International Journal of Research (IJR)
e-ISSN: 2348-6848, p- ISSN: 2348-795X Volume 2, Issue 07, July 2015
Available at http://internationaljournalofresearch.org

Using structural similarity index measuring the Patch locally optimal wiener filter in discrete wavelet transform

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Abstract

Image denoising has been a well studied quandary in the field of image processing and it is still a conundrum for researches. More expeditious shutter speeds and higher density of image sensors (pixels) result in higher calibers of noise in the captured image, which must then be processed by denoising algorithms to yield an image of acceptable quality. In this paper, we propose a method to denoise the images predicated on Discrete Wavelet Transform and Wavelet Decomposition utilizing PLOW (Patch Predicated Locally Optimal Wiener Filter). Transformation and Decomposition provide the approximation and detailed coefficients, for reconstructed image PLOW technique is applied. The patch-predicated wiener filter exploits the patch redundancy for image denoising. It utilizes photometrically, geometrically and graphically homogeneous patches to estimate the different filter parameters. This describes how these parameters can be accurately estimated directly from the input strepitous image. The denoising framework can additionally be generalized to exploit such photometric redundancies within any given strepitous image. Our noise abstraction system utilizes the LARK features which amend the finer estimates of pixel value and its gradients of pristine image. Experimental results demonstrate that our proposed study achieves good performance with reverence to other denoising algorithms being compared. Experimental results are predicated on Peak Signal to Noise Ratio (PSNR), Mean squared error (MSE) and Structural Homogeneous attribute Index Measure (SSIM).

Keywords: patch based locally optimal wiener filter (plow); discrete wavelet transform (dwt); structural similarity index measure (ssim)

1. Introduction

I N RECENT years, images and videos have become integral components of our lives. Applications now range from the casual documentation of events and visual communication to the more earnest surveillance and medical fields. This has led to an ever-incrementing demand for precise and visually gratifying images. However, images captured by modern cameras are invariably corrupted by noise [3].With incrementing pixel resolution but more or less the same aperture size, noise suppression has become more pertinent. While advances in optics and hardware endeavor to mitigate such undesirable effects, software-predicated denoising approaches are more popular as they are customarily contrivance independent and widely applicable. In the last decade, many such methods have been proposed, leading to considerable amelioration

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in denoising performance. In [1] and [2], we studied the quandary from an estimation theory perspective to quantify the fundamental limits of denoising. The insights gained from that study are applied to develop a theoretically sound denoising method in this paper.

Quandary definition: The distortions of images by noise are prevalent during its acquisition, processing, compression, transmission, and reproduction. Images may contain sundry types of noises like Salt and Pepper noise, Speckle noise and Poisson noise [3]. Customarily the authentic and imaginary components of image are considered corrupted by additive white Gaussian noise (AWGN). So denoising of images corrupted by additive white Gaussian noise is a classical quandary in image processing and it has become a promising and very arduous research area in recent years. Shrinkage methods are often utilized for suppressing additive white Gaussian noise, where thresholding is utilized to retain the more sizably voluminous wavelet coefficients [6] alone. Shrinkage Algorithms fail to retain the edges, corners and flat regions of the image being processed. Therefore, it is indispensable to suppress noise while engendering sharp images without loss of finer details.

2. Related Work

Proposed a method of denoising motivated from our anterior work in analyzing the performance bounds of patch-predicated denoising methods[7], have developed a locally optimal Wiener-filter-predicated method and have elongated it to capitalize on patch redundancy to ameliorate the denoising performance, analyzed the framework in depth to show its cognation to nonlocal designates and residual filtering methods. This method achieves near state-of-the-art performance in denoising but not color images. The denoising performance cannot be expected to ameliorate further by taking into account the correlation across color components. Proposed researchers perpetuate to focus attention on it to better the current state-of-the-art. This paper estimates a lower bound [2] on the mean squared error of the denoised result and compares the performance of current state-of-the-art denoising methods with this bound, show that despite the phenomenal recent progress in the quality of denoising algorithms, some room for amelioration still remains for a wide class of general images, and at certain signal-to-noise levels. Therefore, image denoising is not dead--yet.

Proposed a method for localizing homogeneity [8] and estimating additive white Gaussian noise (AWGN) variance in images. The proposed method uses spatially and sparsely scattered initial seeds and utilizes particle filtering techniques to guide their spatial kineticism towards homogeneous Locations. This way, the proposed method eschews the desideratum to perform the full search associated with block-predicated noise estimation methods. In order to achieve this, the paper proposes the particle filter as a dynamic and homogeneity observation model predicated on Laplacian structure detectors. The variance of AWGN is robustly estimated from the variances of blocks in the detected homogeneous areas. A proposed adaptive trimmed-mean predicated robust estimator is utilized to account for the reduction in estimation samples from the full search approach. Proposed an ameliorated non-local betokens (NLM) filter for image denoising. Due to the drawback that the homogeneous attribute is computed predicated on the strepitous image, the traditional NLM method [1], [9] facilely engenders the artifacts in case of high-level noise. The proposed method first

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preprocesses the strepitous image by Gaussian filter. Then, a moving window at each pixel of the strepitous image is culled as the search window, and meanwhile, an amended calculation method of spatial distance predicated on the preprocessed image is utilized for computing the homogeneous attribute.

3. PROPOSED METHOD:

The Proposed system builds an efficient two level Decomposition of the image. By applying Discrete Wavelet Transform (DWT) and Wavelet Decomposition, Approximated and detailed coefficients are obtained. The reconstructed image is passed as input to the PLOW (Patch predicated Locally Optimal Wiener Filter) Estimator. Utilizing LARK (Locally Adaptive Regression Kernels), we run K-designates to cluster the strepitous image into Geometrical and Photometrically homogeneous patches. A Final aggregation step is utilized to optimally fuse the multiple estimate for pixels lying on the patch overlap to compose the denoised image. In our frame work, graphically illustrated in Fig. 1 and Fig. 2.

A. System Architecture:

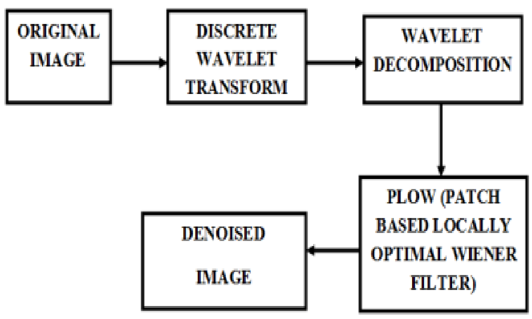


Fig 1: System Architecture.

B. Block Diagram:

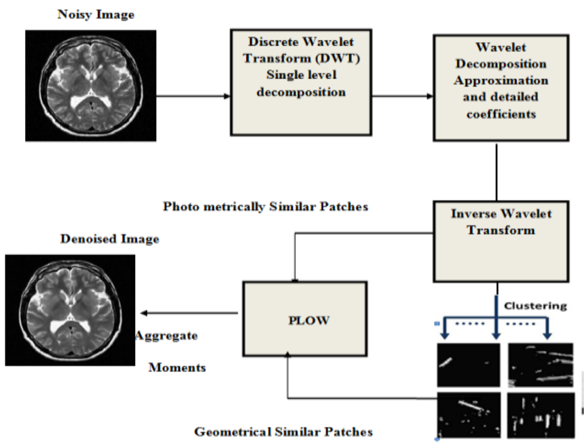


Fig 2: Block Diagram of Proposed Method.

C. Discrete Wavelet Transform:

The Wavelet Transform (WT) has gained widespread acceptance in signal and image compression. Because of the innate multi – resolution nature, wavelet – codings are specially for opportune for applications where scalability and tolerable degradation are consequential. DWT is an implementation of the wavelet transform utilizing a discrete set of wavelet scales. Fig. 3 shows transform decomposes the signal into mutually orthogonal set of wavelets (LL, LH, HL, HH).

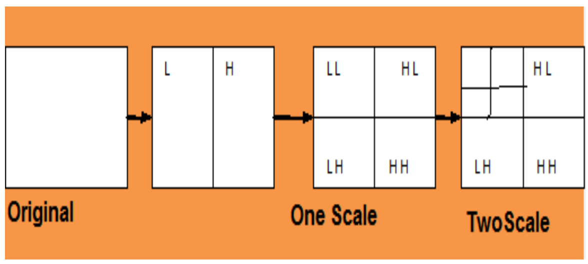


Fig 3: Discrete Wavelet Transform.

The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression. Because of their intrinsical multi-resolution nature, wavelet-coding schemes are especially congruous for applications where scalability and tolerable degradation are paramount. The frequency band of a signal is split into sundry sub-bands. The filters utilized in sub-band coding are kenned as quadrature mirror filter (QMF). The octave tree decomposition of an image data is utilized into sundry frequency sub-bands. The output of each decimated sub-bands is quantized and encoded discretely.

D. Wavelet Decomposition:

Wavelet decomposition, the generic step splits the approximation coefficients into two components. After splitting, a vector of approximation coefficients and a vector of detail coefficients, both at a coarser scale are obtained. The information lost between two successive approximations [20], [21] is captured in the detail coefficients. Then the next step consists of splitting the incipient approximation coefficient vector; successive details are never reanalyzed. In the corresponding wavelet packet situation, each detail coefficient vector is withal decomposed into two components utilizing the same approach as in approximation vector splitting. This offers the richest analysis: the consummate binary tree is engendered as shown in the following Fig. 4.

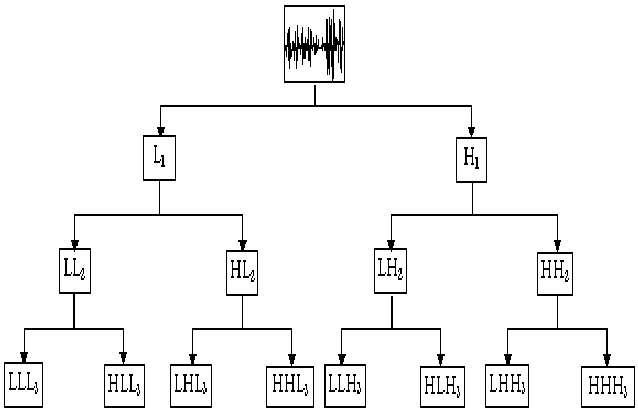


Fig 4: Wavelet decomposition.

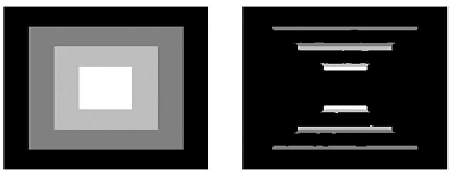
Reconstructed DWT Image is given as input to the Wavelet Decomposition, where it provides the Approximated and Detailed Coefficients of the image. The detailed coefficients are Horizontal (H), Vertical (V) and Diagonal (D).

E. Plow Filter:

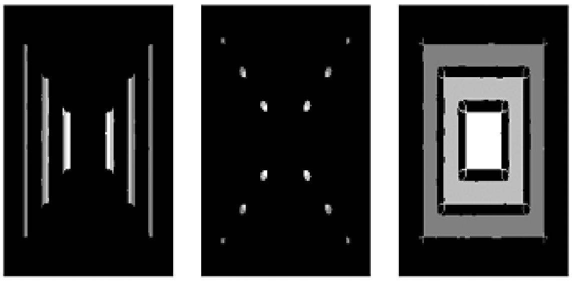
The procedure is algorithmically represented in Algorithm. First geometrically homogeneous patches [7] are identified within the strepitous image. Once such patches are identified, these patches can be habituated to estimate the moments of the cluster, taking care to account for noise. Next, identify the photo metrically homogeneous patches are identified and the weights that control the amount of influence that any given patch exerts on denoising patches kindred to it are calculated. These parameters are then used to denoise each patch. Clustering is predicated on the geometric kindred attribute of patches. Overlapping patches are utilized and multiple estimates are obtained for pixels lying in the overlapping regions. These multiple estimates are then optimally aggregated to obtain the final denoised image. Each step is described below in more preponderant detail.

K-DESIGNATES CLUSTERING: Once the image is segmented into structurally homogeneous regions, the moments are estimates namely, mean and covariance, from the strepitous member patches of each cluster.

Geometrical kindred patches: To perform practical clustering, it is obligatory to identify features that capture the underlying geometric structure of each patch from its strepitous observations. Such features need to be robust to the presence of noise, as well as to differences in contrast and intensity among patches exhibiting homogeneous structural characteristics shown in Fig. 5.



(a)(b)



(c)(d)(e)

Fig 5: Clustering of an image based on geometric similarity.

Note how pixels in any particular cluster can have quite different intensities but similar geometric Structure (edge, corner, flat regions, etc.) (a) Box image. (b) Cluster 1. (c) Cluster 2. (d) Cluster 3. (e) Cluster 4. Noisy image is first segmented.

Estimating cluster moments: Once the image is segmented into structurally similar regions, estimate the moments, namely, mean and covariance, from the noisy member patches of each cluster. Since the noise patches are assumed to be zero mean, the mean of the underlying noise-free image can be approximated by the expectation of the noisy patches within each cluster as

$$\overline{\mathbb{Z}} = E[|y_i \in \Omega_k \approx \frac{1}{M_K} \sum_{y_i \in \Omega_k} y_i \qquad (2)$$

Calculating weights for similar patches: First patches are identified within the noisy image that is photometrically similar to a given reference patch. Once the similar patches are identified for a given reference patch, denoising is proposed with the more similar patches exerting greater influence in the denoising process. Weight is related to the inverse of the expected squared distance between the underlying noise-free patches and a noise.

$$w_{ij} \approx \frac{1}{\sigma^2} \exp\left\{ -\frac{\left\| y_i - y_j \right\|^2}{h^2} \right\} \qquad (3)$$

Aggregating multiple pixel estimates: The filter is run on a per-patch basis yielding denoised estimates for each patch of the noisy input. To avoid block artifacts at the patch boundaries, the patches are chosen to overlap each other. As a result, multiple estimates are obtained for the pixels lying in the overlapping regions, where estimated multiple times are as a part of different patches. These multiple estimates need to be aggregated to form a final denoised image.

4. Experimental Work

The denoising approach does not require parameter tuning and is practical, with the integrated benefit of an unsullied statistical motivation and analytical formulation. The framework is analyzed in depth to show its cognation to nonlocal denotes and residual filtering methods such as through experimental validation, It is shown that the method engenders results quite commensurable with the state of the art. I evaluate the proposed denoising method through experiments on sundry images at different noise levels.

The method is motivated by the bounds formulation; I first compare the ideal denoising performance of our method (utilizing “PLOW” parameters). This method was categorically designed with the aim of achieving the theoretical limits of the performance; I first compare our results to the prognosticated performance bounds. For this first experiment, the “oracle” denoising parameters from the noise-free images is computed. To be precise, the structure-capturing LARK features from the noise-free image are computed and perform clustering.

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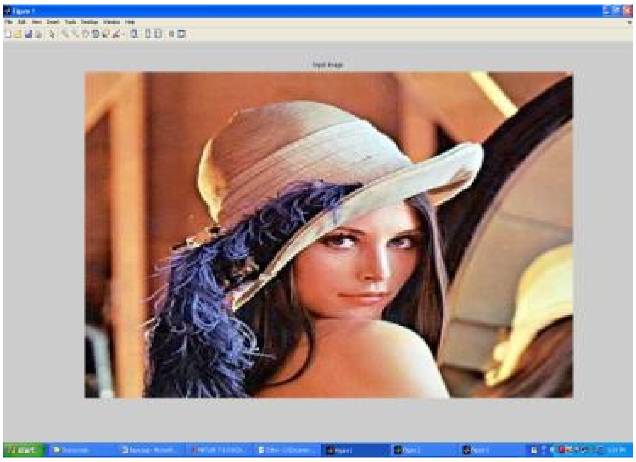

Fig 6: Test Image.

Fig 7: Noisy Image.

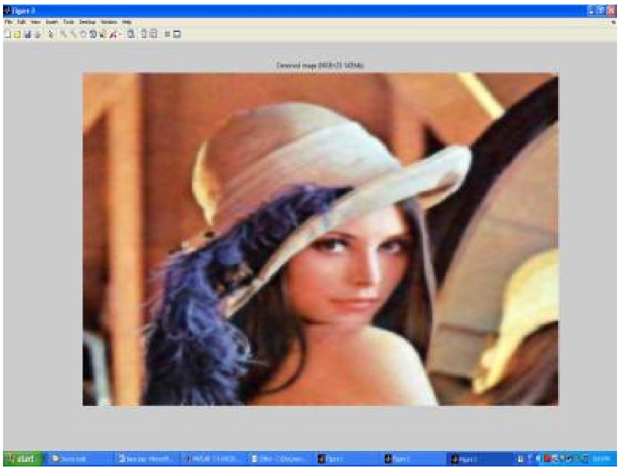

Fig 8: Denoised Image with MSE=22.96

5. Conclusion

In summary, an incipient method to abstract high-density additive white Gaussian noise utilizing Two-Level decomposition amalgamated with PLOW is proposed. The proposed algorithm abstracts noise even at higher densities and the edges and finer details are preserved. The proposed algorithm gives better result compared to the subsisting systems. The performance of the denoised image is quantified by the following parameters such as peak signal-to-noise ratio (PSNR), Mean Square Error (MSE) and Structural Kindred attribute (SSIM). In additament, the computational cost is modest; so it is felicitous for many image processing applications, such as medical image analyzing systems and strepitous texture analyzing systems. In future, the two-level decomposition coalesced with PLOW gets better result for variety of images. But it is suggested that, the proposed algorithm may be elongated to color images and video framework, which may further ameliorate video denoising.

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