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Cairo University
Institute of Statistical Studies & Research
Dept. of Mathematical Statistics

**Nonparametric Bayesian Regression Using Wavelet
Analysis**

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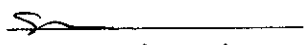
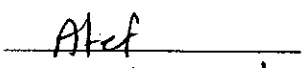
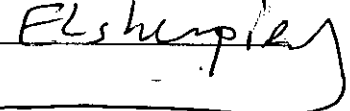
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**TO MY MOTHER, MY
WIFE AND MY SON
YAHYA**

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Chapter I

Introduction

In recent years there has been a considerable development in the use of wavelet methods in statistics. The wavelet analysis, in common with many other mathematical and algorithmic techniques used in statistics, did not originate from statisticians, nor with statistical applications in mind. The wavelet transform is a synthesis of ideas emerging over many years from different fields, notably mathematics, physics and engineering. Like Fourier analysis, with which analogies are often drawn, wavelet methods are general mathematical tools.

The wavelet transform can provide economical and informative mathematical representations of many different objects of interest (e.g. functions, signals or images). Such representations can be obtained relatively quickly and easily through fast algorithms which are now readily available in a variety of computer packages. As a result, wavelets are used widely, not only by mathematicians in areas such as functional and numerical analysis, but also by researchers in the natural sciences such as physics, chemistry and biology, and in applied disciplines such as computer science, engineering and econometrics. Signal processing in general, including image analysis and data compression, is the obvious example of an applied field of multidisciplinary interest where the use of wavelets has proved of significant value. Good general surveys of wavelet applications in that and other fields are given, for example, in Morlet et al. (1982), Mallat (1986), Strang (1986), Daubechies (1988), Meyer (1993), Meyer (1993), Young (1993), Aldroubi and Unser (1996) or Mallat (1998), Fernandez (2005), Crowley

(2007), Ge. (2008) and Rua.(2010). Within that framework of multidisciplinary interest, statisticians are among the more recent users of the technique. They bring their own particular perspective to wavelet applications in areas such as signal processing and image analysis. In addition they have explored a range of wavelet applications which are more exclusively statistical, including nonparametric regression and density estimation.

In general, wavelet is a complex valued function defined on some space. But, we describe a wavelet as a real valued function defined on the real line. It may be viewed as a function of time t or a function of spatial variable x .

Wavelets can be viewed as orthonormal basis functions that are localised in both time and frequency, with time-widths adapted to their frequency. This means that they are able to model a signal with high frequency components, such as discontinuities, in contrast to more traditional statistical methods for estimating an unknown function.

A second advantage comes from the fast orthogonal discrete wavelet transform, which makes the application of wavelets available. A third advantage is that wavelets often provide sparse and, therefore, economical representations of functions. These key properties make wavelets an excellent tool for statistical denoising.

Wavelet theory can be viewed as a modern improvement and extension of the Fourier theory. Wavelet approach is also flexible in handling irregular data sets. It can represent complex structures without the knowledge of the underlying function that generated the structure. It can precisely locate the jump discontinuities, singularities (local extrema, inflection points, cusps, etc), and isolated shocks in dynamical systems.

Wavelet representation of a time series can be done in a manner that is suitable for analyzing non-stationarity of the stochastic process that generated the time series.

Traditional noise removal methods assume the smoothness or at least local smoothness of the underlying signal $f(t)$ while the observed data

$$f(t) + \eta(t),$$

where the noise, $\eta(t)$, is not smooth.

In this thesis, chapter II introduces some of the mathematical notations and tools without proofs that are useful in an understanding of wavelet theory. Fourier transform and its properties, time-frequency analysis and A Short Notes about Time series will be illustrated.

Chapter III introduces Review of Wavelets and Nonparametric Regression. section 1 as introduction about modification Morlet to the Gabor transformation, section 2 discusses continuous and discrete wavelet transform, inverse wavelet Transform, section 3 discusses multiresolution Analysis and Construction of Wavelets and Matrix Expression of DWT section 4 discusses in this section, some types of wavelets are presented like as Haar, Daubechies, and Coiflet wavelets. Section 5 Nonparametric Regression, Kernel Estimations, Local Polynomial Fitting, Smoothing Spline Estimations, Orthogonal Series Estimations. Section 6, wavelet estimation, bayesian and wavelet Shrinkage and Thresholding.

The objective of this chapter IV is to study the effect of wavelet filter on the time series data. By using wavelet transformation and hard thresholding technique, the ARIMA model decomposed into sum of two ARIMA models and the relation between sum of square errors due to the ARIMA model and sum of two ARIMA models will be discussed. . By