IMAGE DENOISING TO ESTIMATE THE GRADIENT HISTOGRAM PRESERVATION USING VARIOUS ALGORITHMS

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ABSTRACT

Natural image statistics plays an important role in image denoising and various natural image priors, including gradient-based have been widely studied and exploited for noise removal. Image denoising aims to estimate the latent clean image from its noisy observation .We apply the pre-processing method using histogram equalization. In our project we propose a textures enhanced image denoising method by enforcing the gradient histogram of the denoised image to be close to a reference gradient histogram of the original image and to enhance the texture structures while removing noise.

Keywords: Denoising, GHP, B-GHP, S-GHP, Histogram

I.INTRODUCTION

Image denoising is a classical yet still active topic in image processing and low level vision, while it is an ideal test bed to evaluate various statistical image modeling methods. With the rapid development of digital imaging technology, now the acquired images can contain tens of megapixels. On one hand, more fine scale texture features of the scene will be captured; on the other hand, the captured high definition image is more prone to noise because the smaller size of each pixel makes the exposure less sufficient. Unfortunately, suppressing noise and preserving textures are difficult to achieve simultaneously, and this has been one of the most challenging problems in natural image denoising. Unlike large scale edges, the fine scale textures are much more complex and are hard to characterize by using a sparse model. Texture regions in an image are homogeneous and are composed of similar local patterns, which can be characterized by using local descriptors. Using histogram specification, a gradient histogram preservation algorithm is developed to ensure that the gradient histogram of denoised image is close to the

Reference histogram, resulting in a simple yet effective GHP based denoising algorithm.

II. RELATED WORK

Generally, image denoising methods can be grouped in two categories: model-based methods and learning-based methods. The use of gradient prior can be traced back to 1990s when Rudin et al. They proposed a total variation (TV) model for image denoising , where the gradients are actually modeled as Laplacian distribution. Another well-known prior model, the mixture of Gaussians, can also be used to approximate the distribution of image gradient. More generally, the local sparsity prior can be well applied to high-pass filter responses, wavelet transform coefficients, or the coding coefficients over a redundant dictionary. In Gaussian scale mixtures are used to characterize the marginal and joint distributions of wavelet transform coefficients. However, many existing image denoising algorithms, including those local sparsity and NSS based ones, tend to wipe out the image fine scale textures while removing noise. Popular prior is the nonlocal self-similarity (NSS) prior; the natural images are often many similar patches (i.e., nonlocal neighbors) to a given patch, which may be spatially far from it. Sparse representation for image leads to State of the art image denoising results; often fail to preserve the image fine scale texture structure. Large scale edges, the fine scale textures are more complex and are hard to characterize by using sparse model.

III. PROPOSED METHOD

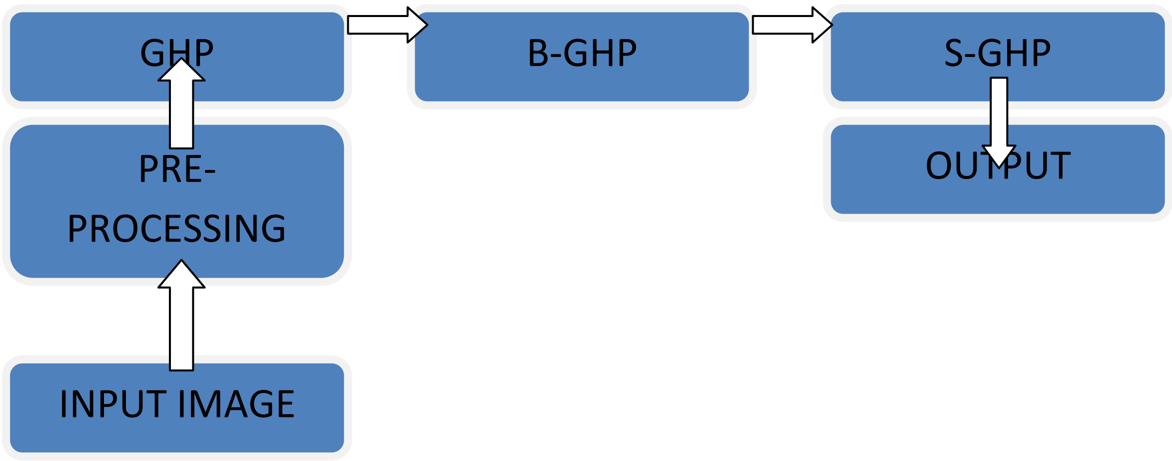


Figure 1: Block Diagram of Proposed Work

We introduce the gradient histogram estimation and preservation framework. It presents the denoising model and the iterative histogram specification algorithm (IHSA). It also introduces two region-based GHP variants, i.e., B-GHP and S-GHP. By segmenting the image into texture homogeneous regions, S-GHP can further achieve better denoising results than B-GHP in terms of PSNR.

3.1 Pre-Processing

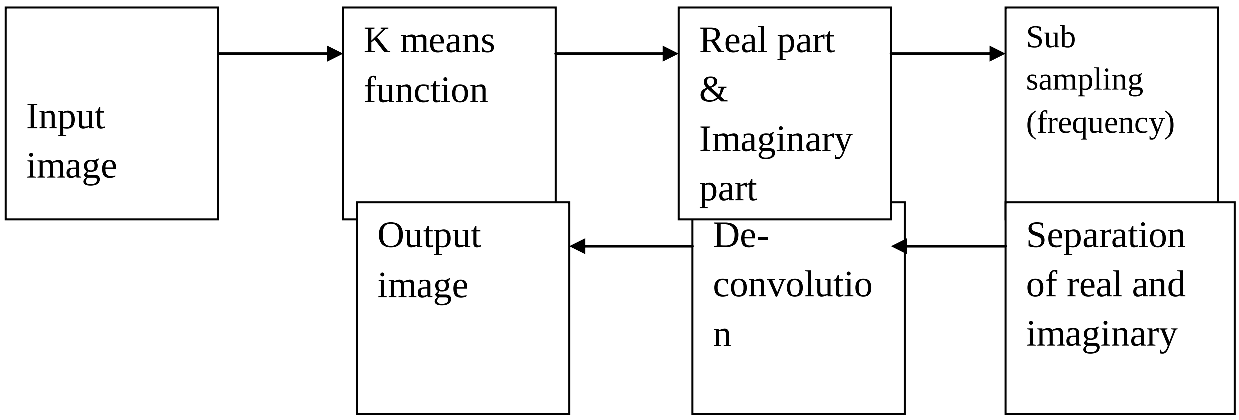
In our project, we are implementing histogram equalization for our input image. A histogram is a graphical representation of the distribution of data. The data appears as colored or shaded rectangles of variable area.

3.2 Histogram Equalization

Histogram equalization uses a non-linear and monotonic mapping. The idea of histogram equalization is that the pixels should be distributed evenly over the whole intensity range. The aim is to transform the image so that the output images has a flat histogram.

3.3 Gradient Histogram Preservation (Ghp):

We propose a texture enhanced image denoising method by enforcing the gradient histogram of original image. Different combinations of pixel brightness values (gray levels) occur in a pixel pair in an image. An GHP algorithm is also developed to effectively estimate the gradient histogram from the noisy observation of the image.



By simply partitioning the image into regular blocks, the block based B-GHP can reduce the possibility of generating false textures.

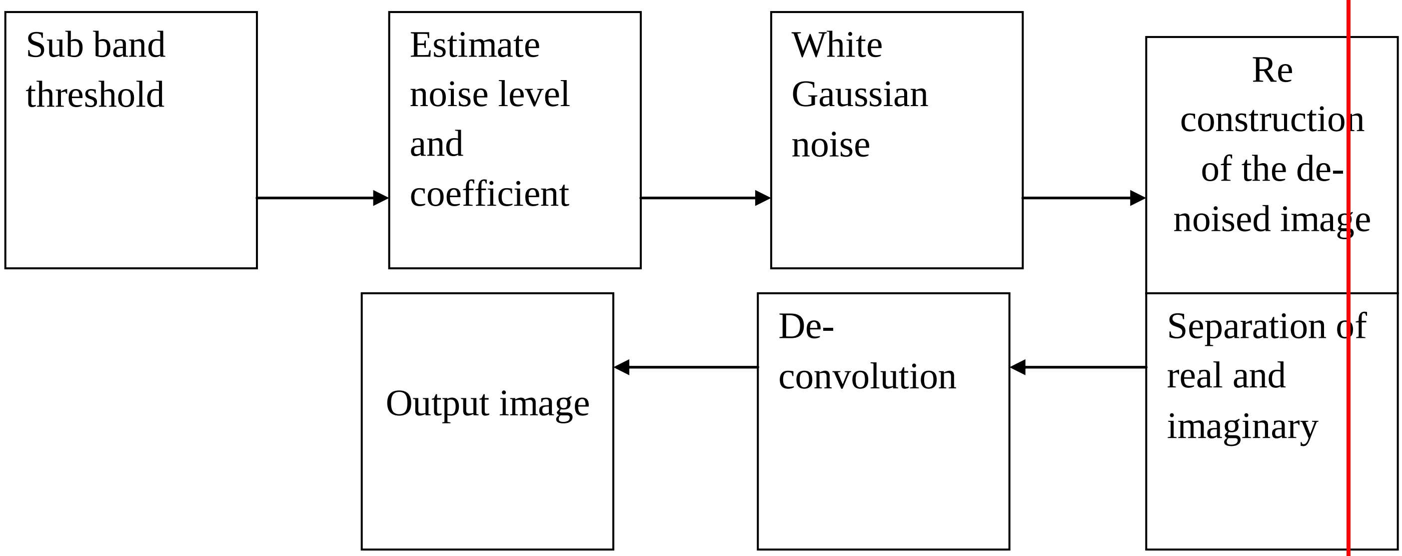


Figure 3: Block Diagram of S-GHP

We then compare S-GHP with some state-of-the-art denoising methods, including shape-adaptive by segmenting the regions. In contrast, S-GHP preserves much better the fine textures in areas of tree and water, making the denoised image looks more natural and visually pleasant. It should also be noted that, the better visual quality in areas of tree and water of S-GHP might not always result in higher PSNR. S-GHP preserves much better the fine texture in tree and water areas, while making the output look more natural. One strategy is to transform the noisy image into an image with additive white Gaussian noise (AWGN) and then apply GHP. Finally it is avoided in our proposed system.

IV. RESULTS AND DISCUSSION

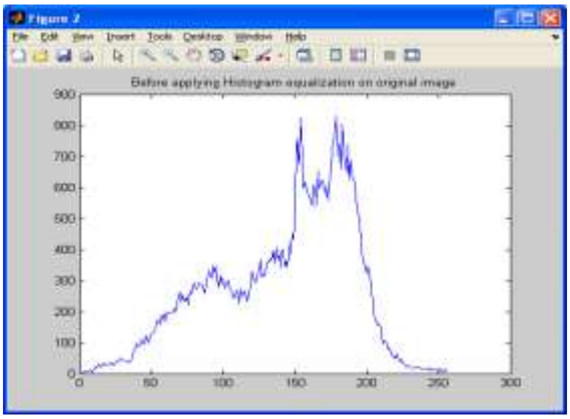
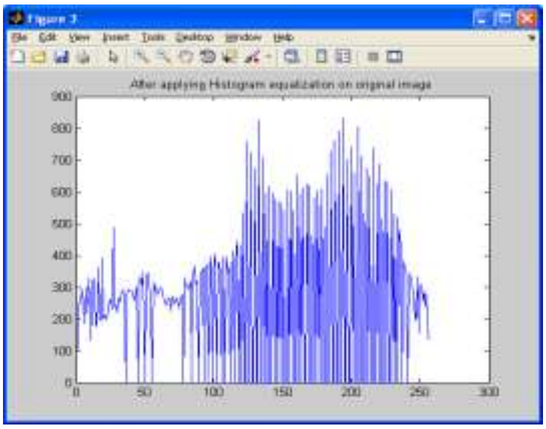


Figure 4 : Input Image **Figure 4: Before applying Histogram equalization**



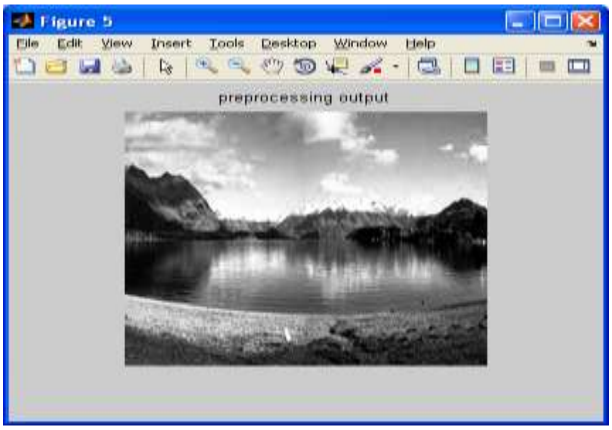
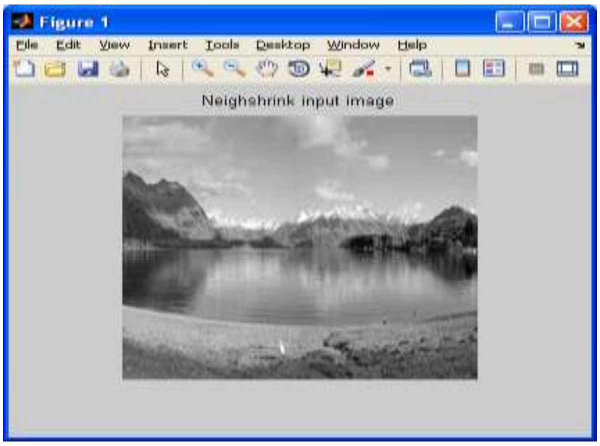
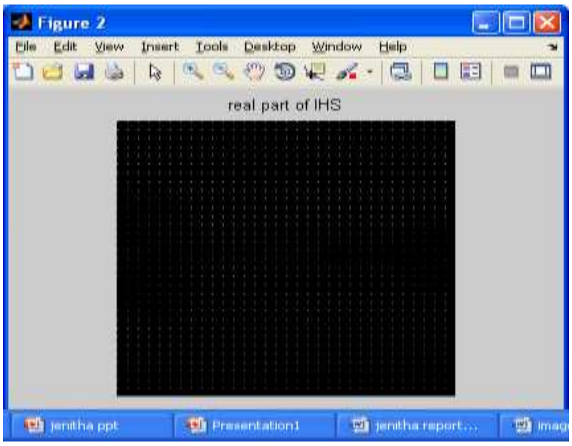


Figure 5: After applying Histogram equalization **Figure 6: Pre-processing output**





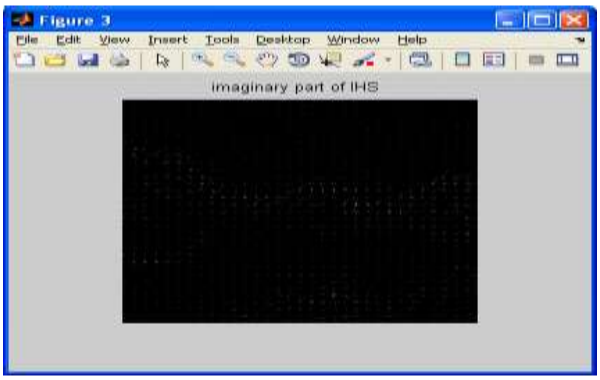


Figure 7: Real and Imaginary Part of HIS **Figure 8: HIS Interpolation**

Output Parameters in GHP

PSNR =31.8478

MSE = 42.4909

V. CONCLUSION

In our project we propose a textures enhanced image de-noising method by enforcing the gradient histogram of the de-noised image to be close to a reference gradient histogram of the original image and to enhance the texture structures while removing noise. B-GHP and S-GHP, which leads to improve SNR values compared to GHP. S-GHP can further achieve better de-noising results than B-GHP in terms of PSNR. Less mean square error compared to GHP and B-GHP.

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