Noise Reduction Based On Partial Different, Dual Tree Complex Wavelet Transform Shrinkage

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Abstract- *This work presents a novel way to reduce noise introduced or exacerbated by image enhancement methods, in particular algorithms based on the random spray sampling technique, but not only. According to the nature of sprays, output images of spray-based methods tend to exhibit noise with unknown statistical distribution. To avoid inappropriate assumptions on the statistical characteristics of noise, a different one is made. In fact, the non-enhanced image is considered to be either free of noise or affected by non-perceivable levels of noise. Taking advantage of the higher sensitivity of the human visual system to changes in brightness, the analysis can be limited tothe luma channel of both the non-enhanced and enhanced image. Also, given the importance of directional content in human vision, the analysis is performed through the dual-tree complex wavelet transform (DTWCT). Differently from the discrete wavelet transform, the DTWCT allows for distinction of data directionality in the transform space. For each level of the transform, the standard deviation of the non-enhanced image coefficients is computed across the six orientations of the DTWCT, then it is normalized. The result is a map of the directional structures present in the non-enhanced image. Said map is then used to shrink the coefficients of the enhanced image. The shrunk coefficients and the coefficients from the non-enhanced image are then mixed according to data directionality. Finally, a noise-reduced version of the enhanced image is computed via the inverse transforms. A thorough numerical analysis of the results has been performed in order to confirm the validity of the proposed approach.*

Keywords- Dual-tree complex wavelet transform (DTWCT),

I. INTRODUCTION

Although the field of image enhancement has been active since before digital imagery achieved a consumer status, it has never stopped evolving. The present work introduces a novel multi-resolution denoising method, tailored to address a specific image quality problem that arises when using image enhancement algorithms based on random spray sampling. While inspired by the peculiar problem of such methods, the proposed approach also works for other image enhancement methods that either introduce or exacerbate noise. This work builds and expands on a previous article by Fierro et al. 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.,and Kolas et al.. 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 a-priori, instead they depend on several factors, like image content, spray properties and algorithm parameters. Among image denoising algorithms, multi-resolution methods have a long history. A particular branch is that of transform space coefficients shrinkage, i.e. the magnitude reduction of the transform coefficients according to certain criteria. Some of the most commonly used transforms for shrinkage-based noise reduction are the Wavelet Transform (WT) , the Steerable Pyramid Transform, the Contourlet Transform and the Shearlet Transform . 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. 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 compressing (shrinking) those coefficients that compromise data sparsity. 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. 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., and the work on Wavelet Coefficient Shrinkage by Donoho and Johnstone. depicts the differences between traditional noise-reduction methods and the one proposed. The remainder of this paper is organized as follows. The Dual-tree Complex Wavelet Transform is introduced in Section II, while Section III outlines the concept of random spray sampling, and the image enhancement methods Random Spray.

II. PROPOSED METHODOLOGY

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 , which can be used to decompose an image into a Steerable Pyramid, by means of the Steerable Pyramid Transform (SPT). 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, 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) . 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. Since the topic is extremely vast, only a brief introduction of the 2D DTCWT is given. The reader is referred to the the work by Selesnick et al.for a comprehensive 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.

III. DESCRIPTION

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 scanline analysis for images without a known prior, and computation of PSNR and SSIM on images with a full reference. The proposed method produces good quality output, 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. The method’s main limitations are the necessity of two input images (one non-enhanced and one enhanced) and its iterative nature, which expands computation time considerably with respect to one-pass algorithms.

IV. RESULT

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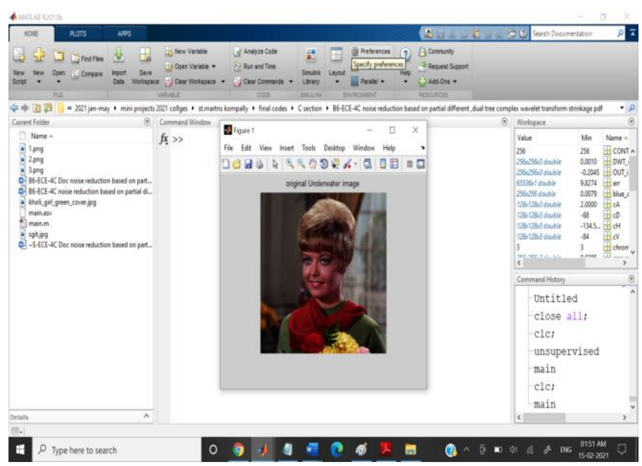

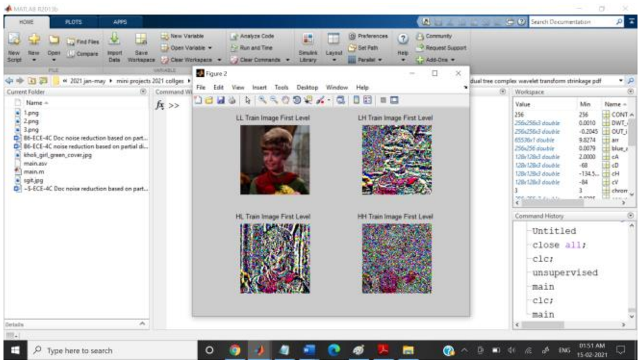

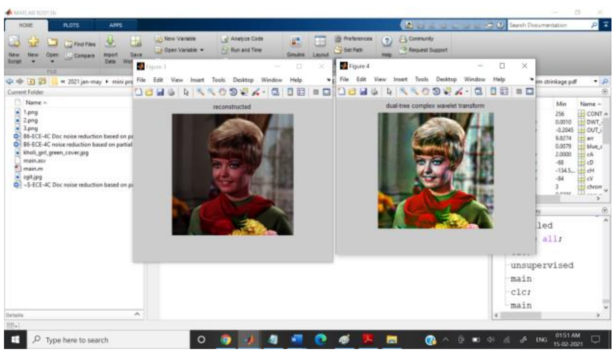

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