Chapter

Perspective Chapter: New Image Denoising Approach Based on SWT and 2-D Dual-Tree Discrete Wavelet Transform

Mourad Talbi and Riadh Baazaoui

Abstract

In this chapter, we propose a new image denoising approach. It consists in applying a Stationary Wavelet Transform (SWT) based image denoising technique, in the domain of 2-D Dual-Tree Discrete Wavelet Transform. In fact, this proposed approach consists first of applying the 2-D Dual-Tree Discrete Wavelet Transform to the noisy image. Then, the obtained noisy wavelet coefficients are denoised by applying to each of them a SWT based image denoising technique. Finally, the denoised image is reconstructed by applying the inverse of the 2-D Dual-Tree Discrete Wavelet Transform to the obtained denoised wavelet coefficients. For applying this SWT based image denoising technique, we use soft thresholding, the Daubechies 4 as the mother wavelet and the decomposion level is equal to 5. The performance of this proposed image denoising approach, is pouved by the results obtained from the computations of PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity).

Keywords: image denoising, 2-D dual-tree discrete wavelet transform, SWT-2D, PSNR, SSIM, standard deviation

1. Introduction

Noisy images frequently arise in the high-level vision tasks and this makes image denoising becoming an important task in the low-level vision domain [1]. For example, take a given denoising model:

$$y = x + n \tag{1}$$

With x, y and n are respectively the clean images, the given noisy image and the Additive Gaussian Noise (AWGN) having σ as standard deviation [1]. There are diverse approaches for reducing noise that various researchers have done. Each of these approaches owns its advantages and disadvantages. In [2], a review of some significant work in the domain of image denoising based on the denoising techniques were presented. These techniques can be classified as wavelet domain, spatial domain, or both techniques can combine for obtaining an advantage of them. In the medical domain, Mittal et al. [3] have presented a methodology for improving and eliminating the high noise of the medical image employing the Stationary Wavelet Transform (SWT) technique. In their work, an efficient and simple approach for adaptive noise elimination was used, the SWT-2D denoising method on the medical image that is degraded by noise. In this chapter, we propose a novel approach of Image denoising. It consists in applying a Stationary Wavelet Transform (SWT) based image denoising technique [4] in the domain of 2-D Dual-Tree Discrete Wavelet Transform. This SWT-based image denoising technique [4] is based on soft thresholding of the noisy wavelet coefficients obtained from the noisy image decomposition using the SWT-2D. For this decomposition, we use Daubechies 4 as the mother wavelet and the level is equal to 5. Those choices are the same as those in ref. [4].

This proposed denoising approach is completely different from the other denoising technique based on thresholding in the domain of 2-D Dual-Tree Complex Wavelet Transform [5]. In fact, this difference lies in the fact that we apply SWT-based image denoising technique [4] not to the noisy image to be denoised, but to each noisy wavelet coefficient obtained from the application of this Transform [5] to this image. Consequently, this idea can introduce more adaptability compared to the application of this technique based on thresholding in the domain of 2-D Dual-Tree Discrete Wavelet Transform [5], to this image.

The remaining of this chapter is organized as follows: in Section 2, we will deal with 2-D Dual-Tree Complex Wavelet Transform [5]. In Section 3, we will deal with the SWT-2D-based image denoising technique [4]. In Section 4, we will detail the image-denoising approach proposed in this work. In Section 5, we will present results and discussion and we will conclude in Section 6.

2. 2-D dual-tree complex wavelet transform

It turns out that, for some applications of DWT (Discrete Wavelet Transform), ameliorations can be obtained by employing an expansive wavelet transform in place of a critically sampled one [5]. An expansive transform is one that permits to convert an N-point signal into M coefficients with $M > N$. There are numerous sorts of expansive DWTs; here is described the dual-tree complex DWT [5, 6]. The dual-tree complex DWT of a signal x is implemented employing two critically sampled DWTs in parallel on the same data, as illustrated in **Figure 1**.

The transform is 2-times expansive because for an N-point signal, it permits to have $2NDWT$ coefficients. If the filters in the upper and lower DWTs are the same, consequently no advantage is added. Though, when the filters are designed in a specific way, consequently the sub-band signals of the upper DWT can be considered as the real part of a complex wavelet transform, and sub-band signals of the lower DWT can be viewed as the imaginary part. Equivalently, for specially designed filters sets, the wavelet associated with the upper DWT can be viewed as an approximate Hilbert transform of the wavelet associated with the lower DWT. When designed in this manner, the dual-tree complex DWT is approximately shift-invariant, in contrast with the critically sampled DWT. Furthermore, the dual-tree complex DWT can be employed for implementing 2-D wavelet transforms where each wavelet is oriented, which is precisely useful for image processing. For the separable 2–D DWT, recall that

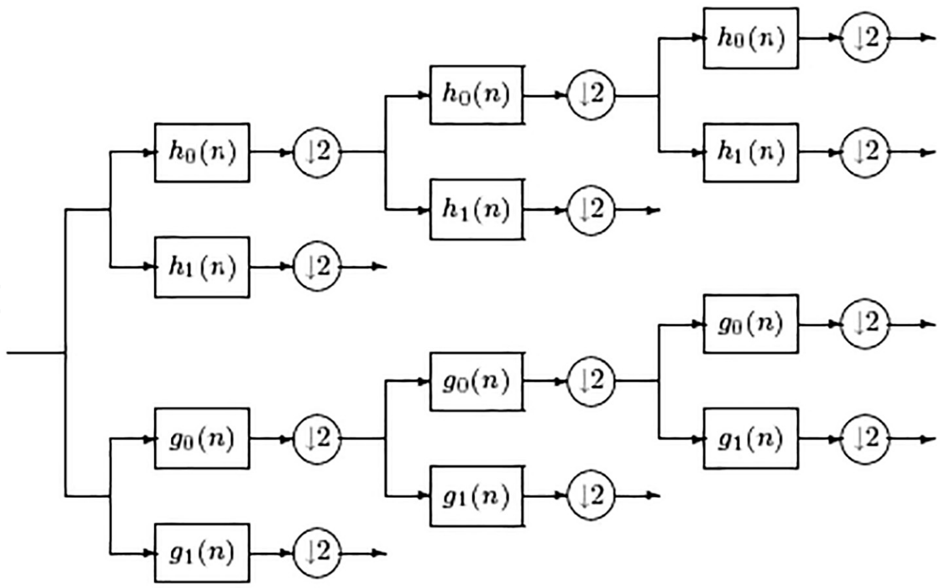

Figure 1.
The dual-tree complex DWT.

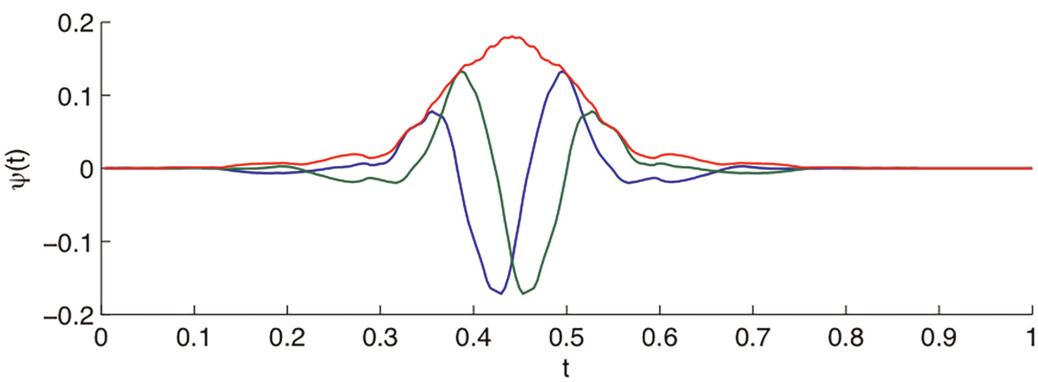

Figure 2.
Complex 1-D wavelet, $\psi(t)$ [5, 6].

one of the three wavelets does not own a dominant orientation. The dual tree complex DWT outperforms the critically sampled *DWT* for applications such as image denoising and enhancement. The complex wavelet associated with the dual-tree complex DWT is illustrated in **Figure 2**. For determining the real part of the complex wavelet, we set all coefficients to zero, except for one coefficient in the upper DWT, and after that applying the inverse transform. For determining the imaginary part, the exception is a single coefficient in the lower DWT.

3. A stationary wavelet transform (SWT) based image denoising technique

The SWT (Stationary Wavelet Transform) [7, 8] is similar to the Discrete Wavelet Transform (DWT) except the signal is never sub-sampled and instead the filters are up sampled at each level of decomposition [7]. Each level's filters are up-sampled versions of the previous as shown in **Figure 3**.

The SWT is an inherent redundant scheme, as each set of coefficients contains the same number of samples as the input. So for a decomposition of N levels, there is a redundancy of $2N$.

An image denoising technique based on thresholding in the SWT domain, is applied in our denoising system proposed in this work. This technique can be summarized by the block diagram illustrated at **Figure 4**.

According to **Figure 4**, the Stationary Wavelet Transform 2D (SWT–2D) is firstly applied to the noisy image, I_b, in order to obtain noisy stationary wavelet coefficients. Those obtained coefficients are then denoised by employing soft thresholding and finally the inverse of SWT–2D, $SWT^{-1} - 2D$ is applied to the obtained thresholded coefficients for having the denoised image, I_d.

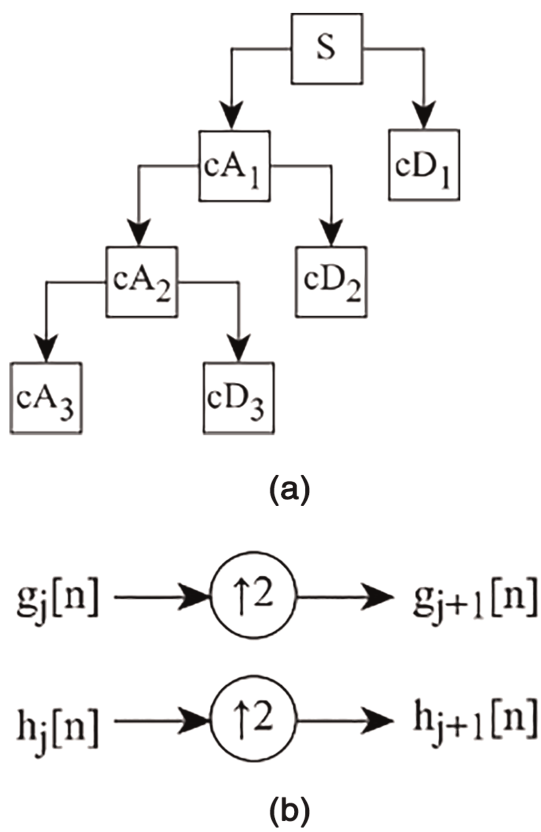

Figure 3.
(a) Wavelet decomposition tree, (b) SWT filters [7].

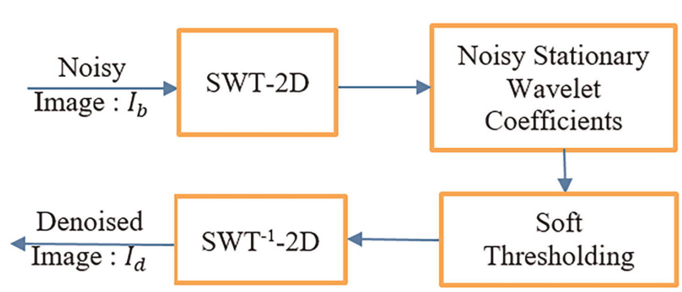

Figure 4.
The block diagram of an image denoising technique based on thresholding in the SWT domain.

4. The proposed image denoising approach

As previously mentioned, in this work, we propose a new image denoising approach. It consists in applying a SWT based image denoising technique [4] in the domain of 2-D Dual-Tree Discrete Wavelet Transform [5]. In fact, this proposed approach consists firstly in applying the 2-D Dual-Tree Discrete Wavelet Transform to the noisy image and the obtained noisy wavelet coefficients are then denoised by applying to each of them, a SWT based image denoising technique [4]. Finally, the denoised image is reconstructed by applying the inverse of the 2-D Dual-Tree Discrete Wavelet Transform to the obtained denoised wavelet coefficients. This proposed image denoising approach can be summarized by the block diagram illustrated at **Figure 5**.

According to **Figure 5**, the 2-D dual-Tree Discrete Wavelet Transform is firstly applied to the noisy image, I_b in order to obtain noisy wavelet coefficients, $Wb\{j\}\{s\}, 1 \leq j \leq 2, 1 \leq s \leq 3$. Each of those coefficients is then denoised by applying a technique of image denoising based on thresholding in SWT domain [4] and we obtain denoised wavelet coefficients, $Wd\{j\}\{s\}, 1 \leq j \leq 2, 1 \leq s \leq 3$. To those denoised coefficients, is applied the inverse of the 2-D dual-Tree Discrete Wavelet Transform in order to have finally the denoised I_d.

As previously mentioned, for the application of the denoising technique based on thresholding in the SWT domain, is used Daubechies 4 as the mother wavelet. Moreover, the decomposition level is equal to 5. Those choices are the same to those in [4]. Those choices are justified by the fact that in our comparative study, we want to use the same mother wavelet and the same decomposition level such as used in [4].

5. Results and discussion

In this section, we will present the results obtained from the computations of Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM). Those results are obtained from the application of the proposed image denoising approach, the denoising

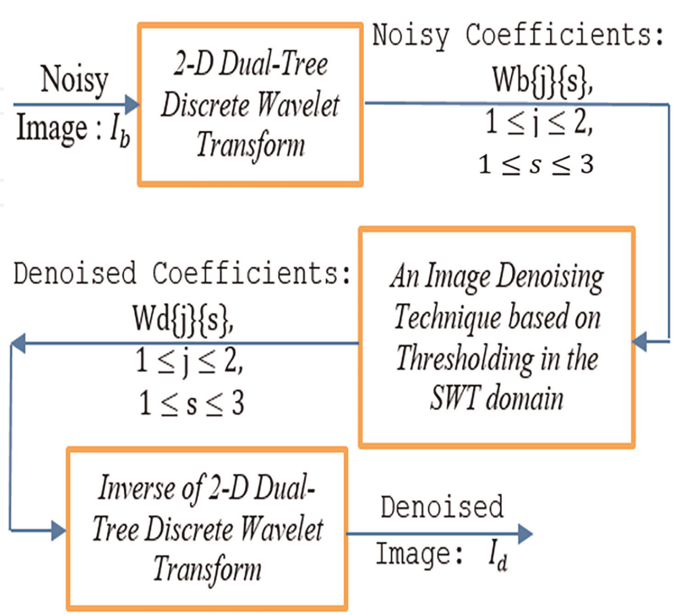

Figure 5.
The block diagram of the proposed image denoising approach.

technique based on thresholding in the SWT domain [4], the image denoising technique based on thresholding in the domain of 2-D Dual-Tree Discrete Wavelet Transform [5] and the image denoising approach using deep neural network [9].

In the following sub-section we will present the previously mentioned evaluation criterion, which are the PSNR and the SSIM. The PSNR is a better test since it takes the signal strength into consideration (not only the error). The PSNR and SSIM are expressed as follow [10]:

$$SSIM = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_{xy} + c_2\right)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)} \tag{2}$$

Where σ, σ_{xy} and μ are respectively the variance, the covariance of the image and c_1 and c_2 are the stabilizing constants. The SSIM value is generally between 0 and 1 and similar images have value of SSIM near to 1.

$$PSNR = 10 \bullet log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{3}$$

With MSE is the Mean Square Error, expressed as follow:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - X_i^*\right)^2 \tag{4}$$

The MSE is one of the earliest tests which performed to test whether two images are similar.

As previously mentioned, those results (**Table 1**) are in terms of PSNR and SSIM and they are obtained for different images and diverse values of level (σ) of noise

Noisy image	**The denoising technique**			
	The proposed Image denoising technique	**The image denoising technique based on thresholding in the SWT domain [4]**	**The Image denoising technique based on deep neural network [9]**	**The image denoising technique based on thresholding in the domain of 2-D Dual-Tree Discrete Wavelet Transform [5]**
Noisy st.tif ($\sigma = 10$)	PSNR: **34.2517** SSIM: 0.8791	PSNR: 33.7831 SSIM: **0.8962**	PSNR: 28.3030 SSIM: 0.5425	PSNR: 34.1453 SSIM: 0.8675
Noisy st.tif ($\sigma = 20$)	PSNR: **30.6126** SSIM: **0.7722**	PSNR: 30.1884 SSIM: 0.6950	PSNR: 22.4725 SSIM: 0.2850	PSNR: 30.2840 SSIM: 0.7306
Noisy st.tif ($\sigma = 30$)	PSNR: **28.1244** SSIM: **0.6131**	PSNR: 24.5706 SSIM: 0.3719	PSNR: 18.9533 SSIM: 0.1789	PSNR: 27.7900 SSIM: 0.5977

Noisy image	The denoising technique			
	The proposed Image denoising technique	**The image denoising technique based on thresholding in the SWT domain [4]**	**The Image denoising technique based on deep neural network [9]**	**The image denoising technique based on thresholding in the domain of 2-D Dual-Tree Discrete Wavelet Transform [5]**
Noisy st.tif ($\sigma = 40$)	PSNR: **26.4861** SSIM: **0.5138**	PSNR: 20.6093 SSIM: 0.2171	PSNR: 16.4559 SSIM: 0.1248	PSNR: 25.9906 SSIM: 0.4953
Noisy Peppers..tif ($\sigma = 10$)	PSNR: **32.8048** SSIM: **0.8250**	PSNR: 32.4622 SSIM: 0.8019	PSNR: 28.6273 SSIM: 0.6497	PSNR: 32.6519 SSIM: 0.8180
Noisy Peppers.tif ($\sigma = 20$)	PSNR: **29.6501** SSIM: **0.7233**	PSNR: 29.3674 SSIM: 0.6821	PSNR: 22.4648 SSIM: 0.3569	PSNR: 29.5645 SSIM: 0.7038
Noisy Peppers.tif ($\sigma = 30$)	PSNR: **27.8670** SSIM: **0.6406**	PSNR: 27.8481 SSIM: 0.6264	PSNR: 18.8973 SSIM: 0.2208	PSNR: 27.4151 SSIM: 0.5968
Noisy Peppers.tif ($\sigma = 40$)	PSNR: **26.3256** SSIM: **0.5462**	PSNR: 26.2747 SSIM: 0.5424	PSNR: 16.3708 SSIM: 0.1497	PSNR: 25.7770 SSIM: 0.5109
Noisy House. tif ($\sigma = 10$)	PSNR: **35.0397** SSIM: **0.9203**	PSNR: 34.2284 SSIM: 0.8466	PSNR: 28.4578 SSIM: 0.5576	PSNR: 35.0360 SSIM: 0.9121
Noisy House. tif ($\sigma = 20$)	PSNR: **30.7882** SSIM: **0.8462**	PSNR: 30.3082 SSIM: 0.7360	PSNR: 22.4921 SSIM: 0.3090	PSNR: 30.5116 SSIM: 0.7766
Noisy House. tif ($\sigma = 30$)	PSNR: **28.1921** SSIM: **0.6586**	PSNR: 27.0232 SSIM: 0.5584	PSNR: 18.9670 SSIM: 0.2049	PSNR: 27.9388 SSIM: 0.6487
Noisy House. tif ($\sigma = 40$)	PSNR: **26.2186** SSIM: 0.5368	PSNR: 25.4000 SSIM: 0.4792	PSNR: 16.4148 SSIM: 0.1455	PSNR: 26.0214 SSIM: **0.5416**

Table 1.
Results obtained in terms of PSNR and SSIM.

corrupting the original image (clean image). This noise is an Additive Gaussian White Noise (AGWN).

In **Figure 6**, are illustrated some examples of image denoising by applying the denoising approach proposed in this work and the other previously mentioned techniques, used in our evaluation [4, 5, 9]. According to **Figure 6**, the noise is

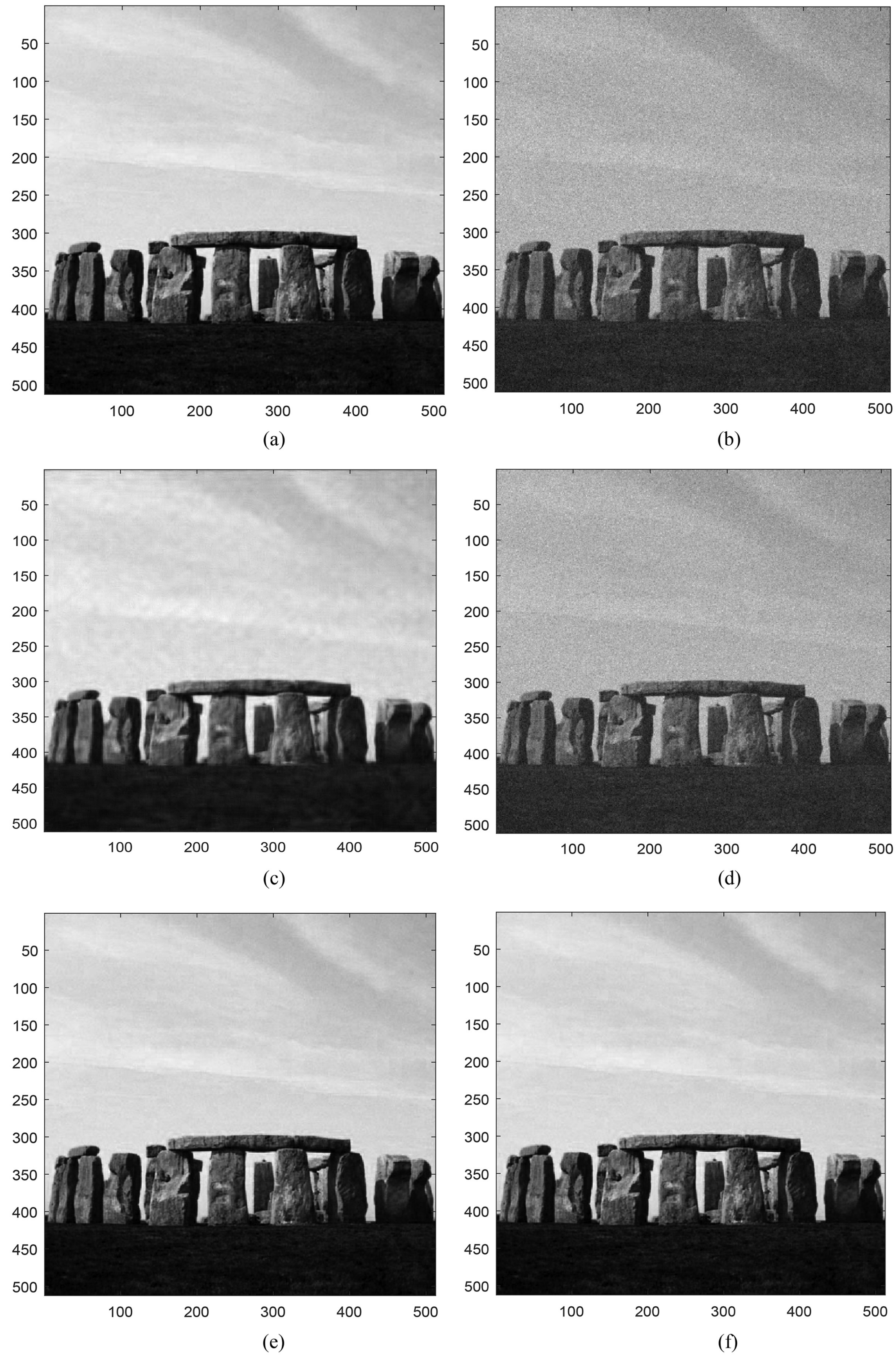

Figure 6.
An example of image denoising: (a) clean image, (b) Noisy image ($\sigma = 20$), (c) Denoised image obtained by applying the proposed technique (PSNR = 30.6924), (d) Denoised image obtained by applying deep learning *(PSNR = 22.4978), (e) Denoised image obtained by applying soft thresholding in the SWT domain (PSNR = 30.1884) (f) Denoised image obtained by applying soft thresholding in the domain of 2-D dual-tree discrete wavelet transform (PSNR = 30.2840).*

considerably reduced while preserving the original image and this precisely when applying the image denoising approach proposed in this work.

According to **Table 1**, the best results are highlighted in purple color and they are practically obtained by applying the proposed image denoising approach. Consequently, this proposed approach outperforms the other three techniques [4, 5, 9], used for our evaluation.

6. Conclusion

In this chapter, we proposed a new image denoising approach. It consists in applying a Stationary Wavelet Transform (*SWT*) based image denoising technique [4] in the domain of 2–*D* Dual-Tree Discrete Wavelet Transform. In fact, this proposed approach consists firstly in applying the 2–*D* Dual-Tree Discrete Wavelet Transform to the noisy image and the obtained noisy wavelet coefficients are then denoised by applying to each of them a *SWT* based image denoising technique [4]. Finally, the denoised image is reconstructed by applying the inverse of the 2–*D* Dual-Tree Discrete Wavelet Transform to the obtained denoised wavelet coefficients. The performance of this proposed image denoising approach, is proved by the results obtained from the computations of PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity). In fact, it permits to obtain the best values of PSNR and SSIM compared to three other image denoising techniques existing in literature. These three techniques are as follows: the Image denoising approach based on neural network [9], the denoising technique based on thresholding in the *SWT* domain [4], and the denoising approach based on thresholding in the domain of 2-DDual-Tree Discrete Wavelet Transform [5]. For example, when the noisy image is Noisy House.tif with standard deviation of Additive Gaussian White Noisen, ($\sigma = 20$), the proposed denoising approach permits to obtain $PSNR = \mathbf{30.7882}$ and $SSIM = \mathbf{0.8462}$. However, the denoising technique based on thresholding in the SWT domain [4], permits to obtain $SNR = 30.3082$ and $SSIM = 0.7360$. The denoising technique based on deep learning [9], permits to obtain $PSNR = 22.4921$ and $SSIM = 0.3090$. The denoising technique based on thresholding in the domain of 2-D Dual-Tree Discrete Wavelet Transform [5], permits to obtain $PSNR = 30.5116$ and $SSIM = 0.7766$. Consequently, this example shows clearly the superiority of the proposed denoising approach compared to the other three techniques existing in literature [4, 5, 9]. The main drawbak of this proposed image denoising approach is its computation complexity compared to the two other denoising techniques [4, 5]. This complexity is due to the fact that we apply the *SWT* based image denoising technique [4] not to the whole noisy image but we apply this technique [4] to each noisy coefficient obtained from the application of the 2–D Dual-Tree Discrete Wavelet Transform, to the noisy image. Moreover, in this proposed denoising approach, we use two completely different wavelet transforms which are the Stationary Wavelet Transform (SWT) and the 2–D Dual-Tree Discrete Wavelet Transform. Consequently, we have more computation complexity compared to the two other image denoising techniques [4, 5].

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