Analysis on Natural Image Denoising Techniques

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Abstract— **The main aim of this paper is to image denoising by several algorithms published as of date and each approach has its assumptions, advantages, and limitations. Based nature of sprays, output images of spray-based methods shows noise with unknown statistical distribution. The noise reduction method is based on the assumption that the non-enhanced image is either free of noise or affected by non-perceivable levels of noise. This paper focuses on noise removal methodologies in images with an insight in the area of denoising. The denoising performance of the wavelet based shrinkage methods are compared in terms of structural similarity index, peak signal to noise ratio, image enhancement factor and the most recent measure namely multiscale structural similarity index. This is an initiative to study and analyze different variants of denoising techniques to improve their performance. In this paper a detailed survey has been carried out on various image denoising approaches and their performances on natural images were analyzed.**

Index Terms— **Dual-tree complex wavelet transform (DTWCT), HAPSO, image enhancement, noise reduction, random sprays, Wavelet Thresholding.**

I. INTRODUCTION

Although the field of image enhancement has been active since before digital imagery achieved a consumer status, it has been never stopped evolving. The present work introduces a novel multiresolution noise reduction method, tailored to address a specific image quality problem expressed by some image enhancement algorithms. A well-known feature of human vision system (HVS) is its ability to recognize the color of objects under variable illumination when this color depends on the color of the light source [1]. A number of algorithms like [10] estimate the illumination locally and then combine multiple local results into one global thus also producing the global illumination estimation. In this paper we propose a similar method based on the Random Sprays Retinex (RSR) [11], an algorithm of Retinex model, which deals with locality of color perception [12], a phenomenon by which the HVS's perception of colors is influenced by the colors of adjacent areas in the scene. The algorithms of the Retinex model provide local white balancing and brightness adjustment producing so an enhanced image and not a single vector. If the assumption of uniform illumination is taken, then a single illumination estimation vector can be created from combined local estimations. RSR was chosen because it has the advantage of being faster than other path-wise Retinex algorithms [11]. The dual-tree complex wavelet transform (CWT) is a relatively recent enhancement to the discrete wavelet transform (DWT).Random sprays are a two-dimensional collection of points with a given spatial distribution around the origin. Sprays can be used to sample an image support in place of other techniques, and have been previously used in works such as Provenzi et al. [2], [3] and Kolas et al. [4]. Random sprays based method have been partly inspired by the Human Visual System HVS). In particular, a random spray is not dissimilar from the distribution of photo receptors in the retina, although the underlying mechanisms are vastly different. Due to the peaked nature of sprays, a common side effect of image enhancement methods that utilize spray sampling is the introduction of undesired noise in the output images. The magnituded and statistical characteristics of said noise are not known exactly because they depend on several factors assumped such as image content based method, spray properties and algorithm parameters. Some of the most commonly used transforms for shrinkage based noise reduction are the Wavelet Transform (WT) [5]–[7], the Steerable Pyramid Transform [8]–[10], the Contourlet Transform [11]–[13] and the Shear let Transform [14]–[16]. With the exception of the WT, all other transforms lead to over-complete data representations. Over completeness is an important characteristics , as it is usually associated with the ability to distinguish data directionality in the transform space. We Independently of the specific transform used, the general assumption in multiresolution shrinkage coefficient is that image data gives rise to sparse coefficients in the transform space. Thus, noise reduction method can be achieved by shrinking those coefficients that compromise data sparsely. Such process is usually improved by an elaborate statistical analysis of the dependencies between coefficients at different scales. Yet, while effective, traditional multiresolution methods are designed to only remove one particular type of noise (e.g. Gaussian noise). The input image is assumed to be given. Due to the unknown statistical distributed properties of the noise introduced by the use of sprays based method, traditional Approaches do not find the expected conditions, and thus their action becomes much more effective. The proposed approach still performs noise reduction via coefficient shrinkage, yet an element of novelty is introduced by image enhancement in the form of partial reference images. Having a reference allows the shrinkage process to be data-driven. A strong source of inspiration were the works on the Dual-tree Complex Wavelet Transform by Kingsbury [17], the work on the Steerable Pyramid Transform by Simoncelli *et al*. [8], and the work on Wavelet Coefficient Shrinkage by Donoho and Johnstone .

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II. METHODS FOR IMAGE DENOISING

A. *Dual-tree complex wavelet transform*

The Discrete Wavelet Transform (DWT) has been a founding stone for all applications of digital image processing: from image denoising to pattern recognition, passing through image encoding and more. While being a complete and (quasi-)invertible transform of 2D data, the Discrete Wavelet Transform gives rise to a phenomenon known as "checker board" pattern, which means that data orientation analysis is impossible. Furthermore, the DWT is not shift-invariant, making it less useful for methods based on the computation of invariant features.

In an attempt to solve these two problems affecting the DWT, Freeman and Adelson first introduced the concept of Steerable filters [15], which can be used to decompose an image into a Steerable Pyramid, by means of the Steerable Pyramid Transform (SPT) [4]. While, the SPT is an over complete representation of data, it grants the ability to appropriately distinguish data orientations as well as being shift-invariant. Yet, the SPT is not devoid of problems: in particular, filter design can be messy [9], perfect reconstruction is not possible and computational efficiency can be a concern.

Thus, a further development of the SPT, involving the use of a Hilbert pair of filters to compute the energy response, has been accomplished with the Complex Wavelet Transform (CWT) [16]. Similarly to the SPT, in order to retain the whole Fourier spectrum, the transform needs to be over complete by a factor of 4, i.e. there are 3 complex coefficients for each real one. While the CWT is also efficient, since it can be computed through separable filters, it still lacks the Perfect Reconstruction property.

Therefore, Kingsbury also introduced the Dual-tree Complex Wavelet Transform (DTCWT), which has the added characteristic of Perfect Reconstruction at the cost of approximate shift-invariance [13].

Since the topic is extremely vast, only a brief introduction of the 2D DTCWT is given. The reader is referred to the work by Selesnick et al. [17] for a comprehensive coverage on the DTCWT and the relationship it shares with other transforms.

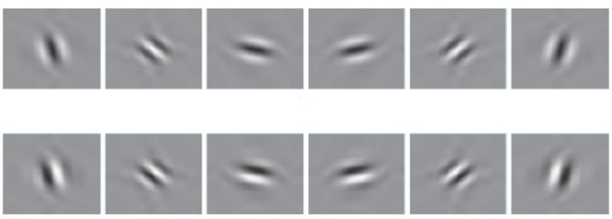

Fig.1. Quasi-Hilbert pairs wavelets used in the Dual Tree Complex Wavelet Transform

Thus, a further development of the SPT, involving the use of a Hilbert pair of filters to compute the energy response, has been accomplished with the Complex Wavelet Transform (CWT) [20]. Similarly to the SPT, in order to retain the whole Fourier spectrum, the transform needs to be over-completing by a factor of 4, i.e. there are 3 complex coefficients for each real one. While the CWT is also efficient, since it can be computed through separable filters, it still lacks the Perfect Reconstruction property.

The 2D Dual Tree Complex Wavelet Transform can be implemented using two distinct sets of separable 2D wavelet bases, as shown below.

$$\begin{aligned}
\psi_{1,1}(x,y) &= \phi_h(x)\,\psi_h(y), & \psi_{2,1}(x,y) &= \phi_g(x)\,\psi_g(y),\\
\psi_{1,2}(x,y) &= \psi_h(x)\,\phi_h(y), & \psi_{2,2}(x,y) &= \psi_g(x)\,\phi_g(y),\\
\psi_{1,3}(x,y) &= \psi_h(x)\,\psi_h(y), & \psi_{2,3}(x,y) &= \psi_g(x)\,\psi_g(y),
\end{aligned} \tag{1}$$

$$\begin{aligned}
\psi_{3,1}(x,y) &= \phi_h(x)\,\psi_h(y), & \psi_{4,1}(x,y) &= \phi_g(x)\,\psi_g(y),\\
\psi_{3,2}(x,y) &= \psi_h(x)\,\phi_h(y), & \psi_{4,2}(x,y) &= \psi_g(x)\,\phi_g(y),\\
\psi_{3,3}(x,y) &= \psi_h(x)\,\psi_h(y), & \psi_{4,3}(x,y) &= \psi_g(x)\,\psi_g(y),
\end{aligned} \tag{2}$$

TABLE I
PSN RATIOS AND SSIM SCORES FOR TEST IMAGE FROM THE USC-SIPI IMAGE DATABASE.

Noise type	Img. Name	Noisy		Denoised	
		PSNR	SSIM	PSNR	SSIM
Gaussian	Lenna	27.43	0.58	35.78	0.95
	Splash	27.68	0.49	36.37	0.93
	Mandrill	27.45	0.73	34.78	0.98
Poissonian	Lenna	30.33	0.84	35.78	0.95
	Splash	30.92	0.82	36.37	0.93
	Mandrill	30.16	0.91	34.78	0.98
Speckle	Lenna	27.07	0.55	33.96	0.94
	Splash	27.55	0.53	33.84	0.94
	Mandrill	26.96	0.69	33.87	0.97

While tuning the parameters, performance was tested using PSNR and the SSIM measure, holding the unaltered luma channel as the absolute reference. Iterations were stopped using a SSIM threshold $t = 0.001$. Scores are given in Table I.

B. *Wavelet thresholding using HAPSO*

Wavelet thresholding is a nonlinear technique wherein an image or the given data is decomposed into wavelet coefficients. These detailed coefficients are then compared with a given threshold value, coefficients smaller than the threshold are set to zero while the others are retained or modified depending on the threshold rule. The image is then reconstructed from the modified coefficients, which is called *Inverse Discrete Wavelet Transform (IDWT)* [4].Wavelet shrinkage denoising involves the following steps:

1. Acquire a noisy digital signal.
2. Compute a linear forward discrete wavelet transform of the noisy signal.
3. Perform a non-linear thresholding operation on the wavelet coefficients of the noisy signal.
4. Compute the linear inverse wavelet transform of the threshold wavelet coefficients.

To avoid this premature convergence and improve the population diversity, a hénon map based adaptive PSO

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(HAPSO) approach is proposed. Here all the deciding parameters of PSO, the inertia weight, the cognitive adaptive by special means. The use of Hénon map chaotic sequences for control parameters in PSO helps in escaping from the local minimum. Hence stochastic property in the PSO to improve the global convergence.

The Adaptive PSO (HAPSO) is then used for selecting the optimum values for the parameters: wavelet threshold, type of wavelet basis and the level of decomposition; to denoise the digital image. In this paper, after providing the necessary background theory for classical wavelet shrinkage denoising technique and standard PSO, we give a detailed description of the proposed HAPSO technique. The principal objective is to compare the performance HAPSO, with standard PSO based wavelet shrinkage denoising technique and classical wavelet shrinkage denoising techniques for effective image restoration.

TABLE II
FINAL COMPARISON OF PSNR VALUES

Shrinkage Methodology	PSNR cameraman.tif	PSNR bird.gif
Visu Shrink	20.6876	22.7382
Sure Shrink	23.7427	26.2087
PSO based Wavelet shrinkage	71.8	72.028
HAPSO based Wavelet Shrinkage	74.184	77.812

A Hénon map based adaptive Particle Swarm Optimization method for wavelet shrinkage thresholding is presented. The use of HAPSO for wavelet shrinkage image denoising is more efficient when compared to the standard PSO based wavelet shrinkage denoising, and far exceeds the classical methods VisuShrink and Sure Shrink in terms of, not only the PSNR value but also the visual quality. The HAPSO was used to optimize three wavelet parameters, the threshold value, the wavelet basis and the level of decomposition.As a result, we get more optimized values of the parameters required for denoising the image using wavelet shrinkage. A tabular comparison of the simulation results and PSNR values of the denoised images as shown in Table 2, proves the effectiveness of the proposed HAPSO.

Wavelet based denoising techniques follow the similar steps irrespective of the shrinkage function. A general framework for wavelet based denoising is shown in Figure 4.

The algorithm of wavelet based image denoising is as follows.
Step 1: Read the noisy image as input
Step 2: Perform 2D Discrete Wavelet Transform and obtain Wavelet Coefficients (Sub bands)
Step 3: Estimate noise variance from the noisy image.
Step 4: Calculate the threshold using suitable nonlinear shrinkage function.
Step 5: Apply soft thresholding.
Step 6: Perform inverse 2D Discrete Wavelet Transform on the thresholded wavelet coefficients.
Step 7: Obtain the denoised image
Step 8: Evaluate the quality of the denoised image.

The performance of the denoising algorithm relies on the optimal value of threshold. Fixed an optimal threshold is not an easy task. The nonlinear threshold functions can be seen as two major categories namely fixed threshold and adaptive threshold. The fixed threshold methods apply same threshold value with hard and soft threshold on the complete set of wavelet coefficients. As shown in Figure 3, the ranges of magnitudes of all wavelet sub bands are not similar. Hence, fixed threshold methods are likely to over smooth image details, failing to preserve image details. On the other hand sub band and scale adaptive threshold methods have been proposed to handle this. These methods use to different threshold value for each sub band at each scale so as to preserve image details.

C. RSR AND RACE

The process of Random Spray Sampling, then introduces Random Spray Retinex (RSR) and RACE, two algorithms that utilize said sampling method.

Random Spray sampling was first introduced by Provenzi et al. [18]. Random sprays are an elaboration over the physical spatial scanning structure used by Land in his seminal work on Retinex [19]. In his experiments, Land used a structure resembling a set of paths departing from a central point, on which he mounted a number of photo-detectors. Land's model given rise to the path-wise family of Retinex algorithms [20], which directly transposed Land's machinery into piece-wise linear paths used to scan the input image. A subsequent thorough mathematical analysis of Retinex allowed the model to be significantly simplified, leading, in Lena (512turn, to Random Sprays and RSR).

The output of the regular RACE algorithm results is very similar to the original input image. The output results of RSR, ACE, and RACE. This will exhibit the benefits of the hybridization, and the chance to put in evidence the failure of all three algorithms on widely extended uniform color areas.

We do not introduce other models in the comparison because, as already explained in, a proper comparison between different perceptually inspired color correction algorithms is still an open problem, and it is beyond the scope of the paper.

Tests have been performed on a set of more than 200 different pictures, composed by real-world images, portraits, landscapes, and geometric images (in [18], a series of photographs taken with different backgrounds and under different color casts can be found).

Among the pictures of our test set, we have chosen four representatives exhibiting typical photographic situations: color cast, landscape.

TABLE III
FILTERED WITH RSR, ACE, RACE, AND THEIR REGULARIZED VERSIONS

Input	RSR	ACE spray	RACE
0.39	3.51	5.49	3.91

A common technique to estimate the amount of noise induced by an algorithm is to compare the standard deviations of small uniform patches in the input images with those

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extracted from the same patches in output images. Using this technique, we can compare noise introduced or amplified by the three algorithms both with and without the regularization techniques just present. Table III.

D. Adaptive thresholding in shearlet domain

Supposing we observe noisy coefficient $g + f$ n where n is independent, zero-mean Gaussian noise. The aim of denoising is to estimate the noise-free coefficient f as accurately as possible according to some criteria. After shearlet transform, the problem can be formulated as $y + x = n$ where y is the noisy shearlet coefficients, x is the noise-free shearlet coefficient and n is noise.

a) PSNR comparisons

Table IV shows the PSNR values (in dB) for the denoised images obtained by the four methods considered in this paper for five different noise standard deviations, 10, 20, 30, 40, 50. In this table, the highest PSNR value is bolded. From Table IV, it is noted that the proposed method is competitive with the existing best denoising methods. The K-SVD algorithm used over-complete dictionary in the denoising process. The noise level is low, it achieves the highest PSNR measures. And when the noise level is high, the proposed method has been high PSNR measures. The PSNR result of the proposed method is higher than the two wavelet-based methods [6].

TABLE IV
COMPARISON OF SOME GRAY SCALE IMAGE DENOISING METHOD IN PSNR (DB)

Noise level	10	20	30	40	50
Method	Lena (512×512)				
SURE	34.38	31.06	29.20	27.96	27.05
BLS-GSM	34.64	31.42	29.52	28.20	27.22
K-SVD	35.45	32.49	30.44	29.02	27.79
Proposed	35.59	32.76	31.09	29.89	28.84

b) SSIM comparison

Although PSNR can measure the difference between two images, it is well-known that it may fail to describe the visual perception quality of an image. The PSNR value is not the best choice for image quality assessment (IQA). Among the recently proposed IQA approaches, the structural similarity (SSIM) index [20] has emerged as a promising measure for image visual quality assessment. Compared with PSNR, SSIM can better reflect the structure similarity between target image and the reference image. Table IV From Table IV we see that although K-SVD has higher PSNR measures at low noise level than the proposed method, it has almost the same SSIM results as the proposed method. When the noise level is higher, the proposed method again achieves the highest SSIM measures. The two wavelet based noise reduction methods have the lowest SSIM measures for Lena, Barbara, and Boat. For Bridge image, when the noise level is higher, SURE has the higher SSIM measures than K-SVD.

TABLE V
COMPARISON OF SOME GRAY SCALE IMAGE DENOISING METHOD IN SSIM

Noise level	10	20	30	40	50
Method	Lena (512×512)				
SURE	0.893	0.831	0.787	0.753	0.726
BLS-GSM	0.896	0.836	0.790	0.753	0.722
K-SVD	0.910	0.863	0.824	0.790	0.758
Proposed	0.911	0.872	0.845	0.822	0.803

E. Adaptive Wavelet Multiscale Thresholding Method

A new adaptive wavelet thresholding method is introduced to improve the image denoising efficiency. Besides, instead of using a traditional wavelet transform for test image an OWB is employed. A small value of threshold may let noisy coefficients be admitted, and hence the resultant images remain noisy. A large threshold value sets a larger number of coefficients to zero, which leads to smoothing of the image and may cause blurring and artifacts and hence the resultant images may lose some signal values. Therefore, an optimum threshold value, which is adaptable to each sub band, is desired to maximize the PSNR and minimize the MSE.

The image noise is assumed to be Random noise. Since image information in low frequency sub band is more than in the high frequency sub band and since the probability of noise in the high-frequency component is greater, applying a greater threshold value to the high-frequency sub bands reduces the effect of noise effectively.

The wavelet shrinkage approach can be summarized as follows:

1. Apply the wavelet transform to the signal.
2. Estimate a threshold value.
   T = sqrt(2*log(N))
   Where N is the number of pixels in the image and T is the threshold value.
3. Remove (zero out) the coefficients that are smaller than the threshold.
   X^(X,T) = Sgn (X) max(0,X-T)
4. Reconstruct the signal.

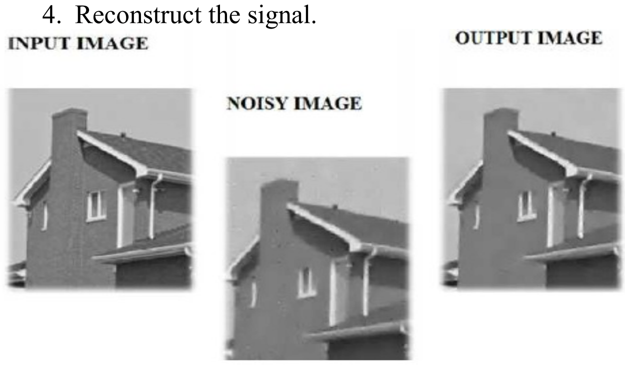

Fig.2.Simulated Output

The performance of the proposed image denoising algorithm is calculated using quantitative performance measures such as peak signal noise ratio (PSNR) and in terms of the visual quality of the images.Figure.2. we evaluated the

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effect of different parts of proposed method on image denoising performance. We conclude that the proposed image denoising algorithm yields the better PSNR value compared to the other methods for all noise intensity situations.

III. RESULTS AND DISCUSSION

Analysis of the various image denoising techniques dealt with the performance parameters of peak signal to noise ratio, structural similarity in the process of noise removal for different medical images. It is proposed to obtain a better PSNR, SSIM using the proposed algorithms. From the analysis it's clear that the noise removal using IDTWCT shows better results.

IV. CONCLUSION

This article describes a survey of different noise removal techniques for denoising medical images. These methodologies were carried out on the various medical images to analyze their performance taking into measures such as peak signal to noise ratio, structural similarity etc. From the literature analysis it is inferred that noise removal by the method of Dual-tree Complex Wavelet Transform and Wavelet transform produces very commendable results.

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