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ORIGINAL RESEARCH ARTICLE

Wavelet transform based image enhancement: A noise reduction approach

Koteswararao Mallaparapu*, Kota Venkata Ramarao

Chalapathi Institute of Engineering and Technology, Guntur 522034, India

*** Corresponding author:** Koteswararao Mallaparapu, raodecs@gmail.com

ABSTRACT

This paper introduces a new thresholding function that mixes the soft thresholding functions and Smoothly Clipped Absolute Deviation (SCAD) for denoising images using the decimated wavelet transform technique, which is widely popular in various applications. The proposed method is applied to denoise noisy images contaminated with additive white Gaussian noise, employing the Top rule. The efficiency of this new thresholding function is also evaluated within the context of the Translation Invariant method. The results are compared with existing methods such as SCAD, soft thresholding, and the Wiener filter-based denoising approach. Parameters such as Root Mean Square Error (RMSE) and Peak Signal Noise Ratio (PSNR) are employed to assess the quality of denoising.

Keywords: WT; DWT; image denoising; new thresholding function; top rule; wiener filter; translation invariant method

1. Overview

In many applications, such as satellite communication and medical diagnosis, images are acquired and subsequently transmitted from one location to another[1,2]. During this transmission process, noise can be introduced, which can negatively impact the clarity of the received image[3]. In recent years, Wavelet transform has found widespread use in various image and video signal processing applications, thanks to its excellent localization properties[4]. Image denoising is a key application of wavelets, aimed at removing unwanted information from the image to restore its original quality[5,6].

Data can take various forms, including images, videos, speech, text, and more. Regardless of the data type, noise is often present, characterized as unwanted information. The presence and impact of noise can be quantified by calculating the Signal-to-Noise Ratio (SNR). A high SNR indicates that the impact of noise is relatively low, allowing for noise to be disregarded[7]. However, a low SNR signifies a significant presence of noise, necessitating its removal before further processing. This noise removal process is referred to as denoising, and when applied to images, it is specifically known as image denoising. The difference between a noisy image and the recovered original image is achieved through denoising. Among various types of noise encountered during signal denoising, adaptive white Gaussian noise (AWGN) is the most common. This project thesis primarily focuses on addressing AWGN[8,9].

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To evaluate the performance and optimization of the denoising algorithm, Mean Square Error (MSE) is used. MSE quantifies the dissimilarity between the original signal and the reconstructed signal obtained after denoising. In comparison to other evaluation methods, MSE offers several advantages, including lower computational complexity and straightforward expressions that facilitate analysis. Consequently, Mean Square Error (MSE) is commonly employed for estimating signal denoising errors.

Wavelet transform denoising aims to remove noise from a signal or image while preserving its essential characteristics, regardless of its frequency content. Among the different methods available for image denoising, those based on wavelet transform are particularly popular. This project proposes a denoising method that relies on wavelet transform and employs a thresholding technique.

2. Image denoising

In the field of digital signal processing like image processing, a significant challenge arises when dealing with noisy images. Image denoising is the process of recovering the unique image from a noisy observed image. The wavelet shrinkage technique for image denoising takes in the following steps:

First, apply wavelet decomposition to the noisy image to obtain the wavelet coefficients: p = P (B + N), where p = wavelet coefficients, P = wavelet transform, N = noise data, B = original image.

Next, apply the thresholding function using predefined thresholding rules to the wavelet coefficients: P′ = δΣ(p). In this equation, P′ represents the optimal estimation of the wavelet coefficients, δΣ(p) denotes the wavelet thresholding function, and Σ is the threshold.

Finally, apply the inverse wavelet transform to the modified wavelet coefficients to obtain the denoised image: B′ = P − 1(P′).

3. Shrinkage methods

3.1. Top rule

This method is a global shrinkage function that remains independent of the selected shrinkage function. Let's consider "K" as the fraction of the largest coefficients we wish to retain. The shrinkage is set to be the $(1\text{-}K)^{th}$ quintile of the experimentally derived complete values of the wavelet coefficients[10,11].

3.2. Translation invariant rule

Donoho and Coifman introduced the translation-invariant rule, which involves two key steps. First, it entails performing shrinkage on each basis, and second, it averages the resulting denoised signals. This approach is effective for two main reasons: 1) Enhanced detection of singularities: By accounting for all shifts in the analysis, it improves the detection of singularities in the data. 2) Improved smoothing effect: A more powerful smoothing effect is achieved by averaging the denoised signals obtained from each basis. To implement this strategy effectively, unbalanced wavelets with small support are employed, and soft shrinkage is applied. This method not only enhances edge compensation but is also commonly used for image estimation[12].

4. Thresholding functions

4.1. Soft thresholding function

The coefficient value (p) is taken as the difference between the coefficient value and the threshold value (λ) if p is greater than the threshold value. Otherwise, the value is set to zero[13].

$$S(p,\lambda)=\begin{cases} sgn(p)(|p|-|\lambda|) & for\ |p|>\lambda \\ 0\ otherwise \end{cases}$$

4.2. SCAD

$$\mathrm{SCAD}(p,\lambda)=\begin{cases} \mathrm{sign(p)max}(0,|\mathrm{p}|-\lambda) \\ \quad \text{if } |\mathrm{p}| \leq 2\lambda \\ (\alpha-1)p-\alpha\lambda\, sign(p) \\ \quad \text{if } 2\lambda \leq |\mathrm{p}| < \alpha\lambda \\ \mathrm{p} \quad \text{if } |\mathrm{p}| > \alpha\lambda \end{cases}$$

where $\alpha = 3.7$, SCAD means smoothly clipped absolute deviation[14].

4.3. New thresholding function

This method is developed by combining elements of the SCAD function and the soft thresholding function, specifically through an arithmetic mean. The function's behavior is as follows: If the coefficient value (p) exceeds the thresholding value (λ), the function outputs the value as is. However, if the coefficient value is less than the threshold, the function computes the output as 20% of the coefficient value.

4.4. Wiener filter

The Wiener filter is a powerful tool in image processing for noise reduction. It's a linear estimation method used to effectively remove noise from an image. This method aims to minimize the overall mean square error by performing inverse filtering and noise smoothing simultaneously. The underlying process is mathematically described by the following equation[15–17].

$$\mathrm{W}(y,z)=\frac{H^*(y,z)S_{xx}(y,z)}{|H(y,z)|^2S_{xx}(y,z)+S_{\eta\eta}(y,z)}$$

where $S_{\eta\eta}(y,z)$, $S_{xx}(y,z)$, is the additive noise and power spectral of the original image and $H(y,z)$ is the blurring function.

5. Findings and deliberations from experiments

In this section, we present the outcomes of our experiments and engage in a comprehensive discussion. We evaluate the effectiveness of the proposed thresholding function and compare it to both soft and SCAD thresholding functions, all implemented using wavelets. The experimentation is carried out on a 512 × 512 image, with various levels of Gaussian noise added to the original image[18,19].

Our methodology involves the application of wavelet transforms to acquire the wavelet coefficients, the modification of these coefficients by the chosen shrinkage function, and the subsequent utilization of inverse wavelet transforms to generate either the denoised or original image.

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X(i)-\hat{X}(i)\right)^2}$$

$$\mathrm{PSNR}=20\log_{10}(255/\sqrt{MSE})$$

where $X(i)$ the original image is $\hat{X}(i)$ the de-noised image, n is the number of samples. The simulation experiment was repeated 100 times, and the average values were computed. This process was conducted on different images, yielding consistent results. The simulation was implemented within the MATLAB environment[20,21].

5.1. Results and tables

Tables 1 and **2** display the results of Lenna images for noise levels σ = 10, 20, and 30 using Soft, SCAD, and a new thresholding function with translation invariant and top rule methods. Meanwhile, **Table 3** presents the denoising results using the Wiener filter method.

Table 1. Denoising results of Lena's image by using the translation invariant method.

σ	10		20		30	
Parameters	**RMSE**	**PSNR**	**RMSE**	**PSNR**	**RMSE**	**PSNR**
Noisy image	10.030	28.1042	19.9966	22.1117	30.1327	18.5500
SCAD function	9.1899	28.8645	13.8675	25.2908	17.8197	23.1128
Soft function	9.5555	28.5257	14.0683	25.1660	17.6287	23.2064
New thresholding function	7.6071	30.5064	11.1514	27.1842	14.1289	25.1286

Table 2. Denoising results of Lena's image by using the top rule.

σ	10		20		30	
Parameters	**RMSE**	**PSNR**	**RMSE**	**PSNR**	**RMSE**	**PSNR**
Noisy image	9.9900	28.1395	19.9712	22.1227	30.1073	18.5574
SCAD function	7.9138	30.1631	12.7692	26.0075	19.3086	22.4158
Soft function	6.8959	31.3590	11.1603	27.1773	14.3746	24.9789
New thresholding function	6.6623	31.6583	11.4799	26.9320	17.4095	23.3151

Table 3. Denoising results of Lena's image by using the Weiner filter method.

σ	10		20		30	
Parameters	**RMSE**	**PSNR**	**RMSE**	**PSNR**	**RMSE**	**PSNR**
Noisy image	9.9653	28.1610	19.9630	22.1263	29.8474	18.6327
Wiener filter	5.7431	32.9479	8.8244	29.2171	10.9144	27.3708

Tables 4 and **5** display the results of Canaletto images for noise levels σ = 10, 20, and 30 using Soft, SCAD, and a new thresholding function with translation invariant and top rule methods. Meanwhile, **Table 6** presents the denoising results using the Wiener filter method.

Table 4. Denoising results of Canaletto image's by using the translation invariant method.

σ	10		20		30	
Parameters	**RMSE**	**PSNR**	**RMSE**	**PSNR**	**RMSE**	**PSNR**
Noisy image	9.9616	28.1642	19.9724	22.1222	29.9724	18.5964
SCAD function	7.2515	30.9223	11.0058	27.2984	12.0765	26.4920
Soft function	9.2539	28.8043	12.8294	25.9667	16.3175	23.8777
New thresholding function	5.8235	32.8271	8.3848	29.6610	10.9341	27.3552

Table 5. Denoising results of Canaletto image's by using the top rule method.

σ	10		20		30	
Parameters	**RMSE**	**PSNR**	**RMSE**	**PSNR**	**RMSE**	**PSNR**
Noisy image	9.9878	28.1414	20.0409	22.0925	30.0266	18.5807
SCAD function	6.2210	32.2536	9.8409	28.2701	15.4798	24.3355
Soft function	6.1387	32.3693	8.7308	29.3097	11.6943	26.7713
New thresholding function	5.4591	33.3884	8.6704	29.3700	12.9522	25.8839

Table 6. Denoising results of Canaletto image's by using the Weiner filter method.

σ	10		20		30	
Parameters	**RMSE**	**PSNR**	**RMSE**	**PSNR**	**RMSE**	**PSNR**
Noisy image	10.0153	28.1175	19.9636	22.1260	29.9467	18.6038
Wiener filter	5.1499	33.8949	7.4964	30.6337	9.2518	28.8063

5.2. Visual representation

Figure 1 shows the Denoising results of Lenna image, σ = 20, **(a)** original image; **(b)** noisy image (σ = 20); **(c)** translation invariant method; **(d)** top rule; **(e)** Wiener filter.

Figure 1. Denoising results of Lenna image, σ = 20, **(a)** original image; **(b)** noisy image (σ = 20); **(c)** translation invariant method; **(d)** top rule; **(e)** Wiener filter.

Figure 2 shows the Denoising results of Canaletto image, σ = 10, top method, **(a)** original image; **(b)** noisy image (σ = 10); **(c)** translation invariant method; **(d)** top rule; **(e)** Wiener filter.

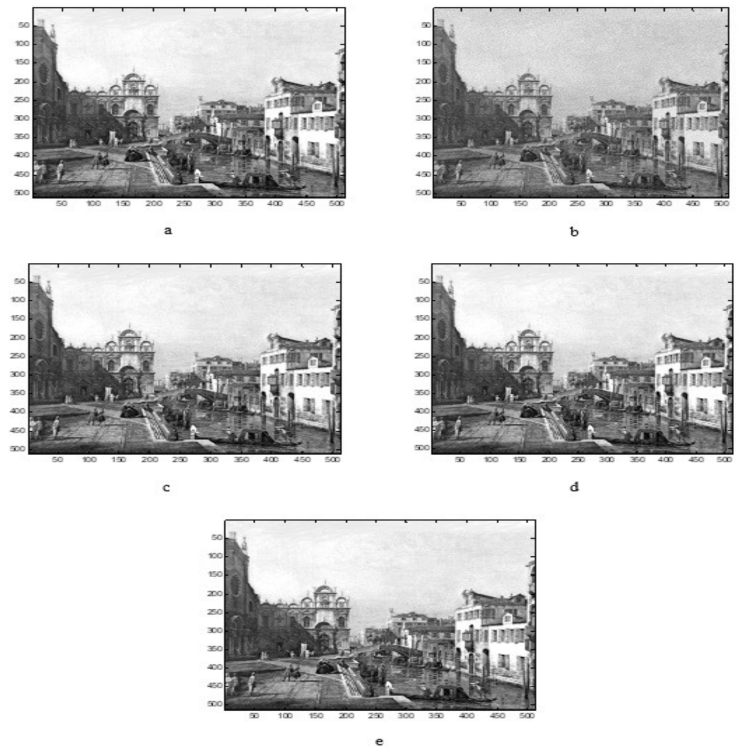

Figure 2. Denoising results of Canaletto image, σ = 10, top method, **(a)** original image; **(b)** noisy image (σ = 10); **(c)** translation invariant method; **(d)** top rule; **(e)** Wiener filter.

5.3. Quantitative results

For σ = 10, when using the SCAD filter, we obtained an RMSE of 9.1899 and a PSNR of 28.8645 for denoising the noisy image. In contrast, using soft thresholding with the translation invariant method, we obtained an RMSE of 9.5555 and a PSNR of 28.5257 (**Table 1**). Notably, the new thresholding function yielded an RMSE of 7.6071 and a PSNR of 30.5064, demonstrating superior performance compared to both SCAD and soft thresholding functions.

Similar favourable results were observed for σ = 20 and 30 (**Table 1**).

5.4. Top rule method

For σ = 10 using the top rule method, we obtained an RMSE of 7.9138 and a PSNR of 30.1631 with the SCAD thresholding filter, while using the soft thresholding filter resulted in an RMSE of 6.8959 and a PSNR of 31.3590. Meanwhile, the Wiener method yielded an RMSE of 5.7431 and an SNR of 32.9479 (**Table 3**). The new thresholding filter exhibited an RMSE of 6.6623 and a PSNR of 31.6583 (**Table 2**). These results consistently highlight the superior performance of the novel shrinkage function in comparison to both SCAD and soft shrinkage functions for σ = 10, 20, and 30.

In summary, the novel shrinkage function consistently outperforms SCAD and soft thresholding functions across different noise levels.

6. Conclusion

In this paper, a novel shrinkage function designed for wavelet shrinkage denoising of images is proposed. The performance of this function is evaluated using Lena’s image and compared with existing SCAD, soft, and Wiener filter methods. It is found that the new thresholding function gives better results than compared to the existing methods in SCAD and soft functions with the Translation invariant method, the new thresholding function gives better results compared with the SCAD function with the Top rule and outperforms the existing Wiener filter method.

Author contributions

All authors contributed equally to this work.

Conflict of interest

The authors declare no conflicts of interest.

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