Chapter

Introductory Chapter: Signal and Image Denoising

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1. Introduction

Both signal and image are unfortunately degraded by different factors that affect as noise during acquisition or transmission. Those noisy effects decrease the performance of visual and computerized analysis. It is clear that cancelling the noise from the signal facilitates its processing. The denoising process can be described as to cancel the noise while retaining and not distorting the quality of processed signal or image [1–4]. The conventional manner of denoising for noise cancelling consists in applying a band/low-pass filter with cut-off frequencies. Though conventional filtering methods are capable to suppress a relevant of the noise, they are not able when the noise is located in the band of the signal to be processed. Consequently, numerous denoising techniques were introduced in order to overcome this problem. The algorithms and processing approaches employed for signals can be also used for images and this is due to fact that an image is viewed as a two-dimensional signal. Consequently, the signal processing methods for one-dimensional signals can be adapted for processing two-dimensional images. Due to the fact that the origin and non-stationarity of the noise corrupt the signal, it is not easy to model it. Nevertheless, when the noise can be considered as stationary, an empirically recorded signal that is degraded by an additive noise is formulated as follows [1]:

$$y(j) = x(j) + \sigma \cdot \varepsilon(j), j = 0, 1, \dots, n-1 \tag{1}$$

With $y(j)$ is the noisy signal, $x(j)$ is the clean signal and $\varepsilon(j)$ are independently normal random variables and σ designates the level noise corrupting (j). The noise can be modeled as stationary independent zero-mean white Gaussian variables [5, 6]. If this model is employed, the objective of noise cancellation consists in reconstructing $x(j)$ from a finite set of $y(j)$ values without considering a particular structure for the signal. The commonly used approach for noise cancellation models noise as a high frequency signal corrupting in additive manner, the clean signal. These high frequencies can be bringing out employing Fourier transform, ultimately cancelling them by an adequate filtering. This noise cancelling method is conceptually clear and efficient since it is depending only on computing DFT (Discrete Fourier Transform) [7]. However, there is some issue that should be considered. The most important having same frequency since the noise owns important information in the original signal. Filtering out these frequency components introduces noticeable information loss of the desired signal. It is clear that a technique is strongly needed for preserving the prominent part of the signal having relatively high frequencies as the noise has. As an example, the wavelet-based noise removal approaches have provided this prominent part conservation. De-noising of natural images degraded by Gaussian Noise employing wavelet based denoising techniques are very efficient due to the fact that it is able to capture the energy of a signal in few energy transform values. The wavelet de-noising scheme thresholds the wavelet coefficients arising from the standard discrete wavelet transform [8]. In Ref. [8], it was introduced to investigate the suitability of different wavelet bases and the size of different neighborhood on the performance of image denoising techniques in term of peak signal-to-noise ratio (PSNR) [8].

In Ref. [9], Di Liu and Xiyuan Chen introduced an image denoising technique applying an ameliorated bidimensional empirical mode decomposition (BEMD) and using soft interval thresholding. At first step, a noise compressed image is constructed. After that, this noise compressed image is decomposed by applying BEMD into a series of intrinsic mode functions (IMFs), which are separated into signal-dominant IMFs and noise-dominant IMFs employing a similarity measure based on $\ell 2$-norm and a probability density function, and a soft interval thresholding is employed in adaptive manner for cancelling the noise inherent in noise-dominant IMFs. The denoised image is finally obtained *via* the combination of the signal dominant IMFs and the denoised noise dominant IMFs. The performance of this image denoising technique [1] was applied to multiple images with different sorts of noise, and the results obtained from the application of this technique [1] were compared to those obtained from the application the some traditional techniques in different noisy environments. Simulation results in terms of peak signal-to-noise ratio, mean square error, and energy of the first IMF, proved that this denoising technique [9] outperforms the other denoising techniques.

Hybridization of the BEMD with denoising approaches has been introduced in the literature as an efficient image denoising technique.

In Ref. [10], Student's probability density function was proposed in the calculation of the Mean Envelope of the data during the BEMD sifting process for making it robust to values that are far from the mean. The obtained BEMD was named tBEMD. To prove the efficiency of the tBEMD, many image denoising approaches were used in the tBEMD field. Among these approaches, we can mention the discrete wavelet transform (DWT), fourth-order partial differential equation (PDE), linear complex diffusion process (LCDP), and nonlinear complex diffusion process (NLCDP). For experiments, a standard digital image and two biomedical images are considered. The original images are degraded by additive Gaussian Noise with three diverse levels. Based on PSNR (peak signal-to-noise ratio), the obtained results show that DWT, PDE, LCDP, and NLCDP, all perform better in the tBEMD domain compared to the conventional BEMD domain. Moreover, the tBEMD is faster than conventional BEMD in case where the noise level is low. However, in case where it is high, the calculation cost in terms of processing time is similar. The efficiency of the presented approach makes it promising for clinical applications.

This book is intended for engineers and researchers in the fields of signal and image processing. Indeed, this book deal with a large number of signal and image denoising techniques. These techniques include an innovative image denoising approaches.

2. Examples of signal and image denoinsing

In this section, we will give some examples of signal and image denoising obtained from the application of the discrete wavelet transform (DWT).

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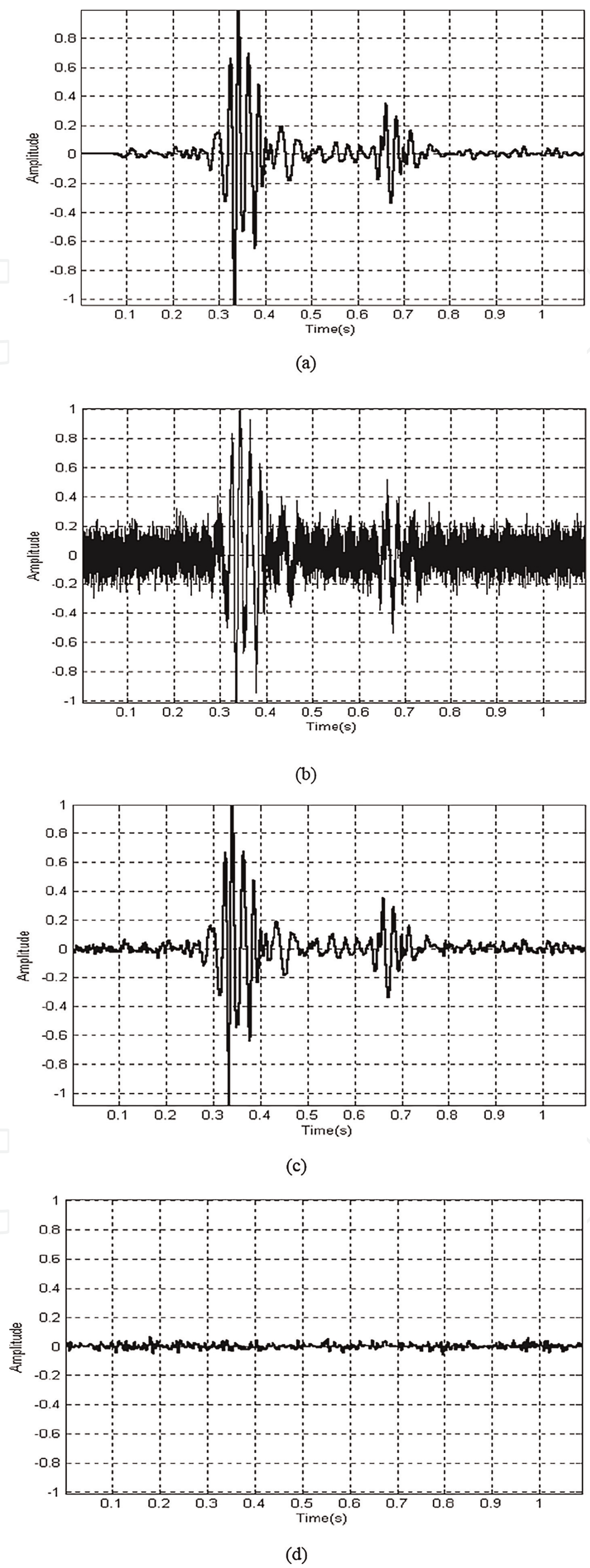

Figure 1.
An example of PCG denoising using DWT [1]: (a) clean PCG signal, (b) noisy PCG signal, (c) denoised PCG signal, (d) difference between the original and the denoised signal.

2.1 Phonocardiogram denoising

The acoustical vibrations records from the heart, acquired through microphones from human chest, named phonocardiogram (PCG), consist of both the murmurs and the heart sounds. Those records of acoustic signals are unfortunately corrupted by diverse factors which effecting as noise. Those effects cause the decreasing of the performance of visual and computerized analysis [1, 11, 12].

Figure 1 illustrates an example of PCG denoising using DWT.

According to **Figure 1**, the noise is considerably reduced and the waveform of the original signal is conserved because the difference between the original and the denoised signals is very small. Consequently, the denoising technique based on thresholding in DWT domain and applied in Ref. [1], shows its performance in noise reduction while conserving the information contained in the original PCG signal.

(a)

(b)

Figure 2.
An example of medical image denoising by applying thresholding in the DWT domain: (a) a noisy medical image with PSNR = 62 dB, (b) denoised image obtained from the application of a denoising technique based on thresholding in the DWT domain.

2.2 Image denoising

All digital images are degraded by different types of noise during their acquisition and transmission. As an example of these images, the medical one is likely disturbed by a complex sort of addition noise depending on the devices that are employed for capturing or storing it. There are no medical imaging devices that are noise free. The most commonly employed medical images are produced from MRI and CT equipment [1]. The additive noise corrupting medical image causes the reducing of the visual quality that complicates diagnosis and treatment.

Figure 2 illustrates an example of a medical image denoising using DWT.

A noise-added medical image and its denoised one obtained from employing a wavelet denoising technique are illustrated in **Figure 2**. The added noise has Gaussian distribution, and symlet 6, decomposition level of two, hard thresholding were used as the parameters for the application the wavelet-based denoising technique [1].

3. Conclusion

In this chapter, we deal with a number of signal and image denoising techniques existing in the literature. We also give two examples of signal and image denoising by applying the denoising techniques based on thresholding in the Discrete Wavelet Transform domain. Those examples show the performance of these denoising techniques.

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