A WAVELET BASED SCHEME FOR ADAPTIVE NOISE CANCELING FROM IMAGES

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Abstract

In the context of image denoising, the only available information is the image contaminated with noise. In order to be able to apply adaptive noise cancelation algorithms for reducing this noise, a reference noise signal would be required. This paper presents the application of the idea of wavelet coefficient thresholding to obtain this reference signal, and enable the use of adaptive noise cancelation through the least mean squares algorithm. This scheme has been found to provide, depending on the filter size, an improvement in SNR close to or exceeding that obtained by Wiener filtering, for low values of SNR at the noisy input image.

1 Introduction

The problem being addressed is the estimation of an image from a version of itself contaminated with additive noise, which in a lot of practical cases, and hence in our discussion, is Gaussian noise.

A major problem with denoising images by filtering is that filtering leads to blurring of the image. Hence filtering can be practically used only to remove noise which is out of the band of frequencies of the signal. The wavelet decomposition of a signal not only indicates the frequency content of the signal, but also the temporal or spatial position of that component. Hence, by working in the wavelet domain, it should be possible to reduce the blurring of image edges which occurs in image denoising by filtering.

A number of wavelet based denoising schemes based on thresholding the wavelet coefficients are already in use. Donoho proposed the universal threshold [4], but this was not sub-band and scale adaptive. Later approaches like Chang et al's [5] BayesShrink threshold and Pan et al's [6] threshold, overcame this. The drawbacks of thresholding schemes are that they may lead to discontinuities in the wavelet coefficient values at the threshold values (in case of hard thresholding), and that they direct thresholding schemes do not take into account inter-scale correlations. The denoised images are thus not greatly improved in SNR, and may be at best considered as filtered versions of the image.

If instead of suppressing the noisy coefficients by thresholding, if the 'clean' coefficients (i.e. due to the signal) were to be suppressed along with the coarsest scale image approximation, then taking the inverse wavelet transform would yield a filtered version of the noise. This reconstructed noise image could then be used as a reference noise signal for an adaptive noise cancelation algorithm like the least mean squares algorithm.

2 Adaptive Noise Cancelling with Reference Noise Obtained in the Wavelet Domain

Practically, the reference noise signal required for adaptive denoising of signals through algorithms like the Least Mean Squares, is not available in case of images, and the only information available is the contaminated image itself. The wavelet decomposition of an image can be used to obtain a reference noise image, by suppressing the coarser scale coefficients and the approximation in order to suppress the desired signal and retain the noise after finding the inverse wavelet transform.

One way to achieve this is to set to zero all the coefficients except those of the finest scale diagonal component (which corresponds to high pass filtering along both rows and columns), in which the noise is significant and the power of the signal coefficients is low for a large class of images. This however would lead to a loss of diagonal edge detail from the image.

A better idea is to follow an approach which is the exact opposite of the direct thresholding schemes. The image approximation is set to zero, and those detail coefficients which are above their respective threshold values are set to zero. The reconstructed noise image can then be considered as a filtered version of and hence correlated with the noise contamination.

The coefficient $W_j^c f(x,y)$ at scale j, sub-band component $c = H, VorD$, and spatial location (x,y) is retained if it is below the threshold value $t(j,c)$, that is,

$$\hat{W}_j^c f(x,y) = \begin{cases} 0 & \text{if } \mid W_j^c f(x,y) \mid \geq t(j,c) \\ W_j^c f(x,y) & \text{if } \mid W_j^c f(x,y) \mid < t(j,c) \end{cases} \tag{1}$$

3 Results of Simulation

The results of simulation of the proposed method using the Daubechies wavelet (DB4) for a 5x5 adaptive filter are presented in figures 1 to 3. The average improvement in SNR obtained for different input SNRs is shown in figure 4 for two filter sizes, 3x3 and 5x5. The Pan threshold used with the LMS algorithm was found to yield a lower improvement in SNR than the direct thresholding scheme for a 3x3 filter, but produced less blurring than the direct threshold. The improvement in SNR using the Pan threshold to apply the LMS algorithm led to considerable improvement in the SNR for input SNRs less than 15 dB.

The improvement in SNR falls off after some level of input SNR, due to the fact that since thresholding is used to obtain the reference noise, beyond some level of SNR, the inverse thresholding process would cause loss of the signal information without reducing noise significantly.

(a) (b)

Figure 1: (a) Original image, (b) Gaussian noise corrupted image (SNR = 10dB)

(a) (b)

Figure 2: BayesShrink threshold: (a) Direct thresholding (SNR = 14.945 dB) (b) ANC following inverse thresholding (SNR = 19.859 dB)


(a)


(b)

Figure 3: Pan threshold: (a) Direct thresholding (SNR = 18.273 dB) (b) ANC following inverse thresholding (SNR = 24.102 dB)

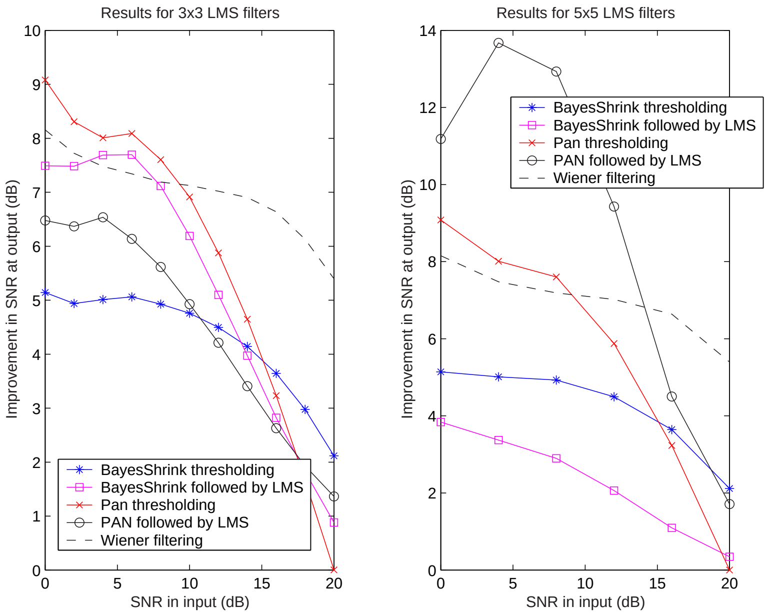

Figure 4: Plot showing the relative performances of the direct thresholding schemes discussed in chapter 3, with the adaptive schemes, and Wiener filtering

4 Conclusions

This scheme can work only in the case of Gaussian noise, as it relies on employing thresholds which were specified for Gaussian noise, and on estimating the level of contamination. To be able to extend this scheme to non-Gaussian noises, we would have to define thresholds for those particular noise types and find a way of estimating their level of contamination. This could be particularly difficult for the multiplicative speckle noise.

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