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Image De-Noising using Improved Optimal Graph Laplacian Regularization with Mean Filter

Shrikant Namdeo Bamne[1], Madhuvan Dixit[2]

[1]*M.Tech (CSE, Student),* [2]*Assistant Professor*

(Department of CSE), MIT, Bhopal

Abstract - Image processing applications like in object tracking, medical imaging, satellite imaging, face recognition and segmentation requires image de-noising as the preprocessing step. Problem with current image de-noising methods are blurring and artifacts introduces after removal of noise from image. Current de-noising methods are based on patches of image has well de-noising ability but implementation of such methods are difficult. The Improved Optimal Graph Laplacian Regularization (IOGLR) is a proposed image de-noising method which progressively removes reduced the noise from image. It has simple implementation using robust noise estimation and deterministic annealing. Its results are artifacts free. It is better for the artificial images i.e. computer generated images or synthetic images. This thesis work presents comparatively results with Optimal Graph Laplacian Regularization (OGLR) and Block Matching and 3D Filtering (BM3D) for both natural and synthetic images contaminated with different levels of noise. A hybrid framework is proposed for image de-noising, in which several state-of-the-art de-noising methods are efficiently incorporated with a well trade-off by using the prior of patches. The restored image is finally synthesized with the de-noised patches of all categories. Experiments show that, by using the hybrid framework, the proposed algorithm is insensitive to the variation of the attributes of images, and can robustly restore images with a remarkable de-noising performance.

Keywords - Improved Optimal Graph Laplacian Regularization, Optimal Graph Laplacian Regularization, Block Matching and 3D Filtering, Robust Noise Estimation, Deterministic Annealing.

1. INTRODUCTION

Images are corrupted with various types of noises. So it is very difficult to get useful information from noisy images. That is why de-noising techniques are very important subject nowadays, For example, medical images obtained by X-ray or computed tomography CT in adverse conditions, or a mammographic image which may be contaminated with noise that can affect the detection of diseases or the object of interest. The aim of this work is to provide the overview of various de-noising techniques. Some of these techniques provide satisfactory results in removing noise from images and also preserve edges with other fine details present in images. Image noise is a random variation of brightness or color information in images. It can be produced by sensor or circuitry of a scanner or digital camera. Noise in digital images arises during image acquisition and/ or transmission.

2. Image Noise Model

Image de-noising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensate for distortion in the optical system of a telescope.

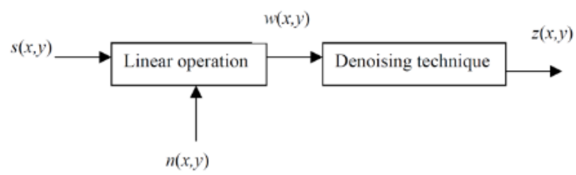

Figure 1: De-noising Concept

3. Types of Noise

Noise is the unwanted signal that affects the performance of the output signal**.** Noise produces undesirable effects such as unseen lines, corners, blurred objects and disturbs background scenes etc. Typical images are corrupted with additive noises modeled with either a Gaussian, uniform, or salts and pepper distribution. Noise is present in an image either in an additive or multiplicative form. An additive noise follows the rule

$$w(x, y) = s(x, y) + n(x, y) ,\ldots\ldots\ldots\ldots\ldots\ldots(1.1)$$

While the multiplicative noise satisfies

$$w(x, y) = s(x, y) \times n(x, y) ,\ldots\ldots\ldots\ldots\ldots\ldots(1.2)$$

Where s(x, y) is the original signal, n(x, y) denotes the noise introduced into the signal to produce the corrupted image w(x, y), and (x, y) represents the pixel location. The above image algebra is done at pixel level. Image addition also finds applications in image morphing. By image multiplication, we mean the brightness of the image is varied.

3.1 Salt and Pepper Noise: Salt and pepper noise is also called as impulsive noise. Impulsive noise generate during data transmission. The image is not fully corrupted by impulsive noise, some pixel values are changed in an image.

3.2 Gaussian Noise: Gaussian noise is also called as electronic noise because it arises in amplifiers or detectors. Gaussian noise is the statistical noise having probability density function (PDF) sequel to that of the normal distribution.

3.3 Poisson Noise: Poisson noise is also called as quantum (photon) noise or shot noise. The Poisson noise is appeared due to the statistical nature of electromagnetic waves such as x-rays, visible lights and gamma rays.

3.3 Brownian Noise: Brownian noise comes under the category of fractal or 1/f noises. The mathematical model for 1/f noise is fractional Brownian motion. Fractal Brownian motion is a non-stationary stochastic process that follows a normal distribution.

4. Previous Work

Inverse imaging problems are inherently underdetermined, and hence it is important to employ appropriate image priors for regularization. One recent popular prior the graph Laplacian regularizer assumes that the target pixel patch is smooth with respect to an appropriately chosen graph (Jiahao Pang, Gene Cheung; 2017) [1].

With people's pursuit of high quality image, image de-noising has always been a popular research. The traditional image de-noising method is based on wavelet transform threshold (Yifeng Cheng, Zengli Liu; 2016) [2].

Image processing applications like in object tracking, medical imaging, satellite imaging, face recognition and segmentation requires image de-noising as the preprocessing step (B. K. Thote, K. C. Jondhale; 2016) [3].

In this paper, a hybrid framework is proposed for image de-noising, in which several state-of-the-art de-noising methods are efficiently incorporated with a well trade-off by using the prior of patches(Ying Chen, Yibin Tangt, Lin Zhou, Aimin Jiangt and Ning Xut; 2016) [4].

Critical issue in the image restoration is the problem of de-noising images while keeping the integrity of relevant image information (Sarbjit Kaur, Er. Ram Singh; 2015) [5].

5. Proposed Work

The basic procedure of propose methodology can be explain through following point

5.1 ALGORITHM

Input: Noisy_ Image I, Noise_Variance

Output: De-noise image

Algorithm: IOGLR

Step 1: Initialize x = total number of noisy patches in an input noisy images.

Step 2: Initialize counter variable k=0.

Step 3: for each noise patch Z_0 in x, go to next step otherwise go to step 9.

Step 4: Perform mean filter on noise patch Z_0 and obtain as Z_01.

Step 5: Perform cluster on similar patches of Z_01 in I.

Step 6: Computation of GL from similar patches.

Step 7: De-noising of Z_01 with optimization.

Step 8: if next patch Z_1 exist in x then go to step 3.

Step 9: Aggregation of the de-noise image DI_k

Step 10: if (noise_var of de-noise image DI_k)>=Threshold value of noise variance and k!= p(total pixel in DI_k) then k=k+1,

Now Estimation of noise variance for k

else

return (DI_{k+1}) and exit //Obtain De-Noised Image

Step 11: go to step 3.

4.2.2 FLOWCHART

The flowchart of proposed methodology is as follows:

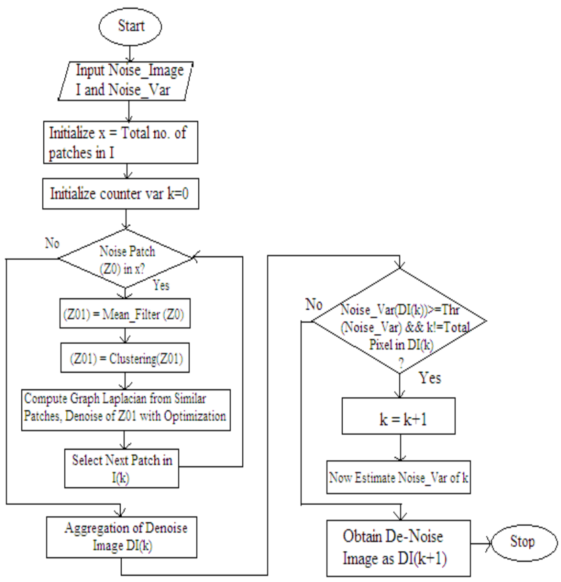

Figure 2: Flowchart of Proposed Methodology (IOGLR)

6. Experimental Works

Experiments set-up performed on general source image, which is mainly uses in MATLAB image processing environment, i.e., these images taken from MATLAB directory and also available online. These images are in grayscale mode. We have setup MATLAB R2013a version for implement the proposed method namely as IOGLR (Improved Optimal Gaussian Laplacian Regularizer).

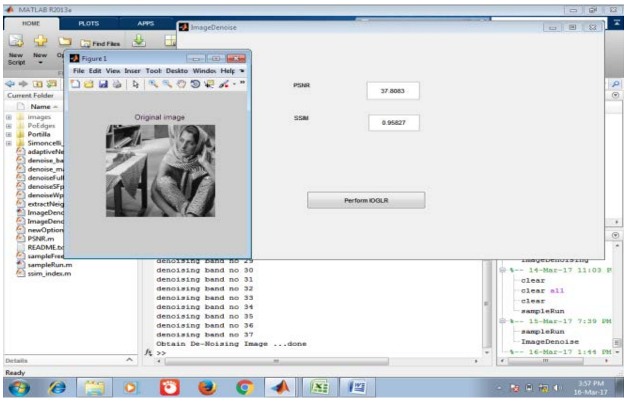

Figure 3: Load Barbara image

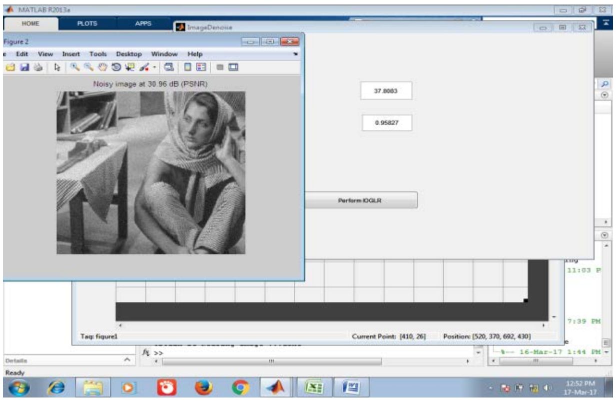

Figure 4: Noisy image through AWGN

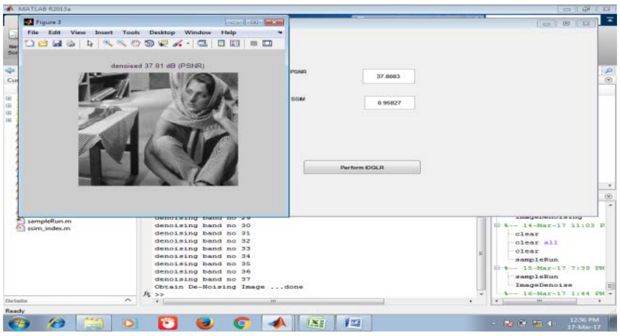

Figure 5: De-Noise Image Using IOGLR

7. Result Analysis

If images are taken from MATLAB image processing repository then the analysis of the existing works Block Matching 3-D (BM3D)[16], Optimal Graph Laplacian Regularizer (OGLR)[1] and the proposed work Improved Optimal Graph Laplacian Regularizer (IOGLR) on the basis of different quality parameters are given in Table 1 and Table 2.

Image	10			20			30			40			50		
	BM3D	OGLR	IOGLR	BM3D	OGLR	IOGLR	BM3D	OGLR	IOGLR	BM3D	OGLR	IOGLR	BM3D	OGLR	IOGLR
Lena	35.89	35.62	36.07	33.02	32.93	33.06	31.23	31.22	31.24	29.82	30.06	30.11	29.00	28.86	29.18
Barbara	34.96	34.46	37.82	31.75	31.45	33.80	29.79	29.63	31.60	28.00	28.31	29.92	27.23	27.36	28.61
Peppers	35.02	34.91	35.11	32.75	32.67	32.78	31.23	31.23	31.33	29.93	30.10	30.54	29.09	28.83	29.12
Mandrill	30.58	29.84	30.62	26.60	26.35	26.66	24.56	24.56	24.68	23.09	23.40	24.12	22.35	22.59	22.64
Cones	40.40	42.93	42.98	35.17	37.39	37.78	32.57	34.08	35.12	31.01	31.78	32.12	29.62	30.36	30.88
Teddy	41.17	42.80	42.89	35.94	37.73	37.86	33.16	34.52	34.98	31.32	32.20	32.97	29.73	30.70	30.86
Art	40.04	42.98	43.12	35.47	37.33	37.49	33.21	34.27	35.66	31.60	32.15	32.44	30.36	30.82	30.96
Moebius	42.03	43.31	43.38	37.15	38.36	38.38	34.70	35.35	35.92	33.09	33.19	33.24	31.75	31.94	32.14
Aloe	40.30	42.86	42.96	35.66	37.47	37.76	33.31	34.53	34.66	31.73	32.56	32.88	30.58	31.18	32.24

Table 1: Analysis of comparisons the value of PSNR in between of BM3D[16], OGLR[1] and Proposed Method IOGLR (Improved Optimal Graph Laplacian Regularizer) with different images and standard deviation.

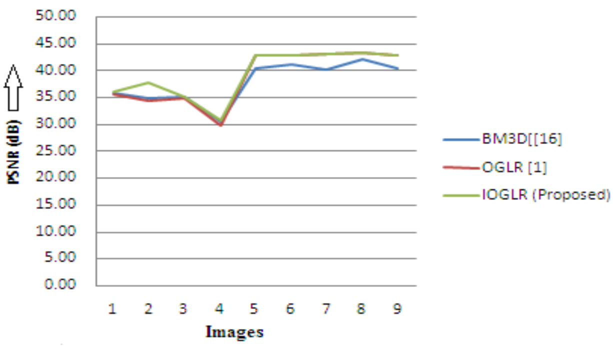

Figure 6: Comparison of PSNR for different methods with σ = 10.

Image	10			20			30			40			50		
	BM3D	OGLR	IOGLR	BM3D	OGLR	IOGLR	BM3D	OGLR	IOGLR	BM3D	OGLR	IOGLR	BM3D	OGLR	IOGLR
Lena	0.915	0.912	0.921	0.876	0.874	0.922	0.843	0.842	0.887	0.813	0.821	0.860	0.796	0.785	0.830
Barbara	0.942	0.937	0.958	0.905	0.902	0.905	0.867	0.867	0.868	0.822	0.838	0.863	0.794	0.801	0.990
Peppers	0.879	0.879	0.892	0.845	0.842	0.852	0.820	0.818	0.822	0.795	0.798	0.802	0.782	0.762	0.785
Mandrill	0.897	0.883	0.899	0.792	0.786	0.801	0.702	0.706	0.708	0.617	0.650	0.672	0.549	0.595	0.602
Cones	0.983	0.987	0.988	0.960	0.968	0.978	0.935	0.944	0.953	0.912	0.922	0.925	0.898	0.900	0.905
Teddy	0.985	0.986	0.992	0.967	0.968	0.977	0.948	0.947	0.977	0.927	0.929	0.932	0.919	0.910	0.922
Art	0.983	0.988	0.995	0.959	0.967	0.968	0.934	0.944	0.968	0.907	0.922	0.928	0.891	0.898	0.902
Moebius	0.983	0.985	0.991	0.962	0.962	0.971	0.940	0.938	0.971	0.918	0.917	0.921	0.911	0.898	0.920
Aloe	0.984	0.988	0.989	0.962	0.968	0.979	0.938	0.946	0.979	0.913	0.928	0.929	0.899	0.907	0.909

Table 5.2: Analysis of comparisons the value of SSIM in between of BM3D[16], OGLR[1] and Proposed Method IOGLR (Improved Optimal Graph Laplacian Regularizer) with different images and standard deviation.

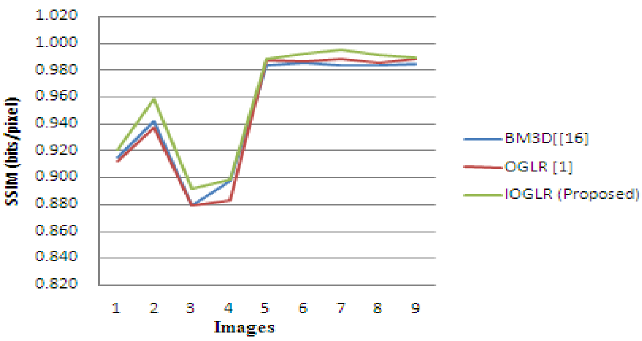

Figure 7: Comparison of SSIM for different methods with σ = 10.

Here the comparisons result tested on the basis of different images and measure the various result parameters shown in the comparisons tables. The de-noised image is compares in between of BM3D, OGLR and IOGLR for different image. The value of PSNR (for IOGLR) is more than value of PSNR (for BM3D and OGLR). The value of SSIM (for IOGLR) is more than value of SSIM (for BM3D and OGLR). Hence the performance of the proposed work (IOGLR) is better as compared to the existing techniques.

8. Conclusion and Future Work

The Optimal Graph Laplacian Regularizer is a popular recent prior to regularize inverse imaging problems. In this work, to study in-depth the mechanism and implication of Optimal Graph Laplacian Regularization. We then derive the Improved Optimal Graph Laplacian Regularizer for image de-noising, assuming non-local self-similarity. To explain the behavior of optimal graph Laplacian regularization, our developed de-noising algorithm, Improved Optimal Graph Laplacian Regularization (IOGLR) for de-noising, produces competitive results for natural images compared to state-of-the-art methods, and out-performs them for piecewise smooth images. After analyzing BM3D, OGLR and IOGLR for various AWGN noise levels, come to a conclusion that IOGLR gives visual and theoretical excellent results for both synthetic and natural images. From tables (1 and 2) the SSIM for IOGLR is more but the results for synthetic images at high noise level (σ = 50) smooth and artifact free compare to BM3D and OGLR. OGLR has less low-frequency noise than BM3D.

In future IOGLR can be improved by reducing the execution time and improve PSNR for algorithm compare to IOGLR. For this purpose, threshold value has been set in machine learning. Through machine learning and different optimization scheme like Min-Max ACO, Neural Network Genetic Algorithm can be efficiently de-noising image.

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