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Dual Tree Complex Wavelet Transform Based On Noise Reduction Using Partial Reference

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ABSTRACT

The main aim of this paper is to reduce noise introduced by image enhancement methods based on the random spray sampling technique. Based on nature of sprays, output images of spray-based methods shows noise with unknown statistical distribution. The non-enhanced image is nothing but either free of noise or affected by noise of non-perceivable levels. The dual-tree complex wavelet transform (CWT) is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties: It is nearly shift invariant and directionally selective in two and higher dimensions. Across the six orientations of the DTWCT the standard deviation of non-enhanced image coefficients can be computed, and then it normalized for each level of the transform. The result is a map of the directional structures present in the non-enhanced image. Then Said map is used to shrink the coefficients of the enhanced image. According to data directionality the shrunk coefficients and the coefficients of the non-enhanced image are mixed. Finally, the enhanced image can be computed by doing the inverse transforms. The theoretical analyses of new algorithm are well verified via computer simulations.

Index Terms — Dual-tree complex wavelet transforms (DTWCT), noise reduction, image enhancement, random sprays, and shrinkage.

INTRODUCTION

The dual-tree complex wavelet transform (CWT) is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties: It is nearly shift invariant and directionally selective in two and higher dimensions. If we use image enhancement algorithms based on random spray sampling a specific image quality problems are raised to remove that this paper introduces a novel multi-resolution denoising method. We can apply this proposed approach for other image enhancement methods that either introduce or exacerbate noise. This work builds and expands based on a previous article by Fierro et al. [1]. 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 Kolås et al. [4]. Random sprays 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 magnitude and statistical characteristics of said noise are not known exactly because they depend on several factors such as image content, 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 characteristic, 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 multi-resolution shrinkage is that image data gives rise to sparse coefficients in the transform space. Thus, denoising 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 multi-resolution methods are designed to only remove one particular type of noise (e.g. Gaussian noise). Furthermore, only the input image is assumed to be given. Due to the unknown statistical properties of the noise introduced by the use of sprays, traditional Approaches do not find the expected conditions, and thus their action becomes much less effective.

The proposed approach still performs noise reduction via coefficient shrinkage, yet an element of novelty is introduced in the form of partial reference images.

This paper is outlined as follows. Section II gives the brief explanation of Dual-tree Complex Wavelet Transform, while the proposed denoising algorithm presented in Section III . Section IV presents the theoretical performance analyses followed by the conclusions in Section V

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, passing through image encoding and more. The Discrete Wavelet Transform which does not gives the analysis of data orientation because it has a phenomenon known as “checker board” pattern, and the DWT is not shift-invariant because of that reason it less useful for methods based on the computation of invariant features. To overcome the problems affected by the DWT concept of Steerable filters was introduced by Freeman and Adel son [18], this Steerable filters can be used to decompose an image into a Steerable Pyramid, SPT is the shift-invariant and as well as it has the ability to appropriately distinguish data orientations. But the SPT has the problems: the filter design can be difficult, perfect reconstruction is not possible and computational efficiency can be a concern. After that the SPT was developed by involving the use of a Hilbert pair of filters to compute the energy response, has been accomplished with the Complex Wavelet Transform Similarly to the SPT, this CWT is also efficient, since it can be computed through separable filters, but it still lacks the Perfect Reconstruction property. Therefore, Kingsbury also introduced the Dual-tree Complex Wavelet Transform (DTCWT), it has the additional characteristic of Perfect Reconstruction at the cost of approximate shift-invariance [17]. The 2D Dual Tree Complex Wavelet Transform can be implemented using two distinct sets of separable 2D wavelet bases, the dual-tree complex wavelet transform (CWT) is a recent enhancement of the discrete wavelet transform (DWT), with important properties like it is nearly shift invariant and directionally selective in two and higher dimensions. It achieves with a redundancy factor of only 2d for d-dimensional signals, which is substantially lower than the un decimated DWT. The multidimensional (M-D) dual-tree CWT is non separable but is based on a computationally efficient, separable filter bank (FB). We use the complex number symbol C in CWT to avoid confusion with the often-used acronym CWT for the (different) continuous wavelet transform

PROPOSED METHODOLOGY

The proposed method circulates around the shrinkage, based on data directionality, of the wavelet coefficients generated by the Dual Tree Complex Wavelet Transform. The DTCWT has useful properties: it’s capable to distinguish the data orientation in transform space and DTWCT is relatively simple. The human visual system (HVS) is more sensitive to changes in the achromatic plane (brightness), than chromatic ones [19]. Hence, the proposed algorithm first converts the image in a space where the chrome is separated from the luma (such as YCbCr), and operates on the wavelet space of the luma channel. The choice to use only the luma channel does not lead to any visible color artifact. Finally the input image is considered to be either free of noise, or contaminated by non perceivable noise. If such an assumption holds, the input image contains the information needed for successful noise reduction.

A. Wavelet Coefficients Shrinkage

Assuming level j of the wavelet pyramid, one can compute the energy for each direction of the non-enhanced image $k \in \{1,2,\dots,6\}$ as the sum of squares of the real coefficients $m^{I}_{j,k}$ and the complex ones $n^{I}_{j,k}$

$$e_{j,k} = \left(m^{I}_{j,k}\right)^2 + \left(n^{I}_{j,k}\right)^2$$

Coefficients associated with non-directional data will have similar energy in all directions. On the other hand, directional data will give rise to high energy in one or two directions, according to its orientation. The standard deviation of energy across the six directions k = 1, 2, . . . , 6 is hence computed as a measure of directionality.

$$e_j = \underset{k}{\mathrm{stddev}}(e_{j,k})$$

Since the input coefficients are not normalized, it naturally follows that the standard deviation is also non-normalized. The Michaelis-Menten function [20] is thus applied to normalize data range. Such function is sigmoid-like and it has been used to model the cones responses of many species. The equation is as follows

$$\mathrm{mm}(x, \mu, \gamma) = \frac{x^\gamma}{x^\gamma + \mu^\gamma}$$

where x is the quantity to be compressed, γ a real-valued exponent and μ the data expected value or its estimate. Hence, a normalized map of directionally sensitive weights for a given level j can be obtained as

$$w_j = \mathrm{mm}(e_j, \underset{k}{\mathrm{median}}(e_{j,k}), \gamma_j)$$

where the choice of γ depends on j as explained later on. A shrunk version of the enhanced image's coefficients, according to data directionality, is then computed as

$$\tilde{b}^E_{j,k} = w_j . b^E_{j,k} + (1 - w_j) . b^I_{j,k}$$

$$\tilde{c}^E_{j,k} = w_j . c^E_{j,k} + (1 - w_j) . c^I_{j,k}$$

Since the main interest is retaining directional information, we obtain a rank for each of the non-enhanced coefficients as

$$i^I_{j,k} = \mathrm{ord}(b^I_{j,k}), \epsilon\{1,2 \dots ,6\}$$

where ord is the function that returns the rank according to natural ordering. The output coefficients are then computed as follows

$$b^o_{j,k} = \begin{cases} \tilde{b}^E_{j,k}, & \text{if } i^I_{j,k} \epsilon \{1, 2\} \\ b^I_{j,k}, & \text{if } i^I_{j,k} \epsilon \{3, 4, 5, 6\} \end{cases}$$

$$c^o_{j,k} = \begin{cases} \tilde{c}^E_{j,k}, & \text{if } i^I_{j,k} \epsilon \{1, 2\} \\ c^I_{j,k}, & \text{if } i^I_{j,k} \epsilon \{3, 4, 5, 6\} \end{cases}$$

Where ord is the function that returns the index of a coefficient in $m^I_k = 1,2, \dots ,6$ when the set is sorted in a descending order. The meaning of the whole sequence can be roughly 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 an 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

RESULTS

A. HISTOGRAM METHOD

Original Image

Enhanced Image

Proposed Image

PSNR w.r.t Noisy 10.9378

PSNR w.r.t Denoised 43.5981

Original Image

Enhanced Image

Proposed Image

PSNR w.r.t Noisy 40.2529

PSNR w.r.t Denoised 40.7176

B.ACE ENHANCED METHOD

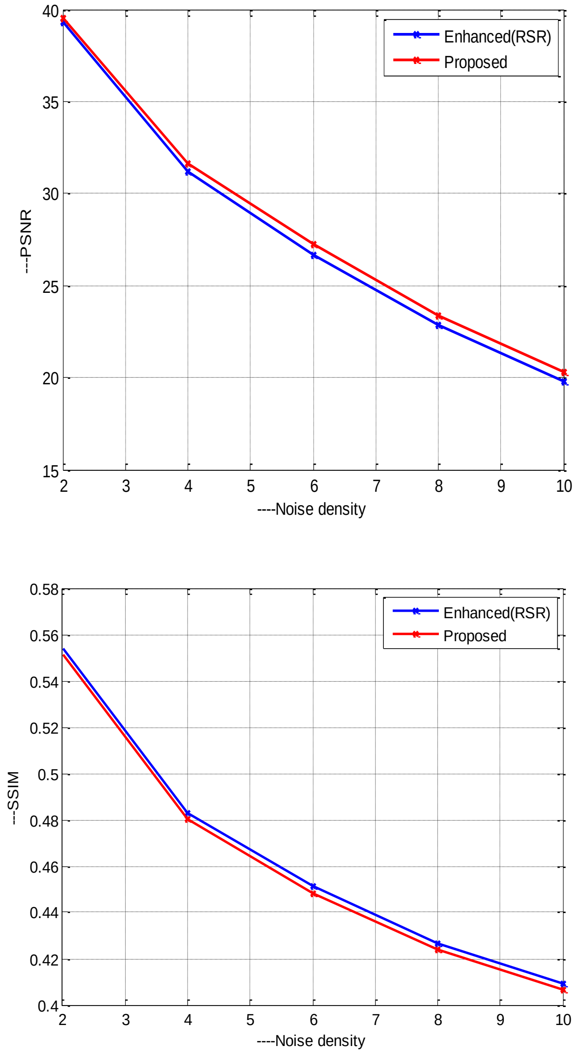

Figure : PSNR vs NOISE DENSITY

ANALYSIS

HISTOGRAM

PSNR w.r.t Noisy 2.35

PSNR w.r.t Denoised 15.0708

ACE METHOD

PSNR w.r.t Noisy 26.9884

PSNR w.r.t Denoised 28.1782

CONCLUSION

This paper presents a noise reduction method based on Dual Tree Complex Wavelet Transform coefficients shrinkage. 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. On the other hand, the non-enhanced image is nothing but noise-free or affected by non perceivable noise. The images are first converted to a color space with distinct chromatic and achromatic axes based on properties of the Human Visual System but only the achromatic part becomes object of the noise reduction process. To achieve perfect denoising, the proposed method exploits the data orientation discriminating power of the Dual Tree Complex Wavelet Transform to shrink coefficients from the enhanced, noisy image. Always according to data directionality, the shrunk coefficients are mixed with those from the non-enhanced, noise-free image. The output image is then computed by inverting the Dual Tree Complex Wavelet Transform and the color transform. Since at the time of writing no directly comparable method was known to the authors, performance was tested in a number of ways, both subjective and objective, both quantitative and qualitative. Subjective tests include a user panel test, and close inspection of image details. Objective tests include scan line analysis for images without a known prior, and computation of PSNR and SSIM on images with a full reference. The proposed algorithm produces good quality output by removing noise without altering the underlying directional structures in the image. Also, although designed to tackle a quality problem specific to spray-based image enhancement methods, the proposed approach also proved effective on compression and latent noise brought to the surface by histogram equalization. it requires two input images (one non-enhanced and one enhanced) and its iterative nature, which expands computation time considerably with respect to one-pass algorithms these are the main limitations of proposed method.

FRUTURE SCOPE:

In this paper, instead of DTCWT we can use Contourlet Transform. This will overcome the challenges of wavelet and curvelet transform. Contourlet transform is a double filter bank structure. It is implemented by the pyramidal directional filter bank (PDFB) which decomposes images into directional subbands at multiple scales. In terms of structure the contourlet transform is a cascade of a Laplacian Pyramid and a directional filter bank. In essence, it first uses a wavelet-like transform for edge detection, and then a local directional transform for contour segment detection. The contourlet transform provides a sparse representation for two-dimensional piecewise smooth signals that resemble images.

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REFERENCES

[1]M. Fierro, W.-J. Kyung and Y.-H. Ha, "Dual-tree complex wavelet transform based denoising for random spray image enhancement methods," in Proc. 6th Eur. Conf. Colour Graph., Image. Vis., 2012, pp. 194–199.

[2] E. Provenzi, M. Fierro, A. Rizzi, L. De Carli, D. Gadia, and D. Marini, "Random spray retinex: A new retinex implementation to investigate the local properties of the model," vol. 16, no. 1, pp. 162–171, Jan. 2007.

[3] E. Provenzi, C. Gatta, M. Fierro, and A. Rizzi, "A spatially variant whitepatch and gray-world method for color image enhancement driven by local contrast," vol. 30, no. 10, pp. 1757–1770, 2008.

[4] Ø. Kolås, I. Farup, and A. Rizzi, "Spatio-temporal retinex-inspired envelope with stochastic sampling: A framework for spatial color algorithms," J. Imag. Sci. Technol., vol. 55, no. 4, pp. 1–10, 2011.

[5] H. A. Chipman, E. D. Kolaczyk, and R. E. McCulloch, "Adaptive bayesian wavelet shrinkage," J. Amer. Stat. Assoc., vol. 92, no. 440, pp. 1413–1421, 1997.

[6] A. Chambolle, R. De Vore, N.-Y. Lee, and B. Lucier, "Nonlinear wavelet image Processing: Variational problems, compression, and noise removal through wavelet shrinkage," IEEE Trans Image Process., vol. 7, no. 3, pp. 319–335, Mar. 1998.

[7] D. Cho, T. D. Bui, and G. Chen, "Image denoising based on wavelet shrinkage using neighbor and level dependency," Int. J. Wavelets, Multiresolution Inf. Process., vol. 7, no. 3, pp. 299–311, May 2009.

[8] E. P. Simoncelli and W. T. Freeman, "The steerable pyramid: A flexible architecture for multi-scale derivative computation," in Proc. 2nd Annu. Int. Conf. Image Process., Oct. 1995, pp. 444–447.

[9] F. Rooms, W. Philips, and P. Van Oostveldt, "Integrated approach for estimation and restoration of photon-limited images based on steerable pyramids," in Proc. 4th EURASIP Conf. Focused Video/Image Process. Multimedia Commun., vol. 1. Jul. 2003, pp. 131–136.

[10] H. Rabbani, "Image denoising in steerable pyramid domain based on a local laplace prior," Pattern Recognit., vol. 42, no. 9, pp. 2181–2193, Sep. 2009.

[11] S. Foucher, G. Farage, and G. Benie, "Sar image filtering based on the stationary contourlet transform," in Proc. IEEE Int. Geosci. Remote Sens. Symp., Jul.–Aug. 2006, pp. 4021–4024.

[12] W. Ni, B. Guo, Y. Yan, and L. Yang, "Speckle suppression for sar images based on adaptive shrinkage in contourlet domain," in Proc. 8th World Congr. Intell. Control Autom., vol. 2. 2006, pp. 10017–10021.

[13] K. Li, J. Gao, and W. Wang, "Adaptive shrinkage for image denoising based on contourlet transform," in Proc. 2nd Int. Symp. Intell. Inf. Technol. Appl., vol. 2. Dec. 2008, pp. 995–999.

[14] Q. Guo, S. Yu, X. Chen, C. Liu, and W. Wei, "Shearlet-based image denoising using bivariate shrinkage with intra-band and opposite orientation dependencies," in Proc. Int. Joint Conf. Comput. Sci. Optim., vol. 1. Apr. 2009, pp. 863–866.

[15] X. Chen, C. Deng, and S. Wang, "Shearlet-based adaptive shrinkage threshold for image denoising," in Proc. Int. Conf. E-Bus. E-Government, Nanchang, China, May 2010, pp. 1616–1619.

[16] J. Zhao, L. Lu, and H. Sun, "Multi-threshold image denoising based on shearlet transform," Appl. Mech. Mater., vols. 29–32, pp. 2251–2255, Aug. 2010

[17] N. G. Kingsbury, "The dual-tree complex wavelet transform: A new technique for shift invariance and directional filters," in Proc. 8th IEEE Digit. Signal Process. Workshop, Aug. 1998, no. 86, pp. 1–4.

[18] W. Freeman and E. Adelson, "The design and use of steerable filters," IEEE Trans. Pattern Anal. Mach. Intell., vol. 13, no. 9, pp. 891–906, Sep. 1991

[19] M. Livingstone, Vision and Art: The Biology of Seeing. New York: Harry N. Abrams, 2002.

[20] L. Menten and M. I. Michaelis, "Die kinetik der invertinwirkung," Biochem, vol. 49, pp. 333–369, Feb. 1913