IJCSN International Journal of Computer Science and Network, Volume 6, Issue 3, June 2017
ISSN (Online) : 2277-5420
www.IJCSN.org
Impact Factor: 1.5

Edge Preserved and Segmented Image Denoising

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Abstract - Denoising of images has been a successful research topic for various image processing applications. Image denoising is basically restoration of images, where the unwanted noises causing degradations are removed to obtain a visually effectual high quality image. The majority existing image denoising algorithms failed to focus on the diminishing edges whilst noise reduction. The net effect is the low quality denoised image. This paper tackle the edge preserving problem by presenting SAIST (Spatially Adaptive Iterative Singular-value Thresholding) image denoising algorithm incorporating bilateral filtering. In this work a two-fold approach is adapted. First is preserving edges through bilateral filtering. A non- maximum suppression on the smoothed image and morphological dilation to stretch the edges are performed. Second is image denoising using iterative regularization and singular valued decomposition (SVD) for estimating signal variances. The pragmatic results and better computational efficiency do better than several state-of-the-art image denoising algorithms.

Keywords *- Image denoising, bilateral filtering, iterative regularization, singular valued decomposition.*

1. Introduction

Image denoising is well renowned owing to the numerous applications in various research fields, specifically in digital image processing. Denoising of an image can be defined as the reduction or removal of unnecessary signals from an image to make it visually plausible. Several noise reduction techniques have been developed so far featuring different characteristics of the image to be denoised. For example, noise strength. Selecting appropriate denoising algorithm completely depends on the type of application. The wide range of applications includes satellite television, magnetic resonance imaging, computed tomography, geographical information systems etc.Additive and multiplicative noises are the two main categories which include Gaussian noise, Salt and Pepper noise, Speckle noise and Brownian noise. Every feature in image processing delivers some sort of noise, which is transmitted through the noisy channel. The amount of noise is determined using SNR (Signal to Noise Ratio). Depending on the noise model different denoising techniques are used. All denoising algorithms are connected with,

- A noise model
- A generic smoothness model

The goal of image denoising is to preserve contents or details of image and reducing random noise to a greater extend. This also recovers minute details having low contrast hidden in the noisy image. The fine details in an image is difficult to be differentiated from noise and this leads to denoising artifacts such as ringing, blur, staircase effect, checkerboard effect. The requisite for effectual image denoising methods has augmented with the greater production of digital images. In every application a development is made in order to extend the range of image. Image denoising is basically restoration of images, where the unwanted noises causing degradations are removed to obtain a visually effectual high quality image. A digital image can be mathematically represented as a matrix of grey level or color values. In grey-scale 0 and 255 denotes black and white respectively.

Listing some of the application areas

- Digital photography and video.
- Medical imaging.
- Astronomy.
- Forensic Science.

2. Related Works

Liu et.al [1] proposed an improved edge detection method. This method combines Canny edge detection [2] and Bilateral filtering [3] which is an efficient edge preserving filter. Field intensity and edge sensing are characterized in this filtering technique. Mean Shift Segmentation, is well known clustering based algorithm is proposed by Comaniciu and Meer [4]. The spatial and range resolution are the input parameters.

The processing time of segmentation depends on the spatial resolution. Katkovnik et.al introduced BM3D [5] the nonlocal image restoration [11][12] algorithm which shows high sparsity. Singular-value decomposition (SVD) [6], a low rank approach is encountering latest advances. Estimation of signal variances involving local and non local data can be performed. The efficient technique called iterative regularization [7] is a promising strategy for spatial adaptation.

3. Proposed System

An improved method of image denoising while preserving edges is proposed. The project is divided into three modules. First edges of the noisy image are extracted while preserving them. Canny edge detection algorithm with bilateral filtering is used. Second, edge removed remaining image is clustered using Mean shift segmentation. As a final point the denoising is performed using SAIST (Spatially adaptive iterative singular-value thresholding) which utilises iterative regularisation technique and SVD for dictionary learning[9].

3.1 Edge Extraction

The primary step in this work is the identification of edges. For this, state-of-the-art method Canny edge detection [] is used. In Canny edge detection, normally a Gaussian filtering is used for image filtering. In Gaussian filter, a kernel according to the function

$$G = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

where σ is the standard deviation chosen according to the image. Matrix values of x and y varies depending on the kernel size selected. But in this project in order to preserve the edges an efficient edge preserving filter called Bilateral filtering is applied.

Bilateral filtering includes smoothing whilst preserving edge, which is non-iterative in manner. This particular technique defines weights based on the selected pixel and nearby pixel. It is given by the expression

$$F(x) = \frac{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I(\mathcal{E})\omega(\varepsilon,x)d\varepsilon}{\int_{-\infty}^{\infty}\omega(\varepsilon,x)d\varepsilon} \quad (2)$$

Where

$$\omega(\varepsilon,x) = exp\left(\frac{-(\varepsilon-x)^2}{2\sigma_{d^2}}\right) exp\left(\frac{-\left(I(\varepsilon)-I(x)\right)^2}{2\sigma_{r^2}}\right) \quad (3)$$

This equation shows the filter intensity as σ_d and edge sensitivity as σ_r. I and F are the input and output images respectively. Through convoluting the two terms of ω(), the smoothed image is obtained. This leads to find the Sobel gradients, which defines G_x and G_y directional gradients expressed as

$$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} and \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

Convolving G_x and G_y with in the particular region and taking square and sum of both yields the gradient. A non-maximum suppression is performed after successfully finding the gradients to suppress the pixels if they do not constitute a local maximum. Gradient direction is normal to the edge. So the pixel of interest is checked with the neighbouring pixels for a local maximum, then the pixel is considered for next stage.

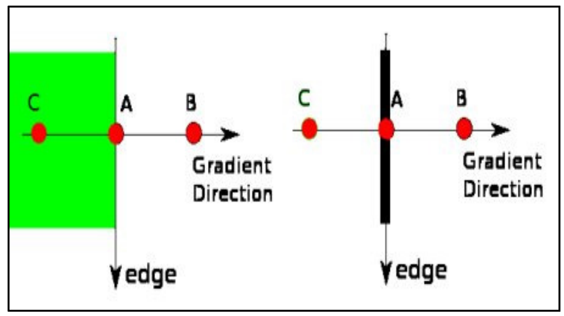

Figure 1: Non maximum suppression

For performing non maximum suppression, angles between the pixels must be set in an order so as to form a cluster.

Table 1: Angle variations

Existing value (°)	New Value (°)
0-22.5	0
22.5-67.5	45
67.5-112.5	90
112.5-157.5	135
157.5-180	0

Depending on the new angle value suppression is applied using the conditions:

- For new angle value 0, check whether the angle of current pixel is less than that of pixels lying parallel to the pixels, then the output pixel is made as 0 else keep it as such.
- For new angle value 45, check whether the angle of current pixel is less than that of pixels which lies at an angle of 45 to it, then the output pixel is made as 0 else keep it as such.
- For new angle value of 90, continue the procedure same as that of 0 but the pixels in the perpendicular side.

- For new angle value of 135, continue the procedure same as that of 45 but the pixels at an angle of 135.

To determine the inter class variant, Otsu's method of thresholding called GRAY THRESHOLD [8] is used after non maximum suppression. This function divides the foreground and background pixels, and the weighted mean and variance is calculated for each pixel. Inter class variant is expressed as

$$\sigma_b^2 w_b + \sigma_p^2 w_f \quad (4)$$

where σ_f and w_f indicates foreground variance and weighted mean respectively. Background variance and weighted mean denoted by σ_b and w_b. Thus a threshold is obtained that leads to either upper or lower second threshold.

Difference in the thresholds shows the edge details. To strech the edges, a morphological dilation[15] is performed for detailed information and visually clear edge. Finally the edge regions are extracted from the noisy input image so as to preserve the edges while denoising.

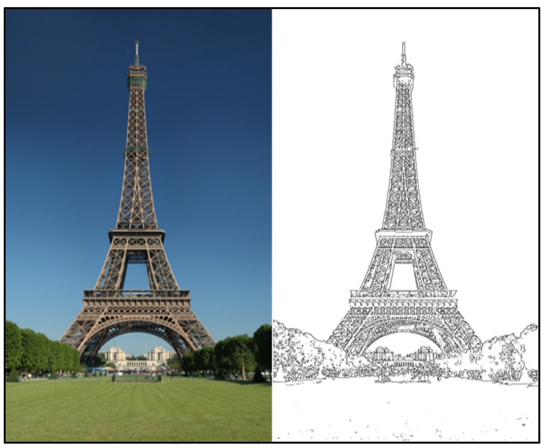

Figure 2: Edge preserved extraction

3.2 Segmentation

The technical term segmentation is defined as the grouping of each pixel in an image to single of different categories, whether objects or parts of objects. Pixels in each category should not be similar to nearby pixels in other categories but should have similarity in pixel values. They should be connected with in the image. Segmentation can be applied directly to the images or after some processing by filters. Three categories of segmentation are listed as

- Thresholding
- Edge-based
- Region-based

In this work, edge based segmentation is opted in which all pixels categorized based on edge labeling. An edge detection filter can perform the edge labeling automatically. Among these, Mean shift segmentation is the best player. This versatile method based on clustering can be simply defined as for each pixel choose a search window, then compute the mean shift vector and repeat till it converges.

Figure 3: Mean Shift Segmentation

The segmentation method, take two parameters as input, spatial resolution and range resolution. These parameters tell which pixels in what neighborhood are to be considered to compute mean. Connectivity, smoothing of segments and number of segments are affected by these parameters. The grey level histogram indicates pixels of what grey level in the neighborhood are taken into consideration. So pixels within the pixel distance and which fall in the bins in the joint histogram are to be considered. Until convergence, mean should be computed.

3.3 Denoising using SAIST

Modern researches on non local image restoration [14] algorithms have contributed much to the field of image processing, specifically for image denoising. State-of-the-art techniques such as BM3D [5] lacks a reasonable explanation for natural images. SAIST (Spatially adaptive iterative singular-value thresholding) employs the concept of SVD (singular value decomposition) and iterative regularization. Singular value decomposition [6][10] is a data reduction method. Linear algebra is the underlying principle of SVD in which a rectangular matrix y can be decomposed into $U, \sum, V$ respectively denoting orthogonal matrix, diagonal matrix and transpose of orthogonal matrix.

$$\boldsymbol{Y}_i: (\boldsymbol{U}_i, \boldsymbol{\Sigma}_i, \boldsymbol{V}_i = svd(\boldsymbol{Y}_i) \quad (5)$$

The basic idea behind SVD is taking a highly variable set of data points and representing a subset of the original data clearly and reordering based on the variation strength, from most to the least. The threshold parameter is given as

$$\tau_i = \frac{2\sqrt{2}\sigma_\omega^2}{\sigma_i} \tag{6}$$

and

$$\hat{\sigma}_i = \sqrt{\max(\tilde{\lambda}_i^2 \;/\; m - \sigma_\omega^2, 0)} \tag{7}$$

where σ_i is the estimated variance at local position *i* and λ_i denotes singular value estimated from noisy data set *y*.

A spatial adaptation approach is given by the iterative regularization [7] [13] technique which is expressed as

$$\mathrm{y}^{(k+1)} = \hat{\mathrm{x}}^{(k)} + \delta\left(\mathrm{y} - \hat{\mathrm{x}}^{(k)}\right) \tag{8}$$

This involves updating noise and signal variance estimation. During the time of iteration, noise variances are decreased while retaining the original or real data. The process is continued until it converges.

Figure 4: Noisy Image (left), Denoised Image (right)

4. Experimental Result

The efficiency of the proposed method can be proved by the experimental analysis. In this paper, comparison of the given model with BM3D is performed. Results from the executable source codes released by the author are used for comparison. Convincingly, a visually plausible output is obtained by using SAIST (Spatially adaptive iterative singular value thresholding). Moreover, the method is robust to type of noise and strength. Denoising is performed at noise levels: 10, 25, and 50 for 256x256 pixel size images. With increasing noise intensity, BM3D failed produce results clearly. However, an improved visual quality is achieved by proposed method. For a noise strength of $\sigma = 25$, PSNR of the noisy image is 20.19 dB and for denoised image is 28.22 dB. The total elapsed time for denoising using SAIST method is 0.5826 minutes which is approximately 30 seconds.

Figure 5: Comparison I) Lena image at noise level $\sigma_n = 25$. II) SAIST (PSNR = 28.22 dB). III) BM3D (PSNR = 27.87 dB)

5. Conclusion

An improved method of image denoising while preserving edges is proposed here. In this method the Canny edge detection with Bilateral filtering is used to extract and preserve edges respectively. Bilateral filtering includes smoothing whilst preserving edge, which is non-iterative in manner. This particular technique defines weights based on the chosen pixel and nearby pixel.
A well-known segmentation method called mean shift segmentation is used for clustering pixels into different patches. For performing denoising after preserving edges, SAIST (Spatially adaptive iterative singular-value thresholding) is used. The iterative regularization technique, noise variance update, singular-value decomposition (SVD) is collaborated to get desired result. Excellent experimental results have been obtained for proposed image denoising.

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