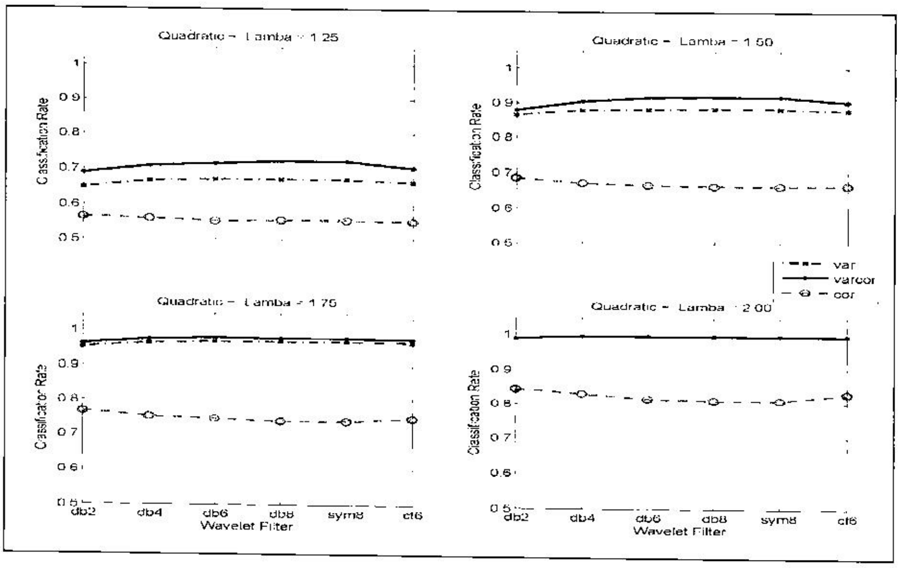

FIGURE 1.6: Classification rates for synthetic ECGs using quadratic discriminant functions.

1.3 Structure of the book

After this chapter, time series concepts essential for what is to follow are discussed in Chapter 2. The rest of the book is divided into three parts. Part 1 consisting of Chapters 3 to 8 is on unsupervised approaches to classifying time series, namely, clustering techniques. Traditional cluster analysis and fuzzy clustering are discussed in Chapters 3 and 4, respectively, and this is followed by observation-based, feature-based, model-based clustering, and other time series clustering approaches in Chapters 5 to 8.

Part 2 is on supervised classification approaches. This includes feature-based approaches in Chapter 9 and other time series classification approaches in Chapter 10. Throughout the book, many examples of simulated scenarios and real-world applications are provided, and these are mostly drawn from the research of the three authors. Part 3 provides links to software packages, some specific programming scripts used in these applications and simulated scenarios, as well as links to relevant data sets.

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