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AN IMAGE DENOISING ANALYSIS WITH ITERATIVE HISTOGRAM SPECIFICATION

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Abstract: In any application image denoising is a challenging task because noise removal will increase the digital quality of an image and will improve the perceptual visual quality. In spite of the great success of many denoising algorithms, they tend to smooth the fine scale image textures when removing noise, degrading the image visual quality. To address this problem, in this paper we propose a texture 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. Given the reference gradient histogram, a novel gradient histogram preservation (GHP) algorithm is developed to enhance the texture structures while removing noise. Simulation results show that the proposed method has given the better performance when compared to the existing algorithms in terms of peak signal to noise ratio (PSNR) and mean square error (MSE). To deal with this crisis, on this paper, we endorse a texture more desirable picture denoising process through implementing the gradient histogram of the denoised image to be just about a reference gradient histogram of the long-established snapshot. Given the reference gradient histogram, a novel gradient histogram renovation (GHP) algorithm is developed to enhance the texture buildings while casting off noise. Two neighborhood-founded editions of GHP are proposed for the denoising of pictures including areas with one-of-a-kind textures. An algorithm is also developed to conveniently estimate the reference gradient histogram from the noisy remark of the unknown snapshot. Our experimental outcome display that the proposed GHP algorithm can good retain the feel looks within the denoised graphics, making them appear more normal.

1. INTRODUCTION

Snapshot denoising, which targets to estimate the latent clean photo x from its noisy observation y, is a classical but nonetheless energetic matter in picture processing and low stage vision. One widely used data observation mannequin [4], [7] is

$$y = x+v,$$

the place v is additive white Gaussian noise (AWGN). One general procedure to photograph denoising is the variational approach, where an vigor useful is minimized to go looking the favored estimation of x from its noisy statement y. The vigour practical traditionally involves two phrases: a data constancy term which is dependent upon the image degeneration process and a regularization time period which items the prior of unpolluted ordinary pix [4], [7]. The statistical modeling of natural Photo priors are principal to the success of picture denoising.

Prompted with the aid of the truth that normal image gradients and wavelet turn out to be coefficients have a heavy-tailed distribution, sparsity priors are commonly used in photo denoising [1]–[3]. The well-known total variant minimization approaches clearly assume Laplacian distribution of photo gradients [4]. The sparse Laplacian distribution can also be used to mannequin the excessive-go filter responses and wavelet/curvelet turn out to be Coefficients [5], [6]. Via representing picture patches as a sparse linear mixture of the atoms in an over-whole redundant dictionary, which will also be analytically designed or realized from ordinary portraits, sparse coding has proved to be very mighty in image denoising via l0-norm or l1-norm minimization. Yet another general prior is the nonlocal self-similarity (NSS) prior; that's, in usual graphics there are usually many similar patches (i.E., nonlocal neighbors) to a given patch, which may be spatially far from it. The connection between NSS and the sparsity prior is mentioned. The joint use of sparsity prior and NSS prior has resulted in ultra-modern photo denoising results. In spite of the quality success of many denoising Algorithms, nevertheless, they traditionally fail to preserve the image satisfactory scale texture constructions degrading a lot the photo visible exceptional.

Images captured from both digital cameras and conventional film cameras will affected with the noise from a variety of sources. These noise elements will create some serious issues for further processing of images in practical applications such as computer vision, artistic work or marketing and

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also in many fields. There are many types of noises like salt and pepper, Gaussian, speckle and passion. In salt and pepper noise (sparse light and dark disturbances), pixels in the captured image are very different in intensity from their neibouring pixels; the defining characteristic is that the intensity value of a noisy picture element bears no relation to the color of neibouring pixels. Generally this type of noise will only affect a small number of pixels in an image. When we viewed an image which is affected with salt and pepper noise, the image contains black and white dots, hence it terms as salt and pepper noise. In Gaussian noise, noisy pixel value will be a small change of original value of a pixel. A histogram, a discrete plot of the amount of the distortion of intensity values against the frequency with which it occurs, it shows a normal distribution of noise. While other distributions are possible, the Gaussian (normal) distribution is usually a good model, due to the central limit theorem that says that the sum of different noises tends to approach a Gaussian distribution.

2. RELATED WORK

Photograph denoising ways can also be grouped into two classes: Mannequin-founded methods and studying-founded approaches. M Most denoising methods reconstruct the clean image bymexploiting some image and noise prior items, and belong to the first class.

Learning-founded methods attempt tostudy a mapping operate from the noisy snapshot to the clean image and have been receiving tremendous research interests. Right here we in short evaluate those model-situated denoising approaches concerning our work from a perspective of natural photo priors experiences on common image priors aim to search out suitable items to describe the characteristics or information (e.G., distribution) of photographs in some domain. One representative classification of photograph priors is the gradient prior situated on the remark that natural graphics have a heavy-tailed distribution of gradients. Using gradient prior may also be traced again to Nineties when Rudin et al. [4] proposed a complete variant (television) model for image denoising, the place the gradients are really modeled as Laplacian distribution. One other famous prior mannequin, themixture of Gaussians, will also be used to approximate the distribution of photo gradient [1].

In addition, hyper- Laplacian mannequin can extra effectively symbolize the heavy tailed distribution of gradients, and has been commonly applied to quite a lot of snapshot restoration tasks [2]. The photo gradient prior is a sort of local sparsity prior, i.e., the gradient distribution is sparse. More most commonly, the neighborhood sparsity prior can also be good applied to excessive-pass filter responses, wavelet/curvelet turn into coefficients, or the coding coefficients over a redundant dictionary. In [5] and [6], Gaussian scale combinations are used to symbolize the marginal and joint distributions of wavelet grow to be coefficients. Via assuming that an image patch can be represented as a sparse linear combination of the atoms in an over-entire dictionary, a quantity of dictionary finding out (DL) approaches (e.G., evaluation and synthesis k-SVD [7] task pushed DL and adaptive sparse domain resolution [8] were proposed and applied to picture denoising and different image restoration tasks.

Established on the truth that a identical patch to the given patch may not be spatially virtually it, a different line of study is to model the similarity between image patches, i.E., the picture nonlocal self-similarity (NSS) priors. The seminal work of nonlocal way denoising [9] has encouraged a extensive variety of studies on NSS, and has led to a flurry of NSS founded state Of-the-artwork denoising ways, e.G., BM3D LSSC and EPLL and many others.

In the recent years there has been a fair amount of research on center pixel weight (CPW) for image denoising [3], because CPW provides an appropriate basis for separating noisy signal from the image signal. Optimized CPW is good at energy compaction, the small coefficient are more likely due to noise and large coefficient due to important signal feature [8]. These small coefficients can be thresholded without affecting the significant features of the image. However, all the above metioned techniques were not suitable for texture enhanced image denoising and will not preserve the fine details of image. In order to overcome the existing systems drawbacks, here in this we propose a texture enhanced image denoising algorithm from the given noisy image y, we estimate the gradient histogram of original image x. Taking this estimated histogram, denoted by h, as a reference, we search an estimate of x such that its gradient histogram is close to hr. As shown in Fig. 1, the proposed GHP based denoising method can well enhance the image texture regions, which are often over-smoothed by other denoising methods. The major contributions of this paper are summarized as follows: (1) A novel texture

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enhanced image denoising framework is proposed, which preserves the gradient histogram of the original image. The existing image priors can be easily incorporated into the proposed framework to improve the quality of denoised images. (2) 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.

(3) By incorporating the hyper-Laplacian and nonnegative constraints, a regularized deconvolution model and an iterative deconvolution algorithm.

3. EXISITING TECHNIQUES

In this section we discussed various spatial filters and their performance when a noisy input will be given to them. Here in this section we had explained about each filter in detail. Firstly, *Savitzky-Golay (SG) filter:* it is a simplified method and uses least squares technique for calculating differentiation and smoothing of data. Its computational speed will be improved when compared least-squares techniques. The major drawback of this filter is: Some of first and last data point cannot smoothen out by the original Savitzky-Golay method. Assuming that, filter length or frame size (in S-G filter number of data sample read into the state vector at a time) N is odd, N=2M+1 and N= d+1,where d= polynomial order or polynomial degree.

Second, *Median filter:* This is a nonlinear digital spatial filtering technique, often used to removal of noise from digital images. Median filtering has been widely used in most of the digital image processing applications. The main idea of the median filter is to run through the image entry by pixel, replacing each pixel with the median value of neighboring pixels. The pattern of neighbors is called the "window", which slides, pixel by pixel, over the entire image. Third, *Bilateral filter:* The bilateral filter is a nonlinear filter which does the spatial averaging without smoothing edges information. Because of this feature it has been shown that it’s an effective image denoising algorithm. Bilateral filter is presented by Tomasi and Manduchi in 1998. The concept of the bilateral filter was also presented in [8] as the SUSAN filter and in [3] as the neighborhood filter. It is mentionable that the Beltrami flow algorithm is considered as the theoretical origin of the bilateral filter [4] [5] [6], which produce a spectrum of image enhancing algorithms ranging from the linear diffusion to the non-linear flows. The bilateral filter takes a weighted sum of the pixels in a local neighborhood; the weights depend on both the spatial distance and the intensity length. In this way, edges are preserved well while noise is eliminated out. Next, *Wavelet filtering:* Signal denoising using the DWT consists of the three successive procedures, namely, signal decomposition, thresholding of the DWT coefficients, and signal reconstruction. Firstly, we carry out the wavelet analysis of a noisy signal up to a chosen level N. Secondly, we perform thresholding of the detail coefficients from level 1 to N. Lastly, we synthesize the signal using the altered detail coefficients from level 1 to N and approximation coefficients of level N. However, it is generally impossible to remove all the noise without corrupting the signal. As for thresholding, we can settle either a level-dependent threshold vector of length N or a global threshold of a constant value for all levels. *Classical Non Local Means:* It is a data-driven diffusion mechanism that was introduced by Buades *et al.* in [1]. It has been proved that it’s a simple and powerful method for digital image denoising. In this, a given pixel is denoised using a weighted average of other pixels in the (noisy) image. In particular, given a noisy image$n$, and the denoised image $d = di$ at pixel i is computed by using the formula

$$\widehat{d_i} = \frac{\sum_j w_{ij} n_j}{\sum_j w_{ij}} \qquad (1)$$

Where wij is some weight assigned to pixel $i\ and$. The sum in (1) is ideally performed to whole image to denoise the noisy image. NLM at large noise levels will not give accurate results because the computation of weights of pixels will be different for some neibourhood pixels which looks like same.

$$w_{l,j} = exp\left(\sum_{k \in P} G_\beta \left(\left(n_{l+k} - n_{j+k}\right)^2 / 2h\right)\right) \qquad (2)$$

In this each weight is computed by similarity quantification between two local patches around noisy pixels nl and nj as shown in eq. (2). Here, $G\beta$ is a Gaussian weakly smooth kernel [1] and P denotes the local patch, typically a square centered at the pixel and h is a temperature parameter controlling the behavior of the weight function.

Another popular approach to image denoising is the variational method, where energy functional is

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minimized to search the desired estimation of x from its noisy observation y. The energy functional usually involves two terms: a data fidelity term which depends on the image degeneration process and a regularization term which models the prior of clean natural images.

The statistical modeling of natural image priors is crucial to the success of image denoising. Motivated by the fact that natural image gradients and wavelet transform coefficients have a heavy-tailed distribution, sparsity priors are widely used in image denoising [10]–[12]. The well-known total variation minimization methods actually assume Laplacian distribution of image gradients [13]. The sparse Laplacian distribution is also used to model the high pass filter responses and wavelet/curvelet transforms coefficients.

By representing image patches as a sparse linear combination of the atoms in an over-complete redundant dictionary, which can be analytically designed or learned from natural images, sparse coding has proved to be very effective in image denoising via l0-norm or l -norm minimization. Another popular prior is the nonlocal self-similarity (NSS) prior that is, in natural images there are often many similar patches (i.e., nonlocal neighbors) to a given patch, which may be spatially far from it. The connection between NSS and the sparsity prior is discussed. The joint use of sparsity prior and NSS prior has led to state of-the-art image denoising results. In spite of the great success of many denoising algorithms, however, they often fail to preserve the image fine scale texture structures, degrading much the image visual quality (please refer to Fig. 1 for example). 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 or textons. Cognitive studies have revealed that the first-order statistics, e.g., histograms, are the most significant descriptors for texture discrimination. Considering these facts, histogram of local features has been widely used in texture analysis.

Meanwhile, image gradients are crucial to the perception and analysis of natural images. All these motivate us to use the histogram of image gradient to design new image denoising models. With the above considerations, in this paper we propose a novel gradient histogram preservation (GHP) method for texture enhanced image denoising.

3. LITERATURE SURVEY

M. Elad and M. Aharon, “Image denoising via sparse and redundant representations over learned dictionaries,” proposed K-SVD algorithm, which is based on local operation & involves sparse decompositions of each image block under one fixed over-complete dictionary. Here K-SVD algorithm used to handle small image patches for image enhancement & cannot be directly deployed on large blocks.W. Dong, L. Zhang, G. Shi, and X. Wu, “Image deblurring and super resolution by adaptive sparse domain selection and adaptive regularization,”proposed a novel sparse representation based image deblurring & super – resolution (single image) method using adaptive sparse domain selection (ASDS) & adaptive regularization (AReg). Here two AReg methods are introduced- AR & non-local self similarity, which gives the better result than other algorithm.W. Dong, L. Zhang, G. Shi, and X. Li, “Non-locally centralized sparse representation for image restoration,” proposed Non-locally centralized sparse representation (NCSR) model used to remove the sparse coding noise. Based on this sparse coding co-efficient of the original image can be estimated & then centralize the sparse coding co-efficient of the observed image to those estimates. NCSR approach can achieve competitive performance to other leading denoising method. K. Suzuki, I. Horiba, and N. Sugie, “Efficient approximation of neural filters for removing quantum noise from images,” Signal Process., vol. 50, no. 7, pp. 1787–1799, Jul. 2002. Proposed efficient filters are presented that approximate neural filters (NFs) that are trained to remove quantum noise from images. The experimental results demonstrated that the approximate filters, constructed of simple hardware, are sufficient for approximation of the trained NFs and efficient at computational cost.L. Zhang, W.

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Dong, D. Zhang, and G. Shi, "Two-stage image denoising by principal component analysis with local pixel grouping," Pattern Recognit., vol. 43, no. 4, pp. 1531–1549, Apr. 2010, proposed efficient image denoising scheme by using principal component analysis (PCA) with local pixel grouping (LPG). Experimental results on benchmark test images demonstrate that the LPG-PCA method achieves very competitive denoising performance, especially in image fine structure preservation, compared with state-of-the-art denoising algorithms.

3. METHOD

The experiment was conducted on different image. Then processed to bring out the final result. The image were
captured using CANNON digital camera. The resolution of the pictures was then brought down to 256 x 256 so as to apply image processing the step wise procedure is given below.

3.1 Initial step

The image were captured and image processing was applied to get good results at the end. The test images are shown in Fig.1.

Figure 1 Ten test images. From left to right and top to bottom, they are labeled as 1 to 10.

3.2 The texture enhanced image denoising framework

Good priors of natural images are crucial to the success of an image denoising algorithm. A proper integration of different priors could further improve the denoising performance. For example, the methods in integrate image local sparsity prior with nonlocal NSS prior, and they have shown promising denoising results. The proposed GHP work used to adopt the sparse nonlocal regularisation term in the nonlocally centralized sparse representation (NCSR) model.

The noisy observation y of an unknown clean image **x** is usually modeled as

Y=x + v, (1)

Where **v** is the additive white Gusian noise (AWGN) with zero mean and standard deviation σ. The goal of image denoising is to estimate the desired image **x** from **y**. Estimation of the reference gradient histogram of **x**, denoted by **h*r*.** The estimation of gradient histogram has following formula,

$$h_r = \arg\min_{h_x}\{ \| h_y - h_x \otimes h_\varepsilon \|^2 + c \cdot R(h_x), \qquad (2)$$

where *c* is a constant and **R(h*x*)** some regularization term based on the prior information of natural image's gradient histogram. Some constant parameters are set in the estimated gradient histogram, which uses iterative histogram specification **(IHS)** for GHP. Iterative histogram specification algorithm uses dictionaries **(D)** via K-means and PCA methods. The proposed GHP based denoising model as follows,

$$\hat{x} = \arg\min \{(1/2\sigma^2) \|y-x\|^2 + \lambda R(x) + \mu \|F(\nabla x) - \nabla x\|^2\},$$
$$\text{s.t. } h_F = h_r, \qquad (3)$$

where F denotes an odd function which is monotonically non-descending, hF denotes the histogram of the transformed gradient image | **F(**∇x)|, ∇ denotes the gradient operator, and **μ** is a positive constant.

CONCLUSION

Type On this paper, we presented a novel gradient histogram renovation (GHP) model for texture more suitable image denoising, and additional introduce two vicinity-founded GHP variations, i.E., B-GHP and S-GHP. A easy but theoretically solid model and the associated algorithm have been presented to estimate the reference gradient histogram from the noisy image, and an efficient iterative histogram specification algorithm was developed to put in force the GHP mannequin. By using pushing the gradient histogram of the denoised picture towards the reference histogram, GHP achieves promising outcome in bettering the texture structure while removing random noise. The experimental outcome validated the effectiveness of GHP in texture better picture denoising. GHP results in similar PSNR/SSIM measures to the modern day denoising ways equivalent to SAPCABM3D, LSSC and

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NCSR; however, it results in more ordinary and visually great denoising results by way of higher preserving the snapshot texture areas. Most of the latest denoising algorithms are founded on the nearby sparsity and nonlocal selfsimilarity priors of ordinary photos. Not like them, the gradient histogram utilized in our GHP process is a type of world prior, which is adaptively estimated from the given noisy snapshot. One challenge of GHP is that it can't be directly applied to non-additive noise removing, such as multiplicative Poisson noise and sign-stylish noise [47]. Hence, it might be exciting and priceless to study extra basic units and algorithms for non-additive noise elimination with texture enhancement. One strategy is to transform the noisy photo into an picture with additive white Gaussian noise (AWGN) and then practice GHP. For example, for picture with Poisson noise, Anscombe root transformation [48], [49] can be used to convert it into an photograph with AWGN..

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