

# Chapter 38

## Wavelet Transform–Based Soft Computational Techniques and Applications in Medical Imaging

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### ABSTRACT

*The aim of this chapter is to highlight the biomedical applications of wavelet transform based soft computational techniques i.e. wavenet and corresponding research efforts in imaging techniques. A brief introduction of wavelet transform, its properties that are vital for biomedical applications touched by various researchers and basics of neural networks has been discussed. The concept of wavelon and wavenet is also discussed in detail. Recent survey of wavelet based neural networks in medical imaging is another facet of this script, which includes biomedical image denoising, image enhancement and functional neuro-imaging, including positron emission tomography and functional MRI.*

### 1. INTRODUCTION

The *wavelet transform (WT)* proves to be the most neoteric solution to conquer the shortcomings of the *Fourier Transform (FT)*. The wavelet functions are localized in space as well as in frequency domains. *Wavelets*, generally speaks about time-scale representations. In contrast of biomedical signals, most of the statistical characteristics of biomedical signals are non-stationary. In particular, the analysis of biological signal should exhibit good resolution in both time and frequency domain. In fact, there are also several other time-frequency analysis methods such as *short-term Fourier transform (STFT)* (Allen and Rabiner 1977), *Hilbert-Huang transform (HHT)* (Boashash and Black 1987), *Wigner-Ville distribution function (WDF)* (Mallat 1989), etc. These methods were proposed to represent the signal in both time and frequency domain simultaneously. In STFT, one has to apply a window to obtain the time-frequency resolution in STFT. The performance of STFT is highly depended on the size of the window. The large

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window size in STFT improves the frequency resolution but at the same time assumption of stationary within the window may be compromised. In another hand, choosing a small window size may lead to poor frequency resolution. WDF offers high clarity in both time and frequency domain, but they suffer from cross term problem. WDF is not suitable for the most of biomedical signals, such as (i) *either they have multiple components* (ii) *or their phase terms are higher than second order*.

The wavelet transform provides an alternative way to analyze non-stationary biomedical signals which have the variable time frequency resolution over the time-frequency plane (Daubechies 1988; Abramovich et al. 2000; Singh and Urooj 2015). The WT decomposes a biomedical signal into frequency bands that are localized in both time and frequency. At low frequency, the window size kept long in order to detect the abrupt changes in the signal on the other hand, at the high frequency the window size kept short. The localization property of WT isolates the singularities and irregular structure in the signal. The WT require little storage space time as match up to other time-frequency analysis. In WT, the size and dimensions of the outputs are almost same as the input, and this scenario results in a very powerful features for the biomedical signal image processing. Nowadays, WT is becoming a very commanding and acknowledged technique in image processing feature detection, noise reduction and signal compression (Ahmed et al 2000; Carmona et al 1997; Louis and Rieder 1997). With the development of computer techniques and improvement in fast and more accurate algorithms, the WT has been widely concerned with application in biomedical signal processing (BSP), magnetic resonance imaging (MRI), computerized tomography (CT), radiography, electrocardiogram (ECG), and electroencephalography (EEG) (Akay 1995)

## **2. WAVELET TRANSFORM**

The wavelets are *wave-like oscillation* whose amplitude begins at zero, increases and then back to zero. In mathematical term, a wavelet series is a combination of square-integrable function by some orthonormal series generated by a wavelet. The wavelet transform provides time-frequency information simultaneously, hence giving a time-frequency representation of image analysis.

### **2.1 A Short Development History of Wavelet Transform**

The first historical reference of the wavelet is *Haar Wavelet*, introduced by Alfred Haar in 1910. His research on the orthogonal system of function led to the development of a set of the rectangular basis function. The Haar transform is a dyadic, orthonormal wavelet transform (Haar A 1910) with compact support. There are two primarily functions in wavelet analysis, the scaling function  $\phi$  (father wavelet) (Figure 1 and Figure 2) and the wavelet  $\psi$  (mother wavelet). Basically, the wavelet analysis is based on Haar scaling function. The Haar function can be defined as:

$$\phi(x) = \begin{cases} 1, & \text{if } 0 \leq x < 1 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

and mother function can be written as:

$$\psi(x) = \phi(2t) - \phi(2x - 1) \quad (2)$$

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