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Dual Tree Complex Wavelet Transform based Noise Reduction Technique

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Abstract: There has been a lot of research work concentrated towards noise reduction in image processing. However, with the wide spread of image usage, the development of new technique for noise reduction is become very important. This paper introduces the novel way to denoise the image, to reduce the noise which is introduced by a particular algorithm based on the random spray sampling technique used for image enhancement. Here a clearer version of an image is recovered from its noisy observation by use of Dual-tree complex wavelet transform (DTCWT). Unlike the discrete wavelet transform, DTCWT allows for distinction of data directionality in the transform space. In each level of the transform, the confirmed deviation of the non-enhanced image coefficient is computed across the DTCWT, then it is normalised which is used to shrink the coefficient of the enhanced image. The coefficients from the non-enhanced image and the shrunk coefficients are mixed and the enhanced image is computed via the inverse transform. An improvement in PSNR and SSIM are observed which clearly tells about the enhancement that can happen in the field of image processing by use of DTCWT.

Keywords: Noise reduction, image enhancement, shrinkage, random spray, Dual-tree complex wavelet transform

I. Introduction

Image denoising can be defined as the process of removing noise from an image. Image acquisition process or transmissions gives erroneous pixel values which do not reflect the actual intensities of a scene which results in noise. It is a difficult to remove noise without blurring the image edges, in image analysis. The present research introduces a novel multi-resolution noise reduction method, tailored to address a specific image quality problem that arises when using image enhancement algorithms based on random spray sampling [1]. Due to the peaked nature of sprays, a usual side effect of image enhancement methods that utilize spray sampling is the introduction of undesired noise in the output images. The magnitude and statistical characteristics of said noise are not known a-priori; instead they depend on several factors, like image content, spray properties and algorithm parameters.

One of the most commonly used transforms for shrinkage-based noise reduction are the Wavelet Transform (WT) [6], With the exception of the WT, all other transforms lead to over-complete data representations. Over-completeness is an important property, as it is normally associated with the ability to distinguish data directionality in the transform space. Another commonly used transforms for image processing includes Discrete Cosine Transform (DCT). DCT is a powerful tool which is widely used for image compression. But, DCT have some disadvantages like high loss of information, low resolution etc makes it undesirable for critical applications. Random sprays [2] 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. The general assumption in multi-resolution shrinkage is that image data gives rise to sparse coefficients in the transform space. Thus, by compressing (shrinking) those coefficients that compromise data sparsity denoising can be achieved. Such process is usually improved by an elaborate statistical analysis of the dependencies between coefficients at different scales. The traditional multi-resolution methods are designed to only remove one particular type of noise (e.g. Gaussian noise) & only the input image is assumed to be given. Traditional approaches do not find the expected conditions due to the unknown statistical properties and thus their action becomes much less effective for noise introduced by the use of sprays.

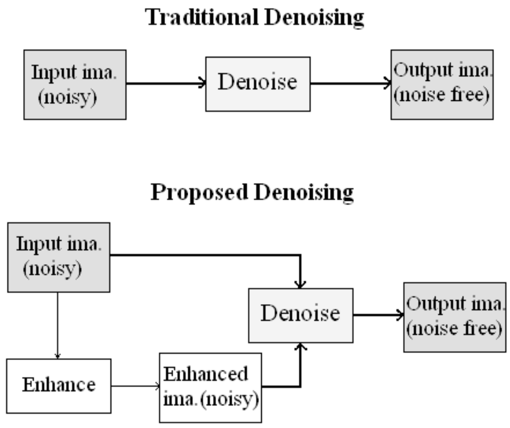

Fig. 1 High-level flow charts for traditional noise-reduction methods and the proposed one. It is evident that the scope of application is different, although the goal is the same.

Dual-tree Complex Wavelet Transform (DTCWT) has the advantage of approximate shift invariance, good directional selectivity in two dimensions, and perfect reconstruction over the traditional discrete wavelet transform [3]. Dual Tree Complex Wavelet Transform

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(DT-CWT) produced the effect of having complex coefficients without using complex filters. At the end outcome gives improved directional selectivity and close shift invariance. In the paper the Dual-tree Complex Wavelet Transform is introduced then the proposed denoising algorithm. The proposed method and results are presented in the last, and some final conclusions are drawn.

II. DUAL TREE COMPLEX WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) is important one for all applications of digital image processing: from denoising of the images to pattern recognition, extremely through image encoding and more. The Discrete Wavelet Transform has a phenomenon known as "checker board" pattern because of which it does not gives the analysis of data orientation and also the DWT is not shift-invariant because of that reason it less useful for methods based on the analysis of invariant features. To overcome the problems affected by the DWT concept of Steerable filters was introduced by Freeman and Adel son [8], which can be used to decompose an image into a Steerable Pyramid Transform, SPT[4] has the ability to appropriately distinguish data orientations as well as it is the shift-invariant. But the problems of SPT are filter design can be difficult, complete reconstruction is not possible and computational efficiency can be a concern. After that the SPT was advanced by involving the use of a Hilbert pair of filters to compute the energy response, has been skilled with the Complex Wavelet Transform[5] Similarly to the SPT, which is also efficient, and computed through separable filters, but again it lacks the Perfect Reconstruction property. The Kingsbury also introduced the Dual-tree Complex Wavelet Transform (DTCWT), having additional characteristic of Perfect Reconstruction at the cost of approximate shift-invariance [7]. The dual-tree complex wavelet transform (DTCWT) is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties of nearly shift invariant and directionally selective in two and higher dimensions.

One of the most promising decompositions that remove the above drawbacks of DWT satisfactorily is the dual-tree complex wavelet transform (DTCWT). DTCWT consist of two classical wavelet trees with real filters are developed in parallel, with the wavelets forming (approximate) Hilbert pairs. WT then interpret the wavelets in the two trees of the DT-CWT as the real and imaginary parts of some complex wavelet $\Psi c(t)$. The necessity for the dual-tree setting for forming Hilbert transform pairs is the well-known half sample delay condition. The resulting complex wavelet is then approximately analytic (i.e., approximately one sided in the frequency domain).

As the topic of DTCWT is extremely huge, only a brief introduction of the 2D DTCWT is given. The reader is referred to the work by Selesnick *et al*. [9] for all over coverage on the DTCWT and the relationship it shares with other transforms. The 2D Dual Tree Complex Wavelet Transform can be implemented using two distinct sets of separable 2D wavelet bases, as shown below.

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

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

The relationship between wavelet filters *h* and *g* is shown below

$$g_0(n) \approx h_0(n-1),\ \text{for } j = 1 \tag{3}$$
$$g_0(n) \approx h_0(n-0.5),\ \text{for } j > 1 \tag{4}$$

where *j* is the decomposition level.

When combined, the bases give rise to two sets of real, two-dimensional, oriented wavelets.

$$\psi_i(x,y) = \frac{1}{\sqrt{2}}(\psi_{1,i}(x,y) - \psi_{2,i}(x,y)) \tag{5}$$
$$\psi_i + 3(x,y) = \frac{1}{\sqrt{2}}(\psi_{1,i}(x,y) + \psi_{2,i}(x,y)) \tag{6}$$
$$\psi_i(x,y) = \frac{1}{\sqrt{2}}(\psi_{3,i}(x,y) + \psi_{4,i}(x,y)) \tag{7}$$
$$\psi_i + 3(x,y) = \frac{1}{\sqrt{2}}(\psi_{3,i}(x,y) - \psi_{4,i}(x,y)) \tag{8}$$

The most interesting characteristic of such wavelets is that they are approximately Hilbert pairs. So it interprets the coefficients deriving from one tree as imaginary, and obtains the desired 2D DTCWT.

III. PROPOSED MODEL

The past research states that: *directional content is what conveys information to the Human Visual System*. The main idea behind this work can be summarized as follows, the Retinex theory as well as the high-order gray-world assumption (alias gray-edges).Specially, the local white patch effect described by Retinex comes into play when, for a given channel, the scanning structure samples a positive intensity change. Intensity variations of a directional nature are more easily crossed (or sampled) than point-like structures such as noise, for obvious geometrical reasons.

Following such idea, the proposed method concentrates on the shrinkage, according to data directionality, of the wavelet coefficients generated by the Dual Tree Complex Wavelet Transform. The DTCWT is chosen for the ability to distinguish data orientation in transform space, its relative simplicity and other useful properties.

The HVS has been proven to be more sensitive to changes in the achromatic plane (brightness), than chromatic ones. Hence, the proposed method first converts the image in a space where the chroma is separated from the luma (such as YCbCr), and operates on the wavelet space of the luma channel. The selection to use only the luma channel does not lead to any visible colorartifact.

At last, a fundamental assumption is made: the input image is considered to be either free of noise or contaminated by non perceivable level of noise.

Due to this assumption, the input image contains the information needed for successful noise reduction. For ease of reference, a visual description is also given in Fig. 2.

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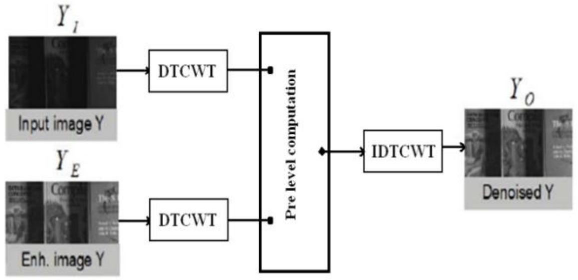

Fig. 2 Proposed method flowchart, Luma channels of both the non enhanced and the enhanced images are transformed using the DTCWT, and the obtained coefficients are elaborated. The output coefficients are transformed into the output image's luma channel via the inverse DTCWT.

Roughly, the meaning of the whole sequence can be expressed as follows: where the enhanced image shows directional content, shrink the two most significant coefficients and replace the four less significant ones with those from the non enhanced image.

The reason why only the two most significant coefficients are taken from the shrunk ones of the enhanced image is to be found in the nature of "directional content".

For a content of an image to be directional, the responses across the six orientations of the DTCWT need to be highly skewed.

In particular, any data orientation can be represented by a strong response on two adjacent orientations, while the remaining coefficients will be near zero. This will make it so that the two significant coefficients are carried over almost un-shrunk.

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.

IV. RESULT

In order to perform tests against existing methods in literature, it is thus necessary to employ a simplified testing model.

Assuming that we have a full-quality reference image R at our disposal, it is also secure to adopt that the non-enhanced image I will be a degraded version of R where the degradation consists only of a reduction in dynamic range, i.e. $I(x, y) = sR(x, y)$

The proposed method was tested against BM3D. BM3D [10] is a work by Dabov *et al.* and it is also part of the non-local family of noise reduction methods. However, it takes a two-step approach, first computing a rough estimate and second using it to drive Wiener estimation.

The input image is Lena shown in fig a. The results of the comparison are shown in Fig. 6 and Fig. 7.

The proposed noise reduction method offers overall a better performance, yet, as expected, when the non-enhanced image I has a very limited dynamic range it falls behind traditional methods (admittedly by a limited amount).

Fig. 3 Original Noisy Image

Fig. 4 Reference Enhanced Image

Iteration required for J=1 denoised image is 17 and whose PSNR value is 36.3675 and SSIM score is 0.95036

Fig. 5 Denoied Image with J=1

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The Table I shows the comparison of Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM) between Noisy, BM3D and Proposed Method for different *J* (the parameter of the Michaelis-Menten function and the depth of the complex wavelet decomposition).

TABLE I: PSNR AND SSIM FOR TEST IMAGE

	NOISY	BM3D	PROPOSED METHOD		
			J=1(17)	*J*=2(8)	*J*=3(7)
PSNR	28.1148	35.188	36.3675	35.6971	32.489
SSIM	0.6504	0.92451	0.95036	0.95671	0.93615

The results which shows that the proposed method is better than that of the convention (BM3D etc.) methods is shown in Fig. 6 and Fig. 7.. Graph shows the comparison between proposed method and BM3D in relation of PSNR and SSIM with Sigma (Gaussian noise factor) respectively in Fig. 6 and Fig. 7. In Graph X-axis represents Sigma and Y-axis represents PSNR and SSIM in respective figure. Sigma is the depth of noise in noisy image.

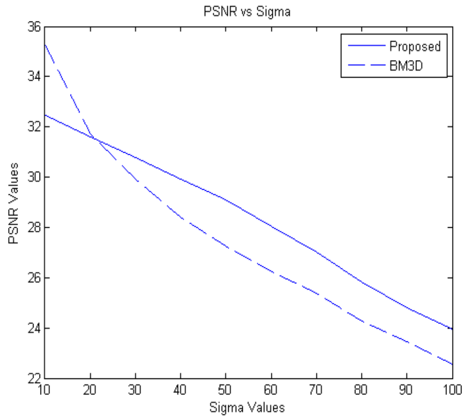

Fig. 6 Graph: PSNR vs Sigma

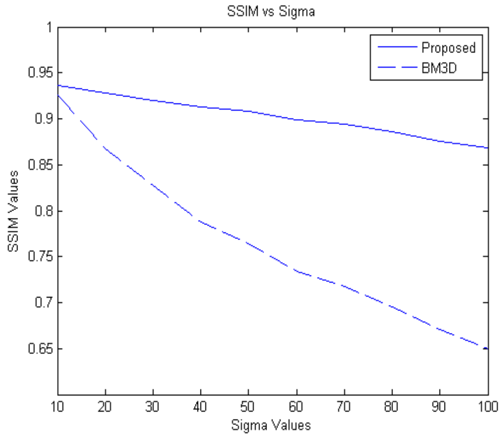

Fig. 7 Graph: SSIM vs Sigma

V. CONCLUSION

The work presents a noise reduction method based on Dual Tree Complex Wavelet Transform. The main point of novelty is represented by its application in post-processing on the output of an image enhancement method (both the non enhanced image and the enhanced one are required) and the lack of assumptions on the statistical distribution of noise. The non-enhanced image is supposed to be noise-free or affected by non perceivable noise.

To achieve pleasant denoising, the proposed method exploits the data orientation discriminating power of the Dual Tree Complex Wavelet Transform from the enhanced, noisy image to shrink coefficients. The shrunk coefficients are mixed with those from the non-enhanced, noise-free image, always according to data directionality. The output image is then computed by inverting the Dual Tree Complex Wavelet Transform and the color transform.

The SSIM and PSNR based value is calculated for different Gaussian value as a quality measure. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human eye perception. The proposed method produces good quality output, removing noise without altering the underlying directional structures in the image.

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