ABSTRACT

Noises present in signals are difficult to recover using the traditional methods. Now wavelet transform is used for denoising techniques. The thresholding both hard and soft are used in wavelet transform. But around discontinuities it creates Gibbs phenomenon. This is the main drawback of using wavelets. Here traditional method of total variation minimization is used for denoising in first step. The Gibbs oscillations are reduced using transformation domain and block matching is used for improvement of SNR. The technique exposes each and every finest details contributed by the grouped set of blocks and also it protects the vital and unique features of every individual block. The blocks are filtered and replaced in their original positions from where they are detached. A technique based on this denoising strategy and its efficient implementation is presented in full detail. The implementation results reveal that the proposed technique achieves a state-of-the-art denoising performance in terms of signal-to-noise ratio.

INTRODUCTION

Signal processing applications always contains noise and it is a major problem. A nonessential signal superimposed over a clear signal. If the regularity of noise lessens, then the method applied to denoise the signal [12] gets more sophisticated. When a signal pass through equipments and it naturally gets added with a noise. Therefore it naturally results in signal contamination. Once a signal is polluted, it is essentially difficult to remove it without degrading the original signal. Hence, the basic task in signal processing [15] is denoising of signals and images. The objective of audio denoising is attenuating the noise, while recovering the underlying signals. Previous methodologies, such as Gaussian (Gabor) filters and anisotropic diffusion, denoise the value of a signal based on neighboring points.

Various authors proposed many global and multiscale denoising approaches [15] in order to overcome the obvious shortcomings of this locality property. By using wavelet thresholding noise is removed from signals and images. To suppress the wavelet coefficients smaller than a given amplitude (using a so-called soft or hard thresholding), and to transform the data back into the original domain, the method has to decompose the noisy data into an orthogonal wavelet basis. A nonlinear thresholding estimator can compute in a different basis, where "large" coefficients to attenuate the noise [16].

Diagonal time-frequency denoising algorithms attenuate the noise, by processing each window Fourier or wavelet coefficient independently, with empirical Wiener, power subtraction or thresholding operators [17] The process of constructing optimal estimates of the unknown signal from the available noisy data is achieved by removing the noise from the data. While performing noise removal process, denoising focuses on shrinking the signal. The core concentration of these techniques is to use wavelets to transform the data into a different basis, where "large" coefficients correspond to the signal and the "small" ones to noise. The denoised data is obtained by an inverse wavelet transform of the modified coefficients [5] and thereby the wavelet coefficients are suitably modified.

Wavelet thresholding has been empirically justified for quite some time and afterwards the optimality properties shown by Donoho and Johnstone [18, 19] advanced its current popularity to a large extent. Coifman and Donoho [20] suggested with the help of a shift-invariant estimate obtained by, averaging of the shifts, that give distinct estimates and they called this as cycle spinning [2]. There may be some residue of noise left or some other kinds of noise gets introduced by the transformation that is affecting the output signal. Several techniques have been proposed so far for the removal of noise from signal, yet, the efficiency remains an issue as well as they have some drawbacks in general. In this article, we propose a signal denoising technique based on an improved block matching technique in transformation domain. The improvement of the block matching is achieved by grouping similar fragments of the audio signal into a set of multidimensional arrays. The noise can be removed well by reconstruction of
the signal. A biorthogonal 1.5 wavelet transform is used for the transformation process which is invertible, but not necessarily orthogonal. A multi dimensional signal vector is generated from the transformed signal vector and the original vector signal is reconstructed by applying inverse transform for the generated multi dimensional signal vector. The result shows that signal to noise ratio (SNR) is comparatively higher than SNR level of the noisy input signal thus increasing the quality of the signal to a remarkable level. The rest of the paper is organized as follows:

Section 2 reviews some recent research works available in the literature. Section 3 presents the proposed technique. Implementation results are given in section 4 and finally conclusion of the work is given in section 5.

RELATED WORKS

Literature presents a number of researches that have made use of various algorithms for signal denoising. Among them, important contributions are given below that have in relation to the proposed concept. Michael T. Johnson et al. [6] have demonstrated the application of the Bionic Wavelet Transform (BWT), derived from a non-linear auditory model of the cochlea, to the task of speech signal enhancement. Results measured objectively by Signal-to-Noise ratio (SNR) and Segmental SNR (SSNR) given for additive white Gaussian noise as well as four different types of realistic noise environments. Enhancement is accomplished through the use of thresholding and the results were compared to a variety of enhancement techniques, including Ephraim Malah filtering, iterative Wiener filtering, and spectral subtraction, as well as to wavelet denoising based on perceptually scaled wavelet packet transform decomposition. Overall results indicated that SNR and SSNR improvements for the proposed approach were comparable to those of the Ephraim Malah filter, with BWT enhancement giving the best results of all methods for the noisiest (−10 db and −5 db input SNR) conditions, but still lower than results for Ephraim Malah filtering and iterative Wiener filtering, but higher than the perceptually scaled wavelet method.

Mohammed Bahoura and Jean Roua [7] have proposed a new enhancement method based on time and scale adaptation of wavelet thresholds. The time dependency was introduced by approximating the Teager energy of the wavelet coefficients. The technique does not require an explicit estimation of the noise level or of the a priori knowledge of the SNR, as was usually needed in most of the popular enhancement methods.

Ching-Ta and Hsiao-Chuan Wang [8] have proposed a method based on critical-band decomposition which converts a noisy signal into wavelet coefficients (WCs), and enhanced the WCs by subtracting a threshold from noisy WCs in each subband. The threshold of each subband is adapted according to the segmental SNR (SegSNR) and the noise masking threshold.

Erk Visser et al. [10] have presented a new enhancement scheme by integrating spatial and temporal signal processing methods for robust speech recognition in noisy environments. The scheme first separates spatially localized point sources from noisy signals. Blind source separation algorithms assuming no a priori knowledge about the sources involved were applied in this spatial processing stage. Then denoising achieved in a combined spatial/temporal processing approach.

The Proposed Denoising Technique Based on Block Matching

In this section, we describe the proposed denoising technique for the effective removal of unwanted noises from any signal. Here, it is considered that the signal is polluted by Additive White Gaussian Noise (AWGN) and the polluted signal is subjected to the removal of noise using the proposed denoising technique. The processes performed in the proposed denoising technique are explained in detail as follows (i) Transformation of the noisy signal to wavelet domain, (ii) Generation of a set of closer blocks (iii) Generating a multidimensional array, (iv) calculating the weight and aggregate value of non-zero elements and finally (v) reconstructing the denoised signal. In the proposed work, initially, the noisy signal is subjected to Wavelet Transformation. Wavelet transformation produces a few significant coefficients for the signals with discontinuities. Once the signal is transformed to wavelet domain, set of closer blocks are synthesized from it. The process of synthesizing the set of closer blocks are depicted in Figure 1 and detailed in the following section.

Figure 1: Generation of a Set of Closer blocks

Let, the input noisy signal for the proposed technique is awgn and it is represented in a vector of length ‘n’ which is shown in Figure 2. Bior 1.5 wavelet transformation is applied to the input noisy signal and a transformed signal is obtained as output through this process. A biorthogonal wavelet transformation is an associated wavelet transform that is invertible but not necessarily orthogonal. Designing biorthogonal wavelets allows more level of choices than orthogonal wavelets. One additional level of choice is the possibility to generate symmetric wavelet functions. For the process of transformation, the vector noisy audio signal is reshaped into a matrix of size same as that of the transformation coefficient matrix.

EXPERIMENTAL RESULTS

Figure 2. Original step-ramp function

Figure 3. Noised step-ramp function u, obtained by adding to a Gaussian white noise of = 0:05. SNR=18.9 db.

Figure 4. Denoised step-ramp function obtained by wavelet hard thresholding. SNR=31.0 db.
CONCLUSION

This paper presented a general framework to perform denoising with wavelets. The method was explained and illustrated in the case of one-dimensional signals and it gives better SNR compared to other traditional methods. It can be extended to multidimensional signals with some modification in the constraint. Also it can be applicable for images and audio signals.

REFERENCES


