

Demosaicing and Sharpening of Color Filter Captured Images using Adaptive Transformation

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ABSTRACT: Tele-dermatology is becoming an important tool for early skin cancer detection in public health, but low-cost cameras tend to cause image blurring, which affect diagnosis quality. Obtaining cost-effective images with diagnosis quality is a current challenge, and this paper proposes a noise removal algorithm for color images corrupted by additive Gaussian noise and a robust open close sequence filter based on mathematical morphology for high probability additive Gaussian noise removal is given. First, an additive Gaussian noise detector using mathematical residues is to identify pixels that are contaminated by the additive Gaussian noise. Then the image is restored using specialized open-close sequence algorithms that apply only to the noisy pixels. But the color blocks that degrade the quality of the image will be recovered by a block smart erase method. This algorithm can be applied to highly corrupted images. Mathematical morphology is a nonlinear image processing methodology that is based on the application of lattice theory to spatial structures. In color images, algorithms are developed for boundary extraction via a morphological gradient operation and for region partitioning based on texture content. Mathematical morphological operations are useful in smoothing and sharpening, which often are useful as per or post processing steps.

KEYWORDS: Adaptive image denoising, Adaptive image enhancement, Color image processing, wavelet domain

I. INTRODUCTION

The goal of removing additive Gaussian noise is to suppress the noise while preserving the integrity of edge and detail information associated with the original image. To this end, nonlinear techniques have been found to provide more satisfactory results in comparison with linear methods. The traditional median filters process all the pixels of the image, without taking account of whether or not a pixel is corrupted by additive Gaussian noise [1]. To avoid this disadvantage, it is important to detect whether the current pixel is corrupted. These approaches involve a preliminary identification of corrupted pixels in an effort to prevent alteration of true pixels. Among those are center weighted median (CWM) filter [2-4], pixel-wise MAD (PWMAD) [5-6], discrete wavelet transform [12], dual tree discrete wavelet transform [12] and recently, additive Gaussian noise removal based on mathematical morphology has been attracting research effort [7-12]. Mathematical morphology is nonlinear image processing methodology. After that mathematical morphology has become popular in the image processing field due to its rigorous mathematical description and its proven applicability in a number of imaging problems including noise elimination, feature extraction and image compression [13-15]. To remove the commonly found noise without losing details of the image, morphological filters with directional, multiple structuring elements, or multiscale filtering have been used. Although the above filters & wavelet transforms give a better performance in terms of additive Gaussian noise removal. In this paper, the performance of a robust open-close sequence (OCS) filter has been evaluated and compared with the performance of other existing filters and discrete wavelet transform to restore images that are corrupted by noise variance from 10 to 80. There is active research in the areas of color image enhancement/ sharpening [6], [15] and denoising [3], [9]. However, denoising and enhancement are somewhat dual problems: denoising tends

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to eliminate fine details, while enhancement tends to amplify noise as well. This paper presents a novel wavelet-based adaptive sharpening technique for color images that prevents the unwanted enhancement of noise, suited for dermatological images acquired with standard cameras. An undecimated wavelet transform is used to estimate color gradient magnitudes at different scales. Next, noise and edges are distinguished based on statistical properties of their gradient magnitudes. In order to further improve the discrimination of edges and noise, inter-scale and contour continuity constraints are applied. This paper also proposes a method for selecting of the number of dyadic scales used in the wavelet decomposition adaptively (i.e., more scales are used when noise contamination is higher). Finally, an adaptive edge enhancement procedure is applied for a better visualization of image details.

The proposed system analyzes coefficients intra and inters scales, directionally smoothes noisy pixels, sharpens edges and selects adaptively an adequate number of scales. Mathematical morphology is nonlinear image processing methodology that is based on the application of lattice theory to spatial structures. In color images, filter bank algorithms are developed for boundary extraction via a morphological gradient operation and for region partitioning based on texture content. Mathematical morphological operations are useful in smoothing and sharpening, which often are useful as per or post processing steps.

A robust open close sequence filter based on mathematical morphology for high probability additive Gaussian noise removal is given. First, an additive Gaussian noise detector using mathematical residues is to identify pixels that are contaminated by the additive Gaussian noise. Then the image is restored using specialized open-close sequence algorithms that apply only to the noisy pixels. But, the color blocks that degrade the quality of the image will be recovered by a block smart erase method. This algorithm can be applied to highly corrupted images.

Consider an image $I[n,m]$ and for each scale 2^j , a common approach for image denoising is to find shrinkage factors $g_j[n,m]$, for $j=1,\dots,J$, where J is the number of scales used in the decomposition. The shrinkage factors are chosen to preserve relevant image structures, while image noise is reduced. The determination of shrinkage factors for noisy images relies on the discrimination between pixels that belong to noisy [6],[8] homogeneous regions, and pixels that are related to sharp transitions.

In homogeneous regions, detail coefficients will be affected mainly by noise; at edges, detail coefficients will be influenced by both noise and the noise free edges, that is, edges with varying degrees of noise corruption. Hence, a detail coefficient d of a noise image, at a given sub band and color channel, can be considered a random variable.

II. MATHEMATICAL MORPHOLOGY

Mathematical morphology is nonlinear image processing methodology that is based on the application of lattice theory to spatial structures. After that, mathematical morphology has become popular in the image processing field, due to its rigorous mathematical description and its proven applicability in a number of imaging problems, including noise elimination, feature extraction, and image compression [13-15]. Two fundamental mathematical morphological operations are: dilation and erosion. In fact, many of the morphological algorithms are based on these two primitive operations. In gray scale images, we develop algorithms for boundary extraction via a morphological gradient operation, and for region partitioning based on texture content. Mathematical morphological operations are also useful in smoothing and sharpening, which often are useful as per or post processing steps [13-15].

III. DISCRETE WAVELET TRANSFORM

A. WAVELET TRANSFORM:

The simplest wavelet transform for multi-dimensional digital data is the critically-sampled separable wavelet transform. This transform uses a 1-D wavelet transform in each dimension and is the one that is conventionally used. However, one way to improve the performance of wavelet based signal and image processing algorithms is to use specialized wavelet transforms in place of the conventional wavelet transform. There are several advances in the design of specific wavelet transforms that lead to substantially improved performance. For example, the undecimated wavelet transform, the steerable pyramid and curvelet transform all give improved results in applications involving multidimensional data. Recently dual-tree transform (an oriented complex-valued wavelet transform) have proved to be highly beneficial for

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multi-dimensional signal processing. This transform has advantages of near shift invariance, directional selectivity and improved energy compaction [8- 12] over the conventional multi-dimensional wavelet transform.

B. SEPARABLE DISCRETE WAVELET TRANSFORM (SDWT)

B.1. 1-D Discrete Wavelet Transform

The analysis filter bank decomposes the input signal $x(n)$ into two sub band signals, $c(n)$ and $d(n)$. The signal $c(n)$ represents the low frequency part of $x(n)$, while the signal $d(n)$ represents the high frequency part of $x(n)$. We denote the low pass filter by $af1$ (analysis filter 1) and the high pass filter by $af2$ (analysis filter 2). The output of each filter is then down sampled by 2 to obtain the two sub band signals $c(n)$ & $d(n)$. The Synthesis filter bank combines the two sub band signals $c(n)$ & $d(n)$ to obtain a single signal $y(n)$. The synthesis filters bank up-samples each of the two sub band signals.

The signals are then filtered using a low pass and a high pass filter. We denote the low pass filter by $sf1$ (synthesis filter 1) and the high pass filter by $sf2$ (synthesis filter 2). The signals are then added together to obtain the signal $y(n)$. If the four filters are designed so as to guarantee that the output signal $y(n)$ equals the input signal $x(n)$, then the filters are said to satisfy the perfect reconstruction condition [9-11].

B.2. 2-D Discrete Wavelet Transform

When wavelet transform is used in image processing applications it is required to implement a 2D version of the analysis and synthesis filter banks. In the 2D case, the 1D analysis filter bank is first applied to the columns of the image and then applied to the rows. If the image has $N1$ rows and $N2$ columns, then after applying the 1D analysis filter bank to each column we have two sub band images, each having $N1/2$ rows and $N2$ columns; after applying the 1D analysis filter bank to each row of both of the two sub band images, four sub band images are obtained, each having $N1/2$ rows & $N2/2$ columns. The 2D synthesis filter bank combines the four sub band images to obtain the original image of size $N1$ by $N2$.

C. BIVARIATE SHRINKAGE FUNCTIONS FOR WAVELET BASED IMAGE ENHANCEMENT.

We have considered non-Gaussian bivariate probability distribution function to model the statistics of wavelet coefficients of natural images. The model captures the dependence between a wavelet coefficient and its parent. Using Bayesian estimation theory we derive from this model a simple non-linear shrinkage function for wavelet denoising, which generalizes the soft thresholding approach of Donoho and Johnstone. The new shrinkage function, which depends on both the coefficient and its parent, yields improved results for wavelet-based image denoising [8-10].

D. LOCAL ADAPTIVE IMAGE ENHANCEMENT

Using the bivariate shrinkage function, we developed an effective and low complexity locally adaptive image denoising algorithm in [8-10]. This shrinkage function requires the prior knowledge of the noise variance and the signal variance for each wavelet coefficient. Therefore the algorithm first estimates these parameters [8- 10] for the recipe of the estimation rules. Briefly, the algorithm is summarized as follows:

1. Calculate the noise variance.
2. For each wavelet coefficient,
 - i. Calculate signal variance,
 - ii. Estimate each coefficient using the bivariate shrinkage function.

E. DUAL TREE DISCRETE WAVELET TRANSFORM (DTDWT)

There are two versions of the 2D dual-tree wavelet transform: the real 2-D dual-tree DWT is 2-times expansive, while the complex 2-D dual-tree DWT is 4-times expansive. Both types have wavelets oriented in six distinct directions. We describe the real version first [8] [10-15].

a) Real 2-D Dual-tree Wavelet Transform

The real 2-D dual-tree DWT of an image x is implemented using two critically-sampled separable 2-D DWTs in parallel. Then for each pair of sub bands we take the sum and difference [8-15].

b) Complex 2-D Dual-tree Wavelet Transform

The dual-tree complex DWT (DT-CDWT) of a signal x is implemented using two critically-sampled DWTs in parallel on the same data, as shown in the Fig. 1. This transform is 2-times expansive because for an N -point signal it gives $2N$ DWT coefficients. If the filters in the upper and lower DWTs are the same, then no advantage is gained. However, if the filters are designed in a specific way then the sub band signals of the



Figure 1: Cameraman with noise variance .01

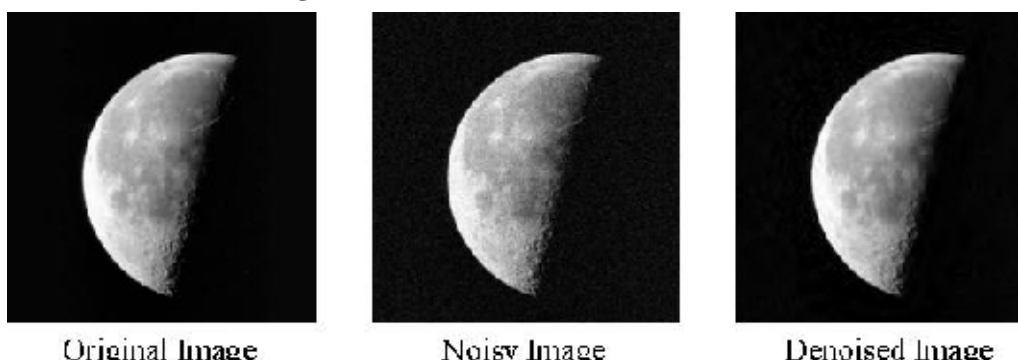


Figure 2: Moon with noise variance .01

upper DWT can be interpreted as the real part of a complex wavelet transform and sub band signals of the lower DWT can be interpreted as the imaginary part. Equivalently, for specially designed sets of filters, the wavelet associated with the upper DWT can be an approximate Hilbert transform of the wavelet associated with the lower DWT. When designed in this way, the dualtree complex DWT is nearly shift-invariant, in contrast with the critically-sampled DWT. Moreover, the dual-tree complex DWT can be used to implement 2D wavelet transforms where each wavelet is oriented, which is especially useful for image processing. For the separable 2D DWT, recall that one of the three wavelets does not have a dominant orientation. The dual-tree complex DWT outperforms the critically-sampled DWT for applications like image denoising and enhancement. The complex 2-D dual-tree DWT also gives rise to wavelets in six distinct directions, however, in this case there are two wavelets in each direction as will be illustrated.

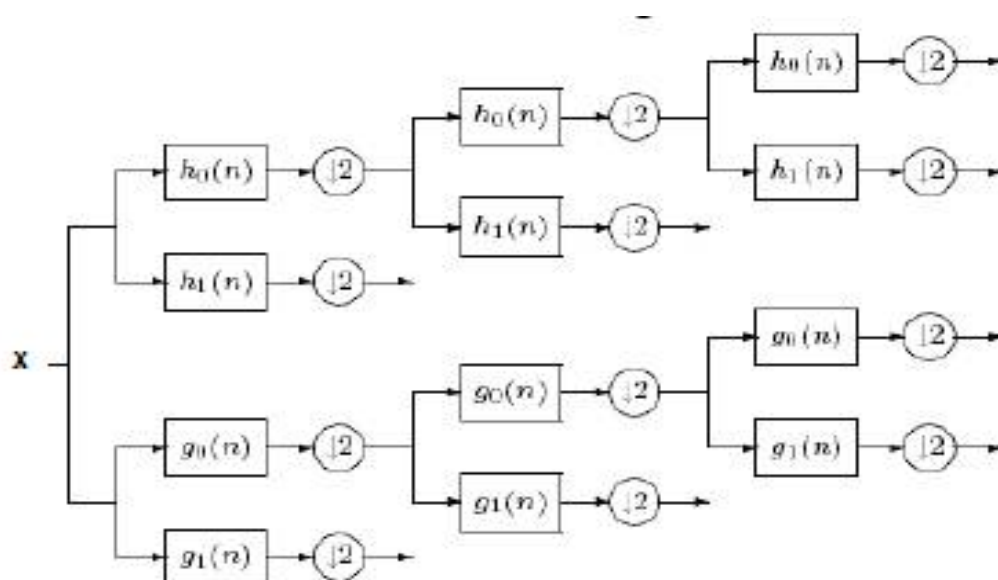


Fig. 3: Dual Tree Complex Discrete Wavelet Transform

In each direction, one of the two wavelets can be interpreted as the real part of a complex-valued 2D wavelet, while the other wavelet can be interpreted as the imaginary part of a complex-valued 2D wavelet. Because the complex version has twice as many wavelets as the real version of the transform, the complex version is 4-times expansive. The complex 2-D dual-tree is implemented as four critically sampled separable 2-D DWTs operating in parallel. However, different filter sets are used along the rows and columns. As in the real case, the sum and difference of sub band images is performed to obtain the oriented wavelets [18-37]. One of the advantages of the dual-tree complex wavelet transform is that it can be used to implement 2D wavelet transforms that are more selective with respect to orientation than is the separable 2D DWT.

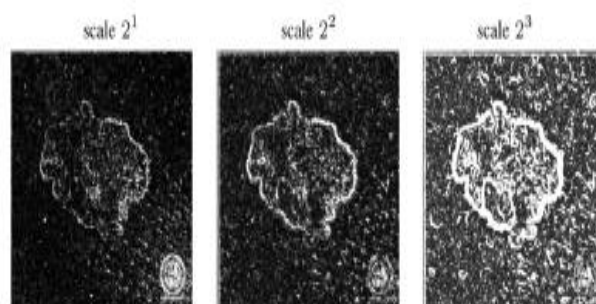


Fig. 4: Shrinkage factors after applying consistency across scales.

IV. EXPERIMENTS

Quantitatively assessing the performance in practical application is a complicated issue because the ideal image is normally unknown at the receiver end. So this paper uses the following method for experiments. One original image is applied with Gaussian noise with different variance. The methods proposed for implementing image de-noising using wavelet transform take the following form in general. The image is transformed into the orthogonal domain by taking the wavelet transform. The detail wavelet coefficients are modified according to the shrinkage algorithm. Finally,

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inverse wavelet is taken to reconstruct the de-noised image. In this paper, different wavelet bases are used in all methods. For taking the wavelet transform of the image, readily available MATLAB routines are taken. In each sub-band, individual pixels of the image are shrunk based on the threshold selection. A de-noised wavelet transform is created by shrinking pixels. The inverse wavelet transform is the de-noised image.

V. CONCLUSION

This work presented a novel technique for denoising and sharpening color images, based on a non-decimated Wavelet Transform. In the proposed approach, a color edge map is computed at each scale, and squared gradient magnitudes are modeled by a mixture of chi-squared and gamma distributions to discriminate edge-related from noise-related coefficients. Then, a nonlinear function is used to enhance edges at different scales, without amplifying the inherent noise contained in the image. The proposed method allows the selection of the number of scales for enhancement and the individual enhancement factor for each scale. Most of the enhanced images will be considered as better than the original. Although the method is intended to serve as an unsupervised tool for aiding tele-dermatology applications, the specialist may change the values of coefficients and interactively to obtain optimal results for each individual image and aspect of analysis (e.g., sharpness, texture/relief, lesion contour and color).

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