

A Review Paper on Various Image Denoising Methods

Mr.Nitin Gondaliya,
Computer Science & Engg. Dept
Parul Institute of Engg.&Tech..
Vadodara,Gujrat,India

Mr.Vishal Patel,
Computer Science &Engg. Dept
Parul Institute of Engg.&Tech..
Vadodara,Gujrat,India

Prof.Astha Baxi
Computer Science & Engg. Dept
Paul Institute of Engg. &Tech..
.Vadodara,Gujrat,India

Abstract—Image processing is basically the use of computer algorithms to perform image processing on digital images. Digital image processing is a part of digital signal processing. Digital image processing has many significant advantages over analog image processing. Image processing allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing of images. Parametric and non-Parametric methods have become a very powerful tool for de-noising an image. In that very popular methods are there like kernel regression method and principal component analysis. In this paper we work on different types of non parametric methods for image denoising like kernel regression and principal component analysis.

Keywords--- Parametric methods, nonparametric method, Kernel Regression, Principal Component analysis.

I. INTRODUCTION

Image de-noising is a vital image processing task i.e. as a process itself as well as a component in other processes. There are many ways to de-noise an image or a set of data and methods exists. The important property of a good image Denoising method is that it should completely remove noise as far as possible as well as preserve edges. Traditionally, there are two types of methods i.e. parametric method and non-parametric method. Generally, parametric methods are used.non parametric methods relies on particular parameter of the image and that is why they require a regular sampling of the image over a grid.

On the other hand, Non-parametric methods rely on the data itself to dictate the structure of the model, and handle edges in a much better way than parametric method. One popular model for nonparametric image Denoising is the Kernel Regression method. We suggest to de-noise a degraded image X given by $X = S + N$, where S is the original image and N is an Additive White Gaussian noise with unknown variance. The rest of the paper is organized as follows:

- In the second section we review parametric methods for image Denoising

- In the third section we present the non parametric methods
- In the fourth section we present principal component analysis.
- The simulation results are discussed in part five.
- We conclude and future work in part six and seven.

II.PARAMETRIC METHODS

Mostly in earlier days parametric methods are used for the purpose of denoising the image Classical parametric image processing methods rely on a specific model of the signal of interest and seek to compute the parameters of this model in the presence of noise. In Parametric methods some particular parameters of the image are calculated and a generative model based upon the estimated parameters is then produced as the best estimate of the underlying signal.

But the main problem with the parametric method is that it generally intended for a more global fit. It doesn't the small characteristic of the data but deals with the overall parameters of the image. Second, it requires the equally spaced sampling structure. So these are the different disadvantages of the parametric methods though it is very useful methods for some particular images which are regularly sampled.

III.NON PARAMETRIC METHODS

Nonparametric methods rely on the data itself to dictate the structure of the model, in which case this implicit model is referred to as a regression function .Non parametric methods doesn't rely on regular sampling over the grid. It depends on the data of the image itself. And this approach is useful for both images denoising as well as image interpolation. Various non parametric methods for image Denoising is described here.

A. Classic Kernel Regression method

Kernel regression provides a rich mechanism for computing point-wise estimates of the function with minimal assumptions about global signal or noise models.

We treat the 1-D case where the measured data are given by

$$y=z(x) +e;$$

Where $z ()$ is the (hitherto unspecified) regression function and

e is the independent and identically distributed zero mean noise values. Kernel Regression method estimates the local linear combinations of the data. Naturally, since this approach is based on local approximations, a logical step to take is to estimate the parameters from the data while giving the nearby samples higher weight than samples farther away.

The choice of the particular form of the function is open, and may be selected as a Gaussian, exponential, or other forms which comply with the above constraints. It is known that for the case of classic regression the choice of the kernel has only a small effect on the accuracy of estimation.

B. Data-Adapted Kernel Regression

Local polynomial kernel regression estimates, independent of the order are always local *linear* combinations of the data. As such, though elegant, relatively easy to analyze, and with attractive asymptotic properties, they suffer from an inherent limitation due to this local linear action on the data. Data-adapted kernel regression methods rely on not only the sample location and density, but also on the radiometric properties of these samples. Therefore, the effective size and shape of the regression kernel are adapted locally to image features such as edges.

1) *Steering kernel Regression*-- It is a two-step approach where first an initial estimate of the image gradients is made using some kind of gradient estimator (say the second order classic kernel regression method). Next, this estimate is used to measure the dominant orientation of the local gradients in the image. In a second filtering stage, this orientation information is then used to adaptively “steer” the local kernel, resulting in elongated, elliptical contours spread along the directions of the local edge structure. With these locally adapted kernels, the Denoising is affected most strongly along the edges, rather than across them, resulting in strong preservation of details in the final output.

So, Data Adapted Kernel becomes

$$K(\mathbf{x}_i - \mathbf{x}, y_i - y) \equiv K\mathbf{H}\mathbf{c}$$

And,

$$\mathbf{H}\mathbf{c}_i = h\mu_i$$

Where,

$$C_i = \mu_i R_{\theta_i} A_i R_{\theta_i}^T$$

$$U_{\theta_i} = \begin{pmatrix} \cos\theta_i & \sin\theta_i \\ -\sin\theta_i & \cos\theta_i \end{pmatrix}$$

$$A_i = \begin{pmatrix} \sigma_i & 0 \\ 0 & \sigma_i^{-1} \end{pmatrix}$$

where is U a rotation matrix and A is the elongation matrix. Now, the covariance matrix is given by the three parameters, and which are the scaling, rotation, and elongation parameters, respectively.

2) *Iterative Steering Kernel Regression*--Steering kernel regression is most effective when an iterative regression/Denoising procedure is used to exploit the output (less noisy) image of each iteration to estimate the radiometric terms of the kernel in the next iteration.

A block diagram representation of this method is shown In fig, where is the iteration number. In this diagram, the data samples are used to create the initial (dense) estimate of the interpolated output image. In the next iteration, the reconstructed (less noisy) image is used to calculate a more reliable estimate of the gradient and this process continues for a few more iteration.

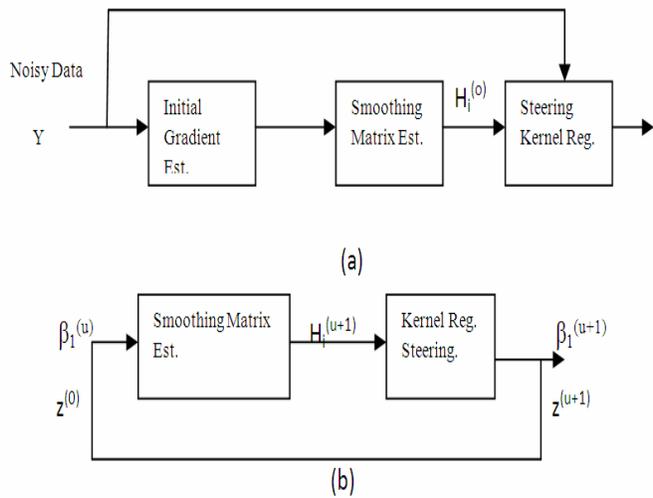


Fig 1. Block diagram representation of the iterative steering kernel regression. (a) Initialization. (b) Iteration.

IV. PRINCIPAL COMPONENT ANALYSIS METHOD

It is an efficient image Denoising scheme by using principal component analysis (PCA) with local pixel grouping (LPG). For a better preservation of image local structures, a pixel and its nearest neighbors are modeled as a vector variable, whose training samples are selected from the local window by using block matching based LPG. Such an LPG procedure guarantees that only the sample blocks with similar contents are used in the local statistics calculation for PCA transform estimation, so that the image local features can be well preserved after coefficient shrinkage in the PCA domain to remove the noise. The LPG-PCA Denoising procedure is iterated one more time to further improve the Denoising performance, and the noise level is adaptively adjusted in the second stage. Experimental results on benchmark test images demonstrate that the LPG-PCA method achieves very competitive Denoising performance, especially in image fine structure preservation, compared with state-of-the-art Denoising algorithms.

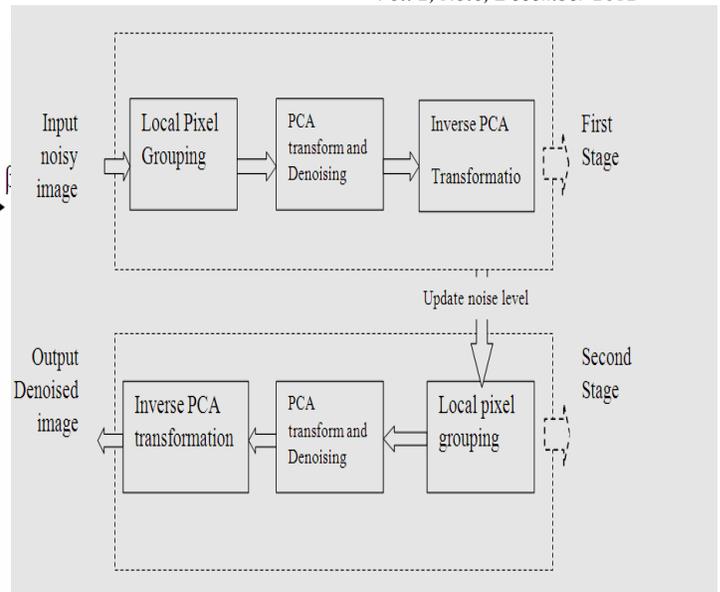


Fig 2. Flowchart of the proposed two-stage LPG-PCA Denoising scheme.

V. SIMULATION RESULTS

Above mentioned image Denoising methods are performed on different images like lena image and cameraman image with different SNR values and the results of them are compared further.



Fig 3. Original image (Lena Image)



Fig 4. Noisy image, SNR = 5:64 [dB]



Fig 7. Denoising using Principal Component analysis



Fig 5. Denoising Using Classic kernel regression method



Fig 6. Denoising using Iterative steering kernel regression.

VI. CONCLUSION AND FUTURE WORK

We used a lena Image and applied different algorithms for image Denoising like kernel regression, iterative kernel regression and principal component analysis and compared the results between them and by seeing this work we can see that iterative steering kernel regression method performs better than the other methods and also principal component analysis is also can be a very good choice to denies the image. Briefly we can say that a non parametric method gives the better result than the parametric methods for Denoising purpose.

There are couple of areas in which we would like to improve further like in iterative steering kernel regression there is no stopping rule for iterations so we can optimize that number of iterations and other part In which we can research further is the choice of the kernel in kernel regression methods. Choice of the kernel plays an effective role in the Denoising of the image. Selection of a proper kernel can improve the performance so that is the thing in which we can go further.

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