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# IMAGE DENOISING BY USING ITERATIVE GRADIENT HISTOGRAM PRESERVATIVE (GHP) ALGORITHM

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**ABSTRACT**

Image denoising is an important image processing task, both as a process itself, and as a component in other processes. There are many ways to denoise an image, which including gradient-based, sparse representation based, and nonlocal self-similarity-based methods. By using of many denoising algorithms which tend to smooth the fine scale image textures. It removes noise but degrading the visual quality of an image. To avoid this problem, in this paper, we propose a Iterative Gradient Histogram Preservative (GHP) algorithm. This algorithm is developed to enhance the texture structures while removing noise. Our experimental results demonstrate that the proposed GHP algorithm can well preserve the texture appearance in the denoised images, making them look more natural.

**Keywords:** image denoising, histogram specification, non-local similarity, sparse representation.

## 1. INTRODUCTION

IMAGE denoising is a classical and flourishing research topic in image processing. The demand for image denoisng approaches comes from the fact that during the process that a digital image is captured, quantized, recorded and transmitted, it will inevitably be contaminate by a variety of noises, which will result in annoying artifacts and decrease the visual quality. To date, a great deal of image denoising algorithms have been proposed originating from various subjects ranging from probability and statistics to differential equations, from spatial-domain filtering to transform-domain spectrum manipulation. Among which many have achieved remarkable performance and been widely used in our social life. Generally speaking, image denoising is an important topic of image restoration, which aims at reconstructing an image with a certain degree of degradation. A generally degradation model of an image can be described as follows:

$$v(x) = u(x) + n(x) \quad (1)$$

Where x represents the two-dimensional location of a pixel, u denotes the original image we want to reconstruct and v is the noisy observation of the image. n denotes the noise, which can be arbitrary digital noise that could occur, such as pulsing noise, salt-and–pepper noise as well as Gaussian valued noise. Usually, when we talk about image denoising, we refer the noise as additive white Gaussian noise (AWGN). The goal of image denoising is to find out $\hat{u}$, which is the estimate of original image u(x) from its noisy observation v(x). Several criterions exist to evaluate the denoising performance of different denoisng algorithms. Among which the PSNR is probably the most widely used one. A higher PSNR indicates a better performance of the algorithm. PSNR is short for Peak Signal to Noise Ratio. Generally in signal processing, signal-to-noise-ratio is used to represent the proportion of power between the signal and the noise.

An idea of learning a dictionary that yields sparse representations for a set of training image-patches has been tudied in a sequence of works. In this work, we propose a global image prior that forces sparsity over patches in every location in the image (with overlaps). For turning a local MRF-based prior into a global one we define a maximum *aposteriori* probability (MAP) estimator as the minimizer of a well-defined global penalty term. Its numerical solution leads to a simple iterated patch-by-patch sparse coding and averaging algorithm and generalizes them. When considering the available global and multi scale alternative denoising schemes (e.g., based on curvelet, contourlet, and steerable wavelet), it looks like there is much to be lost in working on small patches. Is there any chance of getting a comparable denoising performance with a local-sparsity based method. In that respect, the image denoising work is of great importance. Beyond the specific novel and highly effective algorithm described in that paper, Portilla and his coauthors posed a clear set of comparative experiments that standardize how image denoising algorithms should be assessed and compared one versus the other. We make use of these exact experiments and show that the newly proposed algorithm performs similarly, and, often, better, compared to the denoising performance reported in their work.

## 2. RELATED WORKS

Image denoising methods can be grouped into two categories. They are Model-based method and Learning based method. Aim of the image denoising is to get the clean image from noisy image. Most denoising methods reconstruct the clean image by exploiting some image and noise prior models, and belong to the first category. Learning-based methods attempt to learn a mapping function from the noisy image to the clean image, and have been receiving considerable research interests. Studies on natural image priors aim to

ARPN Journal of Engineering and Applied Sciences




find suitable models to describe the characteristics or statistics (e.g., distribution) of images in some domain.

## 3. EXISTING DENOISING ALGORITHMS

### a) A brief overview

Plenty of denoisng algorithms are proposed. Among these algorithms, some perform spatial convolution locally, such as the Gaussian smooth model, some apply spatial convolution in a global range, such as non-local means [2]; some achieve denoising by anisotropic filtering based on the texture and edge information of the image. Some exploit the prior information of the image in both Euclidean space as well as the Intensity space. Also there are some algorithms looks into the denoisng problem in frequency domain, such as BM3D, as well as some approaches using wavelet thresholding. Another class is the optimization- based algorithm, which typically achieve denoising by calculus of variations, such as Total Variation Minimization. Recently, in ICIP2010, a game theory based denoisng algorithm is proposed, which shows the abundant research enthusiasm in image denoisng.

### b) Isotropic filtering

By Riesz theorem, isotropic filtering of image is equivalent to a convolution of the image by a linear symmetric kernel. The most famous isotropic filter is undoubtedly the Gaussian kernel:

$$G(x) = \frac{1}{(4\pi h^2)} e^{\frac{|x|^2}{4h^2}}$$

where h is the standard deviation and the estimated image is then represented as the convolution of the noisy observation and the Gaussian kernel:

$$\hat{u}^{IF} = G * V$$

In practice the filtering range is the rectangle neighborhood around the current pixel. Though Gaussian isotropic filtering is effective to remove slightly contaminated images and simple to implement, usually the texture and edge will also be blurred which limits the denoising performance of this class of algorithms.

### c) SUSAN filtering

SUSAN filtering [8] is a kind of neighborhood filtering which shares the same idea as Bilateral filtering [9]. Instead of consider only the spatial neighborhood which is close to the current pixel spatially, SUSAN filter weights pixels both by the Euclidean distance and the Intensity-space distance, i.e.

$$\hat{u}^{SUSAN}(x) = \frac{\sum_{l \in N(x)} w_{x,l} * v(l)}{\sum_{l \in N(x)} w_{x,l}}$$

$$w_{x,l} = \exp\left\{-\frac{|x-l|^2}{h^2} . \frac{[v(x)-v(l)]^2}{\rho^2}\right\}$$

By exploiting the inherent intensity structure of the image, The SUSAN filter can preserves sharp edges and textures when removing the noise, which is also an important property of anisotropic filter.

Another advantage of SUSAN filter (Bilateral filter) is that unlike the anisotropic filtering, it is a non-iterative edge-preserving denoising algorithm, which makes it widely used, even adopted by the well-known Adobe Photoshop.

## 4. THE TEXTURE ENHANCED IMAGE DENOISING FRAMEWORK

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

$$\mathbf{y} = \mathbf{x} + \mathbf{v}, \tag{2}$$

where **v** is the additive white Gaussian noise (AWGN) with zero mean and standard deviation $\sigma$. The goal of image denoising is to estimate the desired image **x** from **y**. One popular approach to image denoising is the variational method, in which the denoised image is obtained by

$$\hat{x} = arg \min_x \{\frac{1}{2\sigma^2} \|y - x\|^2 + \lambda . R(x)\} \tag{3}$$

where $R(\mathbf{x})$ denotes some regularization term and $\lambda$ is a positive constant. The specific form of $R(\mathbf{x})$ depends on the employed image priors. One common problem of image denoising methods is that the image fine scale details such as texture structures will be over-smoothed. An over-smoothed image will have much weaker gradients than the original image. Intuitively, a good estimation of **x** without smoothing too much the textures should have a similar gradient distribution to that of **x**. With this motivation, we propose a gradient histogram preservation (GHP) model for texture enhanced image denoising. Suppose that we have an estimation of the gradient his to gram of **x**, denote by $\mathbf{h}_r$. In order to make the gradient this to gram of denoised image $\hat{x}$ nearly the same as the reference histogram $\mathbf{h}_r$, we propose the following GHP based image denoising model:

$$\hat{x} = arg \min_x \{\frac{1}{2\sigma^2} \|y - x\|^2 + \lambda . R(x) + \mu \|F(\nabla x) - \nabla x\|^2\}$$

$$\text{s.t.} \quad h_F = h_r , \tag{4}$$

where $F$ denotes an odd function which is monotonically non-descending, $h_F$ denotes the histogram of the transformed gradient image $|F(\nabla\mathbf{x})|$, $\nabla$denotes the gradient operator, and $\mu$is a positive constant. The proposed GHP algorithm adopts the alternating optimization strategy. Given *F*, we can fix $\nabla \mathbf{x}_0 = F(\nabla \mathbf{x})$, and update **x**. Given **x**, we can update *F*by the histogram specification based shrinkage operator. Thus, by introducing *F*, we can easily incorporate the gradient histogram constraint with any existing image regularizer *R(***x***)*.Another issue in the GHP model is how to find the reference histogram $\mathbf{h}_r$ of unknown image **x**. In practice, we need to estimate $\mathbf{h}_r$ based on the noisy observation **y**. We will propose a regularized de convolution model and an associated iterative de convolution algorithm to estimate $\mathbf{h}_r$ from the given noisy image. Once the reference histogram $\mathbf{h}_r$ is obtained, the GHP algorithm is then applied for texture enhanced image denoising.

## 5. DENOISING WITH GRADIENT HISTOGRAM PRESERVATION

### a) The denoising model

The proposed denoising method is a patch based method. Let $\mathbf{x}i = \mathbf{R}_i\mathbf{x}$ be a patch extracted at position *i* , *i* =1, 2, . . . , *N*, where $\mathbf{R}_i$is the patch extraction operator and *N* is the number of pixels in the image. Given a dictionary **D**, we sparsely encode the patch $\mathbf{x}_i$ over **D**, resulting in a sparse coding vector $\alpha_i$. Once the coding vectors of all image patches are obtained, the whole image **x** can be reconstructed by [7]:

$$x = D \circ \alpha \triangleq \left(\sum_{i=1}^{N} R_i^T R_i\right)^{-1} \sum_{i=1}^{N} R_i^T D \alpha_i \tag{5}$$

where $\alpha$is the concatenation of all $\alpha i$. 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 [2], [4], and [8] integrate image local sparsity prior with nonlocal NSS prior, and they have shown promising denoising results. In the proposed GHP model, we adopt the following sparse nonlocal regularization term proposed in the non locally centralized sparse representation (NCSR) model [4]:

$$R(x) = \sum_i \|\alpha_i - \beta_i\|_1, \text{ s.t. } x = D \circ \alpha \tag{6}$$

where $\beta i$ is defined as the weighted average of $\alpha_i^q$:

$$\beta_i = \sum_q w_i^q \alpha_i^q \tag{7}$$

and $\alpha_i^q$ is the coding vector of the *q*th nearest patch(denoted by $x_i^q$) to **x***i* . The weight is defined as

$$w_i^q = \frac{1}{w} exp\left(-\frac{1}{h}\|\hat{x}_i - \hat{x}_i^q\|^2\right) \tag{8}$$

($\hat{x}_i$ and $\hat{x}_i^q$denote the current estimates of **x***i* and $\hat{x}_i^q$, respectively), where *h* is a predefined constant and *W* is the normalization factor. More detailed explanations on NCSR can be found in [4].By incorporating the above *R(***x***)* into Equation (3), the proposed GHP model can be formulated as:

$$\hat{x} = arg\,min_{x,F}\{\tfrac{1}{2\sigma^2}\|y - x\|^2 + \lambda.\textstyle\sum_i\|\alpha_i - \beta_i\|_1 + \mu\|F(\nabla x) - \nabla x\|^2\} \tag{9}$$

s.t. $x = D \circ \alpha, h_F = h_r$

From the GHP model with sparse nonlocal regularization in Equation (7), one can see that if the histogram regularization parameter $\mu$ is high, the function $F(\nabla \mathbf{x})$ will be close to $\nabla\mathbf{x}$.

Since the histogram $\mathbf{h}_F$ of $|F(\nabla \mathbf{x})|$ is required to be the same as $\mathbf{h}_r$, the histogram of $\nabla\mathbf{x}$ will be similar to $\mathbf{h}_r$, leading to the desired gradient histogram preserved image denoising.

### b) Iterative histogram specification algorithm

The proposed GHP model in Eq. (7) can be solved by using the variable splitting (VS) method, which has been widely adopted in image restoration [6],[7],[8]. By introducing a variable $\mathbf{g} = F(\nabla \mathbf{x})$, we adopt an alternating minimization strategy to update **x** and **g** alternatively. Given $\mathbf{g} = F(\nabla \mathbf{x})$,we update **x** (i.e., $\alpha$) by solving the following sub-problem:

$$\hat{x} = \min_x\{\frac{1}{2\sigma^2}\|y - x\|^2 + \lambda.\sum_i\|\alpha_i - \beta_i\|_1 + \mu\|g - \nabla x\|^2\}$$

s.t. $x = D \circ \alpha$ (10)

We use the method in [4] to construct the dictionary **D**ad aptively. Based on the current estimation of image **x**, we cluster its patches into *K* clusters, and for each cluster, a PCA dictionary is learned.. Although in Eq. (8) the *l*1-normregularization is imposed on $\|\alpha_i - \beta_i\|_1$rather than $\|\alpha_i\|_1$,by introducing a new variable $\vartheta i = \alpha i - \beta i$ , we can use the iterative shrinkage/thresholding method [8] to update $\vartheta i$ and then update $\alpha i = \vartheta i + \beta i$ . This strategy is also used in [4] to solve the problem with this regularization term, and thus here we omit the detailed deduction process. To get the solution to the sub-problem in Equation (8), we first use a gradient descent method to update **x**:

$$x^{(k+1)/2} = x^{(k)} + \delta\left(\frac{1}{2\sigma^2}\left(y - x^{(k)}\right) + \mu\nabla^T\left(g - \nabla x^{(k)}\right)\right) \tag{11}$$

where $\delta$ is a pre-specified constant. Then, the coding coefficients $\alpha_i$ are updated by

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$$\alpha_i^{(k+1/2)} = D^T R_i x^{(k+1/2)} \tag{12}$$

By using Eq. (6) to obtain $\beta_i$, we further update $\alpha_i$by

$$\alpha_i^{(k+1)} = S_{\lambda/d}\left(\alpha_i^{(k+1/2)} - \beta_i\right) + \beta_i \tag{13}$$

where $S\lambda/d$ is the soft-thresholding operator, and $d$ is a constant to guarantee the convexity of the surrogate function [7].Finally, we update $\mathbf{x}^{(k+1)}$by

$$x^{(k+1)} = D \circ \alpha^{(k+1)} \triangleq \left(\sum_{i=1}^{N} R_i^T R_i\right)^{-1} \sum_{i=1}^{N} R_i^T D \alpha_i^{(k+1)} \tag{14}$$

Once the estimate of image **x** is given, we can update $F$ by solving the following sub-problem:

$$min_{g,F} \| g - \nabla x \|^2 \text{ s.t } h_F = h_r, \; g = F(\nabla x) \tag{15}$$

Considering the equality constraint **g** = $F(\nabla \mathbf{x})$, we can substitute gin$\| g - \nabla x \|^2$with $F(\nabla \mathbf{x})$, and the sub-problem becomes

$$min_F \| F(\nabla x) - \nabla x \|^2 \text{ s.t } h_F = h_r \tag{16}$$

## 6. SIMULATION RESULT

**Figure-1.**Original image.

**Figure-2.** Noisy image with mean = 0, S.D*=20.

**Figure-3.** Noisy image with mean = 0, S.D*=30.

**Figure-4.** Denoised image.

ARPN Journal of Engineering and Applied Sciences



Above simulation result shows the GHP algorithm applied for TIF file format image.

**Algorithm used**

1. Initialize k = 0, $x^{(k)} = y$
2. Iterate on k = 0,1,2,…,J
3. Update g:

   $g = F(\nabla x)$
4. Update x:

$$x^{(k+1)/2} = x^{(k)} + \delta\left(\frac{1}{2\sigma^2}(y - x^{(k)}) + \mu\nabla^T(g - \nabla x^{(k)})\right)$$

5. Update the coding coefficients of each patch:

$$\alpha_i^{(k+1/2)} = D^T R_i x^{(k+1/2)}$$

6. Update the nonlocal mean of coding vector:

$$\beta_i = \sum_q w_i^q \alpha_i^q$$

7. Update $\alpha$:

$$\alpha_i^{(k+1)} = S_{\lambda/d}\left(\alpha_i^{(k+1/2)} - \beta_i\right) + \beta_i$$

8. Update x:

$$x^{(k+1)} = D \circ \alpha^{(k+1)}$$

9. $k \longleftarrow k + 1$
10. $x = x^{(k)} + \delta\left(\mu\nabla^T(g - \nabla x^{(k)})\right)$

* S.D standard Deviation

## 7. EXPERIMENTAL RESULTS

To verify the performance of the proposed GHP based image denoising method, we apply it to ten natural images with various texture structures, whose scenes are shown in Figure-6. All the test images are gray-scale images with gray level ranging from 0 to 255. We first discuss the parameter setting in our GHP algorithm. Finally, experiments are conducted to validate its performance in comparison with the state-of-the-art denoising algorithms.

### a) Parameter setting

There are 4 parameters in our GHP algorithm and 4 parameters in the reference histogram estimation algorithm. All these parameters are fixed in our experiments.

**1) Parameters in the GHP algorithm:** The proposed GHP algorithm has two model parameters: $\lambda$, and $\mu$. We use the same strategy as in the original NCSR model [4] to determine the value of $\lambda$. The parameter $\mu$ is introduced to balance the non locally centralized sparse representation term and the histogram preservation term. If $\mu$ is is set very large, GHP can ensure that the gradient histogram of the denoising result is the same as the reference histogram. Considering that in practice the reference histogram is estimated from the noisy image and there are certain estimation errors, $\mu$ cannot be set too big. We empirically set $\mu$ to 5 based on our experimental experience.

**Table-1.** PSNR value comparison between the base paper and experimental result.

| Iterations | $\sigma$ = 20 | | $\sigma$ = 30 | |
|---|---|---|---|---|
| | **Base paper result** | **Experimental result** | **Base paper result** | **Experimental result** |
| 1 | 30.59 | 27.94 | 28.47 | 29.04 |
| 2 | 27.90 | 28.70 | 25.87 | 27.62 |
| 3 | 28.15 | 29.28 | 26.34 | 27.12 |
| 4 | 26.59 | 29.45 | 24.46 | 25.41 |
| 5 | 30.54 | 30.36 | 28.61 | 28.53 |
| 6 | 28.39 | 29.97 | 26.12 | 28.71 |
| 7 | 30.07 | 31.01 | 28.15 | 29.24 |
| 8 | 31.27 | 30.66 | 29.23 | 29.12 |
| 9 | 27.31 | 30.71 | 25.21 | 28.63 |
| 10 | 30.83 | 30.86 | 28.85 | 29.45 |
| Average | 29.16 | **29.89** | 27.13 | **28.18** |

Above table shows PSNR value comparison of between base paper value and experimental result value.

**Table-2.** PSNR value of denoised images for zero mean and Standard Deviation = 20.

| Image file format | Iteration 1 PSNR value | Iteration 2 PSNR value | Iteration 3 PSNR value | Iteration 4 PSNR value | Iteration 5 PSNR value | Computational time |
|---|---|---|---|---|---|---|
| TIF | 27.93 | 28.70 | 29.28 | 29.73 | 30.21 | Approximately 40min |
| BMP | 28.58 | 28.71 | 30.01 | 30.45 | 29.97 | Approximately 45min |
| JPG | 27.56 | 26.90 | 27.21 | 29.66 | 27.96 | Approximately 40min |

## 8. CONCLUSIONS

In this paper, we presented a gradient histogram preservation (GHP) model for texture-enhanced imaged noising. An efficient iterative histogram specification algorithm was developed toimplement the GHP model. GHP achieves promising results in enhancing the texture structure while removing random noise. The experimental results demonstrated the effectiveness of GHP in texture enhanced image denoising. GHP leads to PSNR measuresto the state-of-the-art denoising method. However, it leads to more naturaland visually pleasant denoising results by better preserving the image texture areas. Most of the state-of-the-art denoising algorithms are based on the local sparsity and nonlocal self-similarity priors of natural images. Limitations of GHP is that it cannot be directly applied to non-additive noise removal. The computational time is approximately 40 min.

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