Image Denoising Using Graph Laplacian Regularization: A Review

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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. Very many ways to denoise an image or a set of data exists. The main properties of a good image denoising model are that it will remove noise while preserving edges. Removing impulse noise from images is a critical issue in image processing because it may occur frequently during acquisition or transmission of images. So it is necessary to find the techniques for the mechanisms and implications of imposing the graph Laplacian regularizer on the original inverse problem.**

Index terms- **Graph Laplacian regularization, graph signal processing, image denoising**

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.

We are in the digital world so the techniques for processing of images may vary according to their field; the main problem in image processing is to recover the images from the highly corrupted observation. The processing of images is used in different fields such as medical field, military, forensic etc.

There are different types of noise may occur during the processing of images in that impulse noise is one of the most frequently occurring noise. Impulse noise is the instant noise which may easily corrupt the edges and texture of an image. The concept of denoising is used to remove the noise present in the image.

The denoising concept may vary depend upon the techniques we adopted. For recovery of images from the highly corrupted observation is a challenging image processing problem. If the image is highly corrupted by noise then recovery of fine details of an image is a critical task. The impulse is of two types, they are salt-and pepper noise and random valued impulse noise. To recover the details of an image filters are used first to eliminate the unwanted data or signal. The commonly used filters for the impulse noise are adaptive median filter for salt-and-pepper noise and adaptive center weighted median filter for random valued impulse noise. There are many existing techniques which try to eliminate the impulse noise and recover the fine details of an image but there are several drawbacks for this restoration of images from highly corrupted observation.

There are many techniques to restore the corrupted image which was affected by impulse noise. The two-phase approach [1] was proposed by Cai et.al in which noise candidates are selected as an outlier. It restores only the noise candidates that are not affected by impulse noise. To restore the corrupted data the two-phase approach was used instead of variation method.

The IFASDA algorithm was proposed by Yan-Ran Li, Lixin Shen et.al in [2]. This paper deals about the deblurring of the image, recover its discontinuities and remove the impulse noise simultaneously. It regularizes the corrupted data to recover the fine details of an image but the objective quality of an image is less when compared to our work.

To improve the performance and quality of an image the hybrid graph Laplacian regularization algorithm was adopted. The degraded image does not have the fine details of an image such as edges and texture. To recover the intrinsic geometric details of an image the statistical properties of an image have to be studied.

The multiscale decomposition of an image recovers the details of image with the help of scale invariant properties of an image. The hybrid graph Laplacian regularization restores the fine details of an image. It is an iterative approach, to restore the original image from the highly corrupted observation the filtering of image using adaptive median filter, kernel estimation, and regularization of the corrupted image and finally restore the corrupted image to preserve the fine details of an image.

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 Filtering Methods

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 l1data-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 l1 and l2 norms , and the regularizer is formed by the l1 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 l1 and l2 norms. The regularizer in the functional is formed by the l1 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]

B.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 intrascale 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.

III LITERATURE REVIEW

TITLE	METHOD	ADVANTAGES	DISADVANTAGES
"Kernel regression for image processing and reconstructtion," Hiriyuki Takeda, Sina Farsiu, Peyman Milanfar, IEEE Transactions on image processing, vol.16, no.2 (2007).	Classical kernel regression Data adapted kernel regression	In the filtering stage, the orientation information is used to adaptively steer the local kernel in extended, eccentric encircle spread along the directions of the local edge structure.	As the number of iterations increases it reduces the variance and also increases the blurring effect. For high noise level, this method generates some Spurious high frequency artifacts.
"Fast two-phase image deblurring under impulse noise," JianFeng Cai, Raymond H. Chan, Mila Nikolova, J Math Imaging Vis (2010) 36:46-53, Published online: 18 August 2009.	Two-phase deblurring approach consist of Impulse detection Restoration using a variational method	Convex energies are used to find global minima. The two-phase method is better than variational method.	It fails to handle Gaussian noise. For high noise level, this method over blurs the result and cannot keep the edge structure well.

"Framelet algorithm for de-blurring images corrupted by impulse plus Gaussian noise," YanRan Li, Li Lixin Shen, Dao-Qing Dai, IEEE Transactions on image processing vol.20, no.7, and (2011).	This method used to deblur the image, recover its discontinuities and remove the impulse noise. Detection of impulse noise. Framelet based model. IFASA	It eliminates the concentric circles while restoring the image.	For high noise level, this method causes irregular outliers along the edges and texture.
"Progressive image denoising through hybrid graph Laplacian regularization: A unified framework," X.Liu, D.Zhai, D.Zhao, G.Zhai, IEEE transactions on image processing vol.23, no.4 April 2014.	To restore and denoise multiscale decomposition of images was adapted. Graph laplacian regularization. Optimization of implicit and explicit kernel regression.	It achieves best overall visual quality through combining interscale and intra scale correlation.	Computational time is high.
"Graph Laplacian Regularization for Image Denoising: Analysis in the Continuous Domain" Jiahao Pang, Member, IEEE, Gene Cheung, Senior Member, IEEE	Interpret neighborhood graphs of pixel patches as discrete counterparts of Riemannian manifolds and perform analysis in the continuous domain, providing insights into several fundamental aspects of graph Laplacian regularization for image denoising. Focusing on image denoising, we derive an optimal metric space assuming nonlocal self-similarity of pixel patches, leading to an optimal graph Laplacian regularizer for denoising in the discrete domain. Interpret graph tendency to promote piecewise smooth signals under certain settings.	denoising algorithm, optimal graph Laplacian regularization (OGLR) for denoising, produces competitive results for natural images compared to state-of-the-art methods, and out-performs them for piecewise smooth images.	image clarity affected by the noise generated from an outside environment

IV CONCLUSIONS

The graph Laplacian regularizer is a popular recent prior to regularize inverse imaging problems. In this paper, to study in-depth the mechanisms and implications of graph Laplacian regularization, we regard a neighborhood graph as a discretization of a Riemannian manifold, and show convergence of the graph Laplacian regularizer to its continuous-domain counterpart. Hybrid Graph Laplacian Regularization is an effective and efficient image impulse noise removal algorithm as compared with the other methods. But still the noise generated from an outside environment affects the image clarity so it is needed to improve them.

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