A Comparative Study of Image Denoising Methods and Hybrid graph Laplacian Regularised Regression Method

Anjali Bhusagare
Department of Information Technology
Siddhant College of Engineering, Sudumbare
Pune, India
Anjali.bhusagare@gmail.com

Sonali Rangdale (Guide)
Department of Information Technology
Siddhant College of Engineering, Sudumbare
Pune, India
sonali_rangdale@rediffmail.com

***Abstract*—A comparative study is made up of Hybrid Graph Laplacian Regularized Regression Method and other image denoising methods. Hybrid Graph Laplacian Regularized Regression method is an effective and efficient image impulse noise removal method as compared to the previous methods. The multiscale Laplacian Pyramid is used where the intra-scale relationship is modeled with implicit kernel graph Laplacian Regularization while the Inter-scale dependency can be learned and propagated with the explicit kernel extension model in mapped feature space. In this way, both local and nonlocal regularity constraints are exploited to improve the accuracy of noisy image recovery.**

Keywords- Hybrid Graph Laplacian Regularization,Image Denoising, local smoothness,non-local self similarity

I. INTRODUCTION

It is important to remove the noise from the images before they are used for further image processing applications or tasks .So finding the efficient method for noise removal is a challenging task for the researchers. There are a lot of algorithms present which can be used for this purpose with their own merits and demerits. We need to select the algorithm depending upon the kind of noise present in the image. In this paper we study different types of noise removal methods and compare it with the Hybrid Graph Laplacian Regularized Regression method.

Noise is random variation of Image Intensity and visible as grains in the image. Noise may be produced at the time of image capturing or image transmission. Noise means, the pixels in the image show different intensity values instead of true pixel values. Noise removal algorithm is the process of removing or reducing the noise from the image. The noise removal algorithms reduce or remove the visibility of noise by smoothing the entire image leaving areas near contrast boundaries.

The common types of noise that arises in the image are Impulse noise, Additive noise, Multiplicative Noise. Different noises have their own characteristics which make them distinguishable from others.

II. IMAGE DENOISING ALGORITHMS

There are a lot of image denoising algorithms available. The algorithm which removes the noise completely and preserves all the image details is called the best image denoising algorithm. There are linear and non-linear methods for image Denoising. Linear methods are fast but they do not preserve the details of the image, whereas the nonlinear methods preserve the details of the image.

Removing impulse noise from images is a challenging Image processing problem, because edges which can also be modeled as abrupt intensity jumps in a scan line are highly salient features for visual attention. Therefore, besides impulse noise removal, another important requirement for image denoising procedures is that they should preserve important image structures, such as edges and major texture features.

A. Linear Filtering Methods

A vast variety of impulse noise removal methods are available in the literature, touching different fields of signal processing, mathematics and statistics. From a signal processing perspective, impulse noise removal poses a fundamental challenge for conventional linear methods.

1) Image denoising by Mean filter

Mean filter is nothing but the averaging filter. In this method, the filter computes the average value of the corrupted pixels in the predefined area of the image. Then the center pixel value is replaced by that average value. This process is repeated for all the pixel values in the image.

2) Image denoising by Median filter

Median filter is nonlinear filter and its response is based upon the ranking of the pixels contained in the filter region. Median Filter is also used for removing certain type of noise. In this method, center value of the pixel is replaced by the median of the pixel values under the filter region. Median filter is good for removing the Salt and Pepper noise.

B. Nonlinear FilteringMethods

Nonlinear techniques are invoked to achieve effective performance. One kind of the most popular and robust nonlinear filters is the so called decision-based filters, which first employ an impulse noise detector to determine which pixels should be filtered and then replace them by using the median filter and its variants, while leaving all other pixels unchanged. The representative methods include the adaptive median filter (AMF) [3] and the adaptive center weighted filter (ACWMF). [4]

1) Adaptive Median Filter(AMF)

Based on two types of image models corrupted by impulse noise, two new algorithms for adaptive median filters are proposed by Hwand and Haddad. These have variable window size for removal of impulses while preserving sharpness.

The ranked order based adaptive median filter (RAMF), is based on a test for the presence of impulses in the center pixel itself followed by the test for the presence of residual impulses in the media filter output. The second one, called the impulse size based adaptive median filter (SAMF), is based on the detection of the size of the impulse noise [3].

2) Adaptive Center- Weighted Median Filter(ACWMF)

The Center Weighted Filter (CWM), which is a weighted median filter giving more weight only to the central value of each window. This filter can preserve the image details while suppressing additive white and /or impulsive type noise. The CWM filter outperforms the median filter. Adaptive Center Weighted (ACWM) can effectively reduce signal-dependant noise as well as additive white and impulsive noise. ACWM filters enhance images degraded by signal-independent or signal-dependant noise.

3) Noise Removal by Energy Method

In this method, image denoising is considered as a variational problem where a restored image is computed by a minimization of some energy functions.Typically, such functions consists of a fidelity term such as the norm difference between the recovered image and the noisy image and a regularization term which penalizes high frequency noise.[5] For example, Chan propose a powerful two stage scheme, in which noise candidates are selectively restored using an objective function with an $l_1$data-fidelity term and an edge preserving regularization term.

In the first phase, suitable noise detectors are used for identifying image pixels contaminated by noise. Then, in the second phase, based upon the information on the location of noise-free pixels, images are deblurred and denoised simultaneously. For efficiency reasons, in the second phase a super linearly convergent algorithm based upon Fenchel-duality and inexact semi smooth Newton techniques is utilized for solving the associated variational problem[5].

Under the similar scheme, Cai proposes an enhanced algorithm used for Deblurring and denoising, and achieve wonderful objective and subjective performance [6]. Different from Chan and Cai's work, Li formulate the problem with a new variational functional , in which the content dependent fidelity assimilates the strength of fidelity terms measured by the l_1 and l_2 norms , and the regularizer is formed by the l_1 norm of tight framelet coefficients of the underlying image. The proposed functional has a content dependent fidelity term which assimilates the strength of fidelity terms measured by the l_1 and l_2 norms. The regularizer in the functional is formed by the l_1 norm of tight framelet coefficients of the underlying image. The selected tight framelet filters are able to extract geometric features of images. Li proposed an iterative framelet based approximation/sparsity Deblurring algorithm (IFASDA) for the proposed functional [7]. Parameters in IFASDA are adaptively varying at each iteration and are determined automatically. In this sense, IFASDA is a parameter free algorithm. This advantage makes the algorithm more attractive and practical.

4) Noise Removal by Multiscale Decomposition Method

From a statistical perspective, recovering images from degraded forms is inherently an ill-posed inverse problem. It often can be formulated as an energy minimization problem in which either the optimal or most probable configuration is the goal. The performance of an image recovery algorithm largely depends on how well it can employ regularization conditions or priors when numerically solving the problem, because the useful prior statistical knowledge can regulate estimated pixels. Therefore, image modeling lies at the core of image denoising problems. [1]

One common prior assumption for natural images is intensity consistency, which means: (1) nearby pixels are likely to have the same or similar intensity values; and (2) pixels on the same structure are likely to have the same or similar intensity values. Note that the first assumption means images are locally smooth, and the second assumption means images have the property of non-local self-similarity. Accordingly, how to choose statistical models that thoroughly explore such two prior knowledge directly determines the performance of image recovery algorithms. Another important characteristic of natural images is that they are comprised of structures at different scales. Through multi-scale decomposition, the structures of images at different scales become better exposed, and hence are more easily predicted. At the same time, the availability of multi-scale structures can significantly reduce the dimension of problem, hence, make the ill-posed problem to be better posed. [1] [8]

W. Hong introduced a simple and efficient representation for natural images. We view an image (in either the spatial domain or the wavelet domain) as collection of vectors in a high dimensional space. We then fit a piecewise linear model (i.e. a union of affine subspaces) to the vectors at each down sampling scale. We call this a multi-scale hybrid linear model for the image. The model can be effectively estimated via a new algebraic method known as generalized principal component analysis (GPCA). The hybrid and hierarchical

structure allows effectively extracting and exploiting multi-modal correlations among the imagery data at different scales. [8].

The study of natural images reveals that the second order statistics of natural images tend to be invariant across different scales and those scale invariant features are shown to be crucial for human visual perception[10][11].This observation inspires us to learn and propagate the statistical feature across different scales to keep the local smoothness of images. On the other hand, the idea of exploiting the non-local self-similarity of images has attracted increasingly more attention in the field of image processing[12][13]. Semi-supervised learning gives us the additional inspiration to address the problem of image recovery [14]. In the algorithm design, the intrinsic manifold structure is taken into account by making use of both labeled and unlabeled data points. [15][16]

C. Image denoising by Hybrid graph Laplacian Regularised Regression

The non-local self-similarity is based on the observation that image patches tend to repeat themselves in the whole image plane, which in fact reflects the intra-scale correlation. All these findings tell us that the local-nonlocal redundancy and intra-inter-scale correlation can be thought of two sides of the same coin. The multiscale framework provides us a wonderful choice to efficiently combine the principle of local smoothness and non-local similarity for image recovery [1].

In this method, a unified framework is used to perform the progressive image recovery based on hybrid graph Laplacian regularized regression. First the multiscale representation of the target image is constructed by Laplacian Pyramid, then the degraded image is progressively recovered in the scale space from coarse to fine so that the sharp edges and texture can eventually be recovered.

On one hand, within each scale, a graph Laplacian regularization model represented by implicit kernel is learned, which simultaneously minimizes the least square error on the measured samples and preserves the geometrical structure of the image data space. In this procedure, the intrinsic manifold structure is explicitly considered using both measured and unmeasured samples, and the nonlocal self-similarity property is utilized as a fruitful resource for abstracting a priori knowledge of the images.

On the other hand, between two successive scales, the proposed model is extended to a projected high dimensional feature space through explicit kernel mapping to describe the Interscale correlation, in which the local structure regularity is learned and propagated from coarser to finer scales. Thus, this algorithm gradually recovers more and more image details and edges, which could not be recovered in the previous scale. Impulse and Salt & Pepper noise can be recovered by using this algorithm.

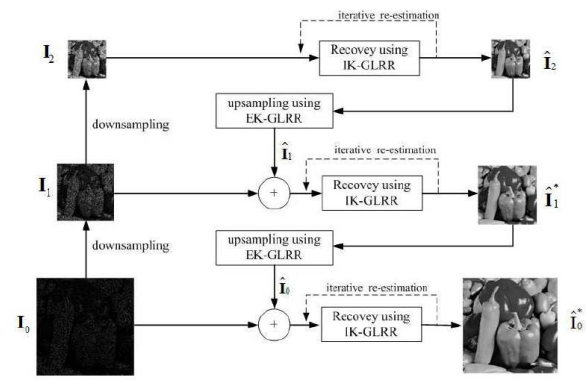

Figure 1 Hybrid Graph Laplacian Regularization Regression Method

The Hybrid Graph Laplacian Regularization Regression method is explained in the above model.

First, the level-l image $\mathbf{I}_l$ passes a low-pass filter F, which is implemented in this method by averaging the existing pixels in a 2x2 neighborhood on higher resolution. Then, the filter image is downsampled by 2 to get a coarser image $\mathbf{I}_{l+1}$.

$$\mathbf{I}_{l+1} = F(\mathbf{I}_l) \downarrow 2, \; l=0\ldots L-1$$

In this way, Laplacian pyramid is constructed. In the practical implementation, a tree-level Laplacian pyramid is constructed.

At the beginning, we have the image $\mathbf{I}_2$ at scale 2 at hand, which is defined on the coarsest grid of pixels G_2. The initial image lacks a fraction of its samples. We start off by recovering the missing samples using the proposed IK-GLRR model to get a more complete grid $\hat{\mathbf{I}}_2$. This procedure can be performed iteratively by feeding the processing results $\hat{\mathbf{I}}_2$ to the GLRR model as a prior for computing the kernel distance k. In the practical experiments, two iterations were found to be effective in improving the processing results of such type of operations.

The recovered image $\hat{\mathbf{I}}_2$ is then interpolated to a finer grid G1 using the proposed EK-GLRR model. The upsampled image $\hat{\mathbf{I}}_1$ can be used as prior estimation for the IK-GLRR model towards a refined estimate $\hat{\mathbf{I}}_1^*$. Then $\hat{\mathbf{I}}_1^*$ can be up converted to $\hat{\mathbf{I}}_0$ in the original resolution grid G_0 by the EK-GLRR model. And the refined estimate $\hat{\mathbf{I}}_0$ can be combined with $\mathbf{I_0}$ into another IK-GLRR recovery procedure towards the final results $\hat{\mathbf{I}}_0^*$.Using the above progressive recovery based on intra-scale and inter-scale correlation, we gradually recover an image with few artifacts.

III. EXPERMENTAL RESULTS AND ANALYSIS

For the comparative study seven widely used images are used. The images are all sized of 512x 512. There are a few parameters involved in the proposed algorithm. σ^2

and ε^2 are fixed to 0.5. λ and γ are set as 0.5 and 0.01 respectively. For comprehensive comparison, the proposed algorithm is compared with some noise removal methods like KR, Cai and IFASDA.

A. Salt and Pepper Noise Removal

The test images are corrupted by salt-and-pepper noise with high noise rates: 80%, 85%, and 90%. For detecting salt-and-pepper noise, AM filter is used with a maximum window size of 19.Table given below tabulates the objective performance of the compared methods.

Figure 2 Seven Sample Images in the test set

Table I
OBJECTIVE QUALITY COMPARISION OF FOUR ALGORITHMS(IN DB) FOR SALT-AND-PEPPER NOISE

Images	80%					85%					90%				
	KR	Cai	IFASDA	HGLRR	Gain	KR	Cai	IFASDA	HGLRR	Gain	KR	Cai	IFASDA	HGLRR	Gain
Lena	29.65	29.11	28.57	**30.44**	**0.79**	27.48	28.12	27.06	**29.13**	**1.01**	25.02	26.56	25.23	**27.49**	**0.93**
Peppers	28.12	28.56	27.25	**28.79**	**0.23**	26.49	27.51	25.91	**27.94**	**0.44**	23.88	26.05	24.21	**26.48**	**0.43**
Wheel	26.67	27.36	27.25	**27.47**	**0.11**	24.81	26.38	25.97	**26.44**	**0.06**	22.98	25.09	24.51	**25.12**	**0.03**
Airplane	26.62	26.84	26.88	**27.34**	**0.46**	24.73	25.72	25.38	**26.31**	**0.59**	22.35	24.39	23.74	**25.02**	**0.63**
Boat	25.99	26.66	25.85	**26.89**	**0.23**	23.97	25.59	24.66	**25.81**	**0.22**	21.96	24.14	22.84	**24.47**	**0.33**
Man	19.25	19.32	19.38	**19.91**	**0.23**	17.39	18.58	18.51	**18.96**	**0.38**	16.04	17.78	17.57	**17.81**	**0.03**
Barbara	25.73	23.75	23.91	**24.89**	**-0.84**	**24.81**	23.26	23.11	**24.19**	**-0.62**	22.41	22.47	22.02	**22.67**	**0.26**
Average	26.00	25.94	25.58	**26.53**	**0.53**	24.24	25.02	24.37	**25.54**	**0.52**	22.09	23.78	22.87	**24.15**	**0.38**

Figure 3 Objective Quality Comparison of Four Algorithms for Salt and Pepper Noise

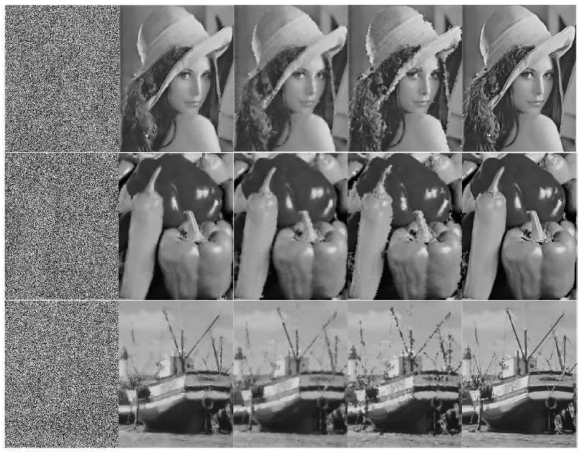

Figure 4 Subjective quality comparison on salt-and-pepper noise removal with the noise level 90% Column1: the noisy image; Column 2: the results of KR; Column 3: Cai's results; Column 4: the results of IFASDA; Column 4: HGLRR method

B. Random-Valued Impulse Noise Removal

For random-valued impulse noise removal, three medium noise levels: 40%, 50% and 60% are tested. The noise is detected by ACWMF. The Table given below shows the PSNR values when restoring the corrupted images with random-valued impulse noise.

Table II
OBJECTIVE QUALITY COMPARISION OF FOUR ALGORITHMS(IN DB) FOR RANDOM-VALUED IMPULSE NOISE REMOVAL

Images	40%					50%					60%				
	KR	Cai	IFASDA	HGLRR	Gain	KR	Cai	IFASDA	HGLRR	Gain	KR	Cai	IFASDA	HGLRR	Gain
Lena	31.58	31.32	32.16	**32.28**	**0.12**	29.59	29.04	29.88	**30.37**	**0.49**	26.5	26.03	26.49	**27.13**	**0.64**
Peppers	29.18	29.36	29.28	**29.57**	**0.21**	27.27	27.41	27.36	**27.73**	**0.32**	23.74	23.45	23.49	**24.04**	**0.3**
Wheel	18.86	19.12	19.08	**19.26**	**0.14**	18.55	18.62	18.5	**18.76**	**0.14**	17.23	17.38	17.11	**17.47**	**0.09**
Airplane	27.93	28.37	27.92	**28.44**	**0.07**	26.63	26.37	26.66	**27.32**	**0.66**	23.68	23.62	23.84	**24.26**	**0.58**
Boat	28.49	28.58	28.96	**29.17**	**0.21**	26.98	26.94	27.11	**27.59**	**0.48**	24.42	24.17	24.39	**24.91**	**0.49**
Man	28.88	29.04	29.35	**29.37**	**0.02**	27.43	27.43	27.73	**28.01**	**0.28**	25.04	24.78	25.08	**25.46**	**0.38**
Barbara	24.15	23.42	23.39	**23.93**	**-0.22**	**23.51**	22.92	23.09	**23.21**	**-0.3**	21.99	21.61	21.25	**21.94**	**-0.05**
Average	27.49	27.03	27.16	**28.02**	**0.53**	26.08	25.53	25.76	**26.63**	**0.55**	23.44	23.01	23.09	**23.88**	**0.44**

Figure 5 Objective Quality Comparison of Four Algorithms for Random Valued Impulse Noise

Figure 6 Subjective quality comparison on random-valued noise removal with the noise level 50% Column 1: the noisy image; Column 2: the results of KR; Column 3: Cai's results; Column 4: HGLRR Method

IV. CONCLUSION

Hybrid Graph Laplacian Regularization is an effective and efficient image impulse noise removal algorithm as compared with the other methods. The input space and high dimensional feature space is used as two complementary views to address such an ill posed problem. This framework uses the multiscale laplacian pyramid where the intra scale relationship can be modeled with implicit kernel graph laplacian regularization model in input space, while the interscale dependency can be learned and propagated with explicit kernel extension model in mapped feature space. After comparison with other methods we can find that this algorithm achieves the highest PSNR value for all the tested images.

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