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Image denoising in the wavelet domain using a new adaptive thresholding function

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ABSTRACT

In this paper, a new thresholding function is proposed for image denoising in the wavelet domain. The proposed function is further used in a new subband-adaptive thresholding neural network to improve the efficiency of the denoising procedure. Some new adaptive learning types are also proposed. In these learning methods, the threshold and the thresholding function effects are considered simultaneously. These methods are used to suppress two types of important noises, Gaussian and speckle, ranging from natural images to ultrasound and SAR pictures. The simulation results show that the proposed thresholding function has superior features compared to conventional methods when used with the proposed adaptive learning types. This makes it an efficient method in image denoising applications.

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1. Introduction

Images may be affected by noise in capturing and transmission stages. Noise sources cover a wide range of unwanted distortions from additive Gaussian noise in natural images to almost-multiplicative speckle noise in ultrasound and synthetic aperture radar (SAR) images. Image denoising is therefore a necessary step in image processing applications.

The first methods introduced for image denoising were based on statistical filters [12]. It is now more than one decade that the wavelet transform has become an important tool to suppress the noise due to its effectiveness and producing better results. The wavelet transform has primary properties such as *compression* or *sparsity* which means that wavelet transforms of real-world signals tend to be sparse. Therefore, they have a few large coefficients that contain the main energy of the signal and other small coefficients which can be ignored [7].

Moreover, the energy of the noise is spread among all the coefficients in the wavelet domain. Due to the fact that the wavelet transform of a noisy signal is a linear combination of the wavelet transform of the noise and the original signal, the noise power can be suppressed significantly with a suitable threshold while the main signal features can be preserved. In the noise reduction method in the wavelet domain that is called *wavelet shrinkage*, the wavelet coefficients of a noisy image are divided into important and non-important coefficients and each of these groups are modified by certain rules. The functionality of the shrinkage process is due to the threshold value and the thresholding rule. Hard and soft thresholding functions that are the basic ones introduced by Donoho and Johnstone [8] together with garrote [10], and semisoft thresholding functions [11] that are more powerful, are used in noise suppression applications. In these methods, the non-important coefficients are set to zero. In hard thresholding, the important coefficients remain unchanged. In soft thresholding, the important coefficients are reduced by the absolute threshold value.

Besides the thresholding function, selection of the optimum threshold value also plays an important role in suitable denoising process. Threshold selection methods are divided into three main groups.

The first group contains *universal-threshold* methods in which the threshold value is chosen uniquely for all wavelet coefficients of the noisy image. The main method of this group (Visu Shrink) is introduced with the above-mentioned hard and soft thresholding function as the first practical technique in signal denoising [8].

The second group includes *subband-adaptive* methods that the threshold value is selected differently for each detail subband [3,7,9].

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Nomenclature

v	original noise-free image in the wavelet domain
s	original noise-free image in the spatial domain
$\bar{v}$	denoised image in the spatial domain
$\hat{s}$	denoised image in the spatial domain
x	noisy image in the wavelet domain
u	noisy image in the spatial domain
η	thresholding function
J	MSE or SURE risk
α	learning rate of threshold
μ	learning rate of parameter k
γ	learning rate of parameter m
p	a detail subband
j	learning step
N	signal length
M	length of P subband

In the third group, *spatially adaptive* group of threshold selection, each detail wavelet coefficient has its own threshold value [19].

From a different angle, denoising problem can be considered as estimation of the original image from the noisy one [28]. Therefore, by modeling the subbands of noise-free wavelet coefficients with different statistical distributions, such as generalized Gaussian [3], Guassian scale mixture [20], Mixture of Laplacians [21], and alpha-stable [1], different methods (based on various estimators such as Bayesian technique) are introduced. Dependency of these methods to a specific noise type and distribution decrease their flexibility to process real world images.

Due to some secondary properties of the wavelet transform, several denoising approaches are presented based on modeling of the dependency of the wavelet coefficients between scales and subbands. It leads to some methods such as *interscale dependency* methods that consider the dependency of the coefficients between scales, namely *parent–child* dependency [24], *intra-subband* methods (that take into account the dependency between coefficients in each subband) [4], and other methods that uses mixture of these dependencies or other dependencies between coefficients such as *intrascale dependency* [6]. Considering these secondary properties in the denoising process may increase the efficiency of the method.

On the other hand, because of the different nature of the Gaussian and speckle noises, different methods are used to suppress each. For speckle noise reduction, some other filters such as Lee [17] and Kuan et al. [16] methods are used in addition to the classic filters such as Wiener and median filtering. These filters are based on local noise statistics in the spatial domain and can effectively reduce speckle in homogeneous areas. However, these filters do not perform well in the edges.

Recently some attempts have been made to reduce the speckle noise using wavelet transform. These methods have lead to better speckle noise reduction [2,5,13,22,26,27].

Current literature does not address the following aspects together:

- The existing methods do not determine the thresholding value and the thresholding function simultaneously.
- None of the existing methods treat both the speckle noise and the Gaussian noise effectively.
- Many of the existing methods need to consider some priori assumptions about the statistical distribution of subbands of noise-free wavelet coefficients. Therefore, presenting a method to suppress the noise regardless of its distribution and modeling of the distribution of the image wavelet coefficients will be very valuable.

In this paper, a new nonlinear thresholding function is proposed for image denoising in the wavelet domain. This function has some advantages over classical methods and produces better results in speckle and Gaussian noise reduction. To improve the capability of the function, three shape tuning factors have been added which lead to a comprehensive-thresholding function that can be adjusted to any desired thresholding function. This function is used in an adaptive manner in a method that inspired form Zhang's Thresholding Neural Network (TNN) [29,30]. A new method of adaptive learning is also proposed for TNN-based image denoising. In this method, the shape tuning parameters of the thresholding function are tuned through an LMS-based learning algorithm similar to the threshold value. Using this method, the effect of two important factors (threshold value and proper thresholding function) is considered in denoising simultaneously.

The organization of the paper is as follows. After a brief review on wavelet-based image noise reduction in Section 2, the proposed thresholding function, its variations and risk calculations are described in Section 3. The TNN structure and the proposed modification are explained in Section 4. Several learning types and the proposed adaptive learning algorithms are also presented in this section. The assessment parameters that are used in evaluating the method are reviewed in Section 5. In Section 6 the results of various proposed methods are compared to classical image denoising methods. Section 7 discusses thoroughly about the obtained results. Finally, conclusion and future work are presented in Section 8.

2. Wavelet-based noise reduction

In this section, the basics of noise reduction in the wavelet domain are presented for both types of Gaussian and speckle noises.

2.1. Gaussian noise

Let us consider the data vector $x = [x_0, x_1, \ldots, x_{N-1}]^T$ which is corrupted by additive Gaussian noise,

$$x_i = v_i + n_i \quad i = 0, 1, 2, \ldots, N-1 \tag{1}$$

in which v_i is the ith wavelet coefficient of noise-free signal and n_i is the element of *iid*[1] Gaussian noise, Therefore, x_i is the noisy observation. The main purpose of denoising is to minimize the mean square error (MSE) risk. In other words, the difference between original noise-free signal and reconstructed one must be acceptably little.

If $V = [v_0, v_1, \ldots, v_{N-1}]^T$ is the vector of coefficients of noise-free signal in the wavelet domain and $\hat{V} = [\hat{v}_0, \hat{v}_1, \ldots, \hat{v}_{N-1}]^T$ is the output of thresholding function in this domain, the MSE risk is calculated in Eq. (2):

$$J_{\mathrm{MSE}} = \frac{1}{2} E\|\hat{V} - V\|^2 = \frac{1}{2N} \sum_{i=0}^{N-1} (\hat{v}_i - v_i)^2 \tag{2}$$

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