

A Survey of Image Denoising Methods

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Abstract— A survey of different image denoising methods is performed. The different noise removal methods can be used based upon the nature of the noise that the images contain. Hybrid Graph Laplacian Regularized Regression method of noise removal gives the best result when the type of noise is Salt and Pepper and Gaussian noise.

Index Terms— Image Denoising, Hybrid Graph Laplacian Regularized Regression, Salt and Pepper Noise, Gaussian Noise

1 INTRODUCTION

There are a lot of noise removal methods present in the literature. Finding the efficient method for noise removal is very challenging task for the researchers. It is important to remove the noise before the images are used for image processing tasks. Noise removal methods can be selected based upon the type of noise contained in the image. In this paper we perform the survey of various noise and noise removal methods. Hybrid Graph Laplacian Regularized Regression Method gives good results for Impulse and Gaussian noise.

2 IMAGE DENOISING

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. The meaning of noise is, the pixels in the image show different intensity values rather than true pixel values. The process of removing or reducing the noise from the image is the purpose of noise removal algorithm. They do this by smoothing the entire image leaving areas near contrast boundaries.

The common type of noises that arises in the image are Impulse noise, Additive noise, Multiplicative Noise. Different noises have their own features which make them distinguishable from others. So we need to analyse the type of noise the image contains and then apply the required noise removal method. There are a lot of image denoising algorithms available. The algorithm which removes the noise completely and preserves all the image details is called best image denoising algorithm.

Impulse Noise:

Each pixel in any image has the probability of $p/2$ ($0 < p < 1$) being contaminated by either a white dot (salt) or a black dot (pepper). Impulse noise is defined as below:

$$Y(i, j) = \begin{cases} 255 & \text{with probability of } p/2 \\ 0 & \text{with probability of } p/2 \\ X(i, j) & \text{with probability of } 1-p \end{cases}$$

$1 \leq i \leq H, 1 \leq j \leq W$ X: noise-free image, Y: noisy image

The noise filtering model can be given as below:



The noisy and denoised image is given as below:

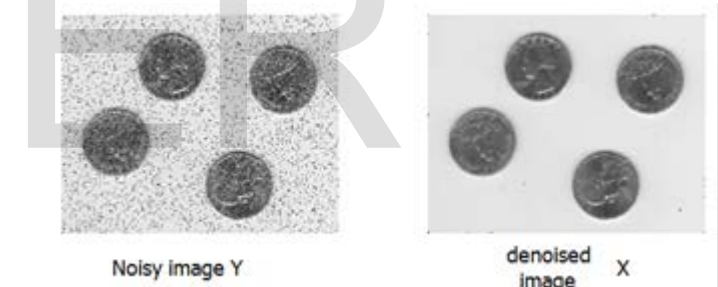


Image denoising is helpful when images are visually unpleasant. Noised images are unsuitable for compression. So it is difficult to do the analysis of such images.

3 IMAGE DENOISING ALGORITHMS

There are linear and non-linear methods for image denoising. The linear methods are fast but they do not preserve the details of the image, whereas the nonlinear methods preserve the details of the image.

Linear Filtering Methods

Mean Filter

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

This has the effect of eliminating pixel values which are

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unrepresentative of their surroundings. Mean filter is usually thought of as a convolution filter. Like all other convolutions it is based around a kernel which represents the shape and size of the neighborhood to be sampled when calculating mean. Often a 3x3 square kernel is used as shown in figure1, although larger kernels (e.g. 5x5 squares) can be used for more severe smoothing. Also note that a small kernel can be applied more than once in order to produce a similar but not identical effect as a single pass with a large kernel.

$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$

Computing the simple convolution of an image with this kernel carries out the mean filtering.

Median Filter

Mean 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.

The main idea of the median filters is to run through the single entry by entry, changing each entry with the median of neighboring entries. Window is the pattern of neighbors which slides by entry, above the entire signal. For 1D signal, the most evident window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals, more complex window patterns are achievable (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then it's easier to define the median: it is the middle value following all the entries in the window are sorted numerically. For the even number of entries, more than one median are possible.

Advantages of median filter is that impulse noise is effectively removed as median effectively suppresses the impulse noise. Median filter is having disadvantages that it affects clean pixels as well. There is noticeable edge blurring after median filtering.

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, that first utilize 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 unaffected. Decision Based Median Filter algorithm processes the corrupted images by first detecting the impulse noise. The processing pixel is checked for noise. If the processing pixel is between maximum and minimum gray level values then it is noise free pixel, it is left as it is. If the processing pixel takes the maximum or minimum gray level then it is noisy pixel which is then processed by median filtering algorithms. The representative methods include the adaptive median filter (AMF) and the adaptive centre weighted filter (ACWMF) [3].

Adaptive Median Filter (AMF)

The Adaptive Median Filter performs spatial processing to determine which pixels in an image have been affected by impulse noise. The Adaptive Median Filter sorts pixels as noise by comparing each pixel in the image to its surrounding neighbor pixels. The size of the neighborhood is changeable, with the threshold for the comparison. A pixel that is different from a most of its neighbours, also being not aligned structurally with those pixels to which it is similar, is termed as impulse noise. These noise pixels are then replaced by the median pixel value of the pixels in the neighborhood that have passed the noise labelling test. The Adaptive Median Filter can be used for removing impulse noise, smoothing the other noise and reducing distortion, like excessive thinning or thickening of object boundaries.

Derived from two types of image models contaminated by impulse noise, two new algorithms for adaptive median filters are proposed by Hwand and Haddad [3]. 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 impulse size based adaptive median filter (SAMF), is based on the detection of the size of the impulse noise [3].

The standard median filter does not perform well when impulse noise is greater than 0.2, while adaptive median filter can better handle these noises. The adaptive median filter conserves the detail and smooth non-impulsive noise, while standard median filter does not.

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 Centre 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 [4].

Noise Removal by Two Phase L^1 -TV 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. 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 [5]

In the first phase, suitable noise detectors are used for identifying image pixels contaminated by the noise. In first or noise detecting phase, it uses either adaptive median (AM) filter or the adaptive center weighted median (ACWM) filter to identify the pixels which are likely to contain noise. Then, in the second phase, based upon the information on the location of noise-free pixels, images are de-blurred and de-noised at the same time. For effectiveness, 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. This method can give outstanding results when compared with several state-of-the-art techniques which are implemented across the whole image. But since the algorithm relies on the alternating fixed point iteration, it is not efficient with respect to its convergence rate. Furthermore, there are three crucial parameters need to adjusted based on information generated in restoration. Collectively with the fixed point-type iteration, the required parameter adjustment based on computational outcomes results in a rather time-consuming method requiring intensive user interaction [5].

Under the similar scheme, Cai proposes an enhanced algorithm used for Deblurring and denoising, and achieves wonderful objective and subjective performance. 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 basic image. The projected functional has a content reliant 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 particular tight framelet filters are able to extract geometric features of images. Li proposed an iterative framelet based approximation/sparsity de-blurring algorithm (IFASDA) for the proposed functional. Parameters in IFASDA are adaptively changing at each iteration and are decided automatically. In this sense, IFASDA is a parameter free algorithm. This benefit makes the algorithm more attractive and practical.

Noise Removal by Multiscale Decomposition Method

From a statistical perspective, recovering images from degraded forms is inherently an ill-posed inverse problem. It frequently can be formulated as an energy minimization problem in which either the optimal or most probable constitution is the objective. The performance of an image recovery algorithm mainly 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 modelling lies at the core of image denoising problems.

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. The first assumption means the 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. One more significant feature of natural images is that they are comprised of structures at different scales. Through multi-scale decomposition, the structures of images at various 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 illposed problem to be better posed [6].

W. Hong introduced a simple and efficient representation for natural images. We show an image (in either the spatial domain or the wavelet domain) as collection of vectors in a high dimensional space. Then we fit a piecewise linear model (i.e. a union of affine subspaces) to the vectors at each down sampling scale. We name this a multi-scale hybrid linear model for the image. The model can be successfully 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.

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. This examination motivates 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. Semi-supervised learning gives us the additional inspiration to address the problem of image recovery. In the algorithm design, the intrinsic manifold structure can be taken into account by making use of both labeled and unlabeled data points.

Noise Removal by Hybrid Graph Laplacian Regularised Regression

The non-local self-similarity is based on the observation that

the image patches have a tendency 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. 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[1][2].

On one hand, within each scale, a graph Laplacian regularization model represented by implicit kernel is learned, which concurrently 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 proposed 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 [1][2].

First, the level- l image I_l passes a low-pass filter F , which is implemented in this method by averaging the existing pixels in a 2×2 neighbourhood on higher resolution. Then, the filter image is downsampled by 2 to get a coarser image I_{l+1} .

$$I_{l+1} = F(I_l) \downarrow 2, l=0 \dots L-1$$

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 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{I}_2 . This procedure can be performed iteratively by feeding the processing results \hat{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{I}_2 is then interpolated to a finer grid G_1 using the proposed EK-GLRR model. The upsampled image \hat{I}_1

can be used as prior estimation for the IK-GLRR model towards a refined estimate \hat{I}_1^* . Then \hat{I}_1^* can be up converted to \hat{I}_0 in the original resolution grid G_0 by the EK-GLRR model. And the refined estimate \hat{I}_0 can be combined with I_0 into another IK-GLRR recovery procedure towards the final results \hat{I}_0^* [1][2]

Using the above progressive recovery based on intra-scale and inter-scale correlation, we gradually recover an image with few artifacts.

4 COMPARISON OF THE NOISE DENOISING METHODS

Mean Filtering has disadvantage that it has effect of eliminating pixel values which are unrepresentative of their surroundings. Median filtering effectively removes impulse noise but it has disadvantage that it affects clean pixels as well. There is noticeable blurring after median filtering. The adaptive median filtering can be used for removing impulse noise, smoothing the other noise and reducing distortion, like excessive thinning or thickening of object boundaries. Two phase L1-TV Method can give excellent results when compared with several state-of-the-art techniques which are implemented across the whole image. But since the algorithm relies on the alternating fixed point iteration, it is not efficient with respect to its convergence rate.

Nonlocal self-similarity and Semi-supervised learning is used to take into account the intrinsic manifold structure by making use of both labeled and unlabeled data points. Hybrid Graph Laplacian Regularization method progressively recovers image by using intra-scale and inter-scale correlation.

5 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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REFERENCES

- [1] X.Liu,D.Zhai,G. Zhai,W.Gao, "Progressive Image Denoising Through Hybrid Graph Laplacian Regularization: A Unified Framework," IEEE Transactions

on Image Processing, Vol.23, No.4, April 2014

- [2] D. Zhai, X.Liu, D.Zhao, H.Chang and W. Gao, "Progressive Image Restoration through Hybrid Graph Laplacian Regularization", in Proc. IEEE Data Compress. Conf. Snowbird, UT, USA, Mar 2013, pp. 103-112
- [3] H. Hwang and R. A.Haddad, "Adaptive median filters: New Algorithms and results" IEEE Trans. Image Process. , vol 4, no.4, pp 499-502 Apr. 1995
- [4] S.-J Ko and Y. H. Lee, "Center weighted median filters and their applications to image enhancement ", IEEE Trans. Circuits Syst. Vol. 38 ,no.9, pp984-993, Sep 1991
- [5] R.H.Chan, Y.Dong and M. Hintermuller, "An Efficient two phase L1-TV method for restoring blurred images with impulse noise", IEEE Trans. Image Process., Vol.19, no.7 pp 1731-1739, Jul 2010.
- [6] W. Hong, J. Wright, K. Huang and Y. Ma, "Multiscale hybrid linear models for lossy image representation", IEEE Trans. Image Process. Vol.15,no.12, pp 3655-3671, Dec 2006

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