ISSN: 2278 – 1323
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 2, Issue 7, July 2013

Edge Preserving MAP Estimation of Images Using Filtering Approach and Wavelet Based Mehods

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Abstract— **This paper presents an effective approach for image restoration in the presence of both blur and noise.Here the image is divided into independent regions. Each region is modelled with a WSS Gaussian prior. This algorithm uses wavelet based methods for image denoising. Classical Wiener filter theory is used to generate a set of convex sets in the solution space, with the solution to the MAP estimation problem lying at the intersection of these sets.The algorithm is suitable for a range of image restoration problems. It provides a computationally efficient means to deal with the shortcomings of Wiener filtering without sacrificing the computational simplicity of the filtering approach. This method provides a better restored image.**

Index Terms*— *Image denoising, image restoration, image segmentation.

I. Introduction

This paper is mainly concerned with the image restoration problem.That is, given a noisy set of degraded observations and we wish to generate an optimal estimate of the original scene. An often addressed problem in image processing is the inverse imaging problem and images are degraded by spatial blur and additive random noise. Spatial blurring is often due to lens abberation and motion, while the additive noise is often due to electronic noise in the imaging system. Image restoration has many applications in different areas. In recovery process some assumptions about the source must be made and it include both denoising and deblurring[1].In this paper wavelet based methods are used for image denoising because this methods are currently the best choice for denoising, both in terms of performance and computational efficiency.Wavelet based methods had a strong impact on denoising[5]. Their success is due the fact that the wavelet transforms of images tend to be sparse (i.e., many coefficients are close to zero). This implies that image approximations based on a small subset of wavelets are typically very accurate, which is a key to wavelet-based compression. The good performance of wavelet-based denoising is also intimately related to the approximation capabilities of wavelets. Deconvolution is most easily dealt with in the Fourier domain. However, image denoising is best handled in the wavelet domain. Classical Wiener filter theory is used for deblurring[2].

Manuscript received July, 2013.

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II. Method Overview

Here, we provide an overview of our proposed method and the major contribution of this paper, using a piecewise stationary prior how to compute the MAP estimate[1]. Here we assumes a known segmentation for the image. Later section discuss how to perform the segmentation problem.
We consider the image formation model

$$\boldsymbol{\zeta} = A(\mathbf{g}) + \boldsymbol{\eta}$$

where **g** the original image is blurred by the LSI filter ***A*** and $\boldsymbol{\eta}$ has additive Gaussian noise . Given this blurred, noisy image ζ we wish to recover an estimate of the original image **g**. Solution to proposed method is the MAP estimate under the assumption of a piecewise stationary Gaussian prior[3]. Here we the computational simplicity of LSI filtering. We introduce the notion of the extension of a region to maintain shift invariance at the boundaries between the regions of the piecewise stationary prior. This algorithm uses wavelet based methods for image denoising. The continuous wavelet transform is defined as follows

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^* \left(\frac{t-\tau}{s}\right) dt$$

As seen in the above equation , the transformed signal is a function of two variables, tau and s , the translation and scale parameters, respectively. psi(t) is the transforming function, and it is called the mother wavelet . The term mother wavelet gets its name due to two important properties of the wavelet analysis as explained below. The term wavelet means a small wave . The smallness refers to the condition that this function is of finite length . The wave refers to the condition that this function is oscillatory. The term mother implies that the functions with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet. In other words, the mother wavelet is a prototype for generating the other window functions. I would like to include two mother wavelets commonly used in wavelet analysis. The Mexican Hat wavelet is defined as the second derivative of the Gaussian function.

$$w(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-t^2}{2\sigma^2}}$$

which is

$$\psi(t) = \frac{1}{\sqrt{2\pi}\sigma^3} \left(e^{\frac{-t^2}{2\sigma^2}} . \left(\frac{t^2}{\sigma^2} - 1 \right) \right)$$

The Morlet wavelet is defined as

$$w(t) = e^{iat} . e^{-\frac{t^2}{2\sigma}}$$

The reconstruction is possible by using the following reconstruction formula:

$$x(t) = \frac{1}{c_\psi^2} \int_s \int_\tau \Psi_x^\psi(\tau, s) \frac{1}{s^2} \psi \left(\frac{t - \tau}{s} \right) d\tau \, ds$$

where C_psi is a constant that depends on the wavelet used. The success of the reconstruction depends on this constant called, the admissibility constant , to satisfy the following admissibility condition:

$$c_\psi = \left\{ 2\pi \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\xi)|^2}{|\xi|} d\xi \right\}^{1/2} < \infty$$

where psi^hat(xi) is the FT of psi(t).

Although the discretized continuous wavelet transform enables the computation of the continuous wavelet transform by computers, it is not a true discrete transform. Wavelet series is simply a sampled version of the CWT It provides information whichis highly redundant as far as the reconstruction of the signal is concerned. This redundancy requires a significant amount of computation time and resources. The discrete wavelet transform (DWT) provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time. The DWT is considerably easier to implement when compared to the CWT. The main idea is the same as it is in the CWT. Using digital filtering techniques we can obtain the time-scale representation of a digital signal. CWT is a correlation between a wavelet at different scales and the signal with the scale (or the frequency) being used as a measure of similarity. The continuous wavelet transform was computed by changing the scale of the analysis window, shifting the window in time, multiplying by the signal, and integrating over all times. In the discrete case, filters of different cutoff frequencies are used to analyze the signal at different scales . The signal is passed through a series of high pass filters to analyze the high frequencies, and it is passed through a series of low pass filters to analyze the low frequencies. The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by the filtering operations, and the scale is changed by up sampling and down sampling (sub sampling)operations. Sub sampling a signal corresponds to reducing the sampling rate, or removing some of the samples of the signal. For example, sub sampling by two refers to dropping every other sample of the signal. Sub sampling by a factor *n* reduces the number of samples in the signal *n* times.

It is instructive to consider the limiting cases of extreme segmentation and no segmentation at all. If there is no segmentation, that is, the image is considered to be all in the same region, the solution is just the ordinary Wiener filter result, and the SOR method converges directly to the solution in a single iteration[4]. At the other extreme, the image can be segmented such that every pixel in the image belongs to its own region. In this case, assuming the prior has infinite power at DC, the extension of each region reduces to simple replication of the single known pixel at the center. This replication means we can do away with the linear prediction equations and replace with in the Wiener filter equations[6].

III. Summary Of Method

The proposed method include the following steps. First, the image is divided into different independent regions**.** An initial segmentation is generated from the observed image. This can be done in a number of ways; (eg : have used a watershed algorithm applied to the Wiener filter estimate).Here modified K means algorithm is used for initial segmentation. After applying this algorithm we get an image with different clusters. Clustres are formed based on the pixel values on the images and also we get the boundaries between the clusters. While the segmentation may sometimes be known in advance, for most applications it is not. An initial segmentation can be determined by applying standard segmentation algorithms to the Wiener filter result. However, the solution is quite sensitive to the exact location of the boundary. We then insert spline control points at boundaries between regions. default pixel spacing is used by the control points and which is adjusted to ensure points are placed on any sharp corners in segmentation. A high resolution segmentation is determined based upon the spline control boundaries. Here we perform the segmentation and spline control point insertion at boundaries simultaneously. Using linear prediction method we generate the extensions for each region. For image denoising wavelet based methods are used. Given the segmentation, we then use the successive over relaxation method to solve for the MAP estimate given the segmentation. Once we have the MAP estimate, we can then compute the local cost function and try different locations for the control points. In many real applications the original scene is a continuous image. The blur operator effectively cuts off all frequencies higher than some frequency , and the blurred image is then sampled. Far from region boundaries, the standard Shannon sampling theorem applies, and provided the image is sampled at greater than the Nyquist rate of , the Wiener filter can be used to generate an alias free reconstruction. However, our prior model allows sharp jumps between neighboring regions, and the location of these jumps can be recovered with greater accuracy than can be represented on a grid at the Nyquist rate.

IV. COMPLEXITY

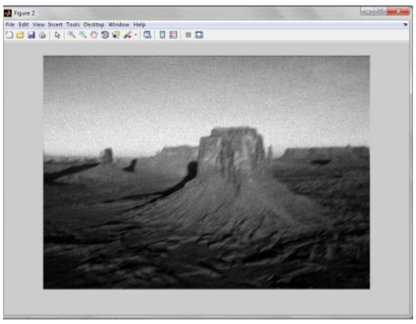
This method provides a better computational time for each iteration of the MAP estimate. It require less computational time than previous methods. It also provide a good PSNR. most of the complexity arises due to the iterations of the segmentation refinement procedure, which varies with the complexity of the image.

V. RESULTS

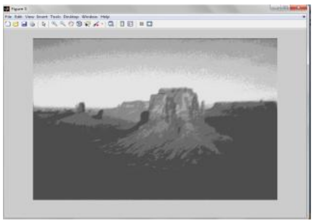
This section describes the present a set of experimental results illustrating the performance of the proposed approach. we always achieve better performance with this proposed method.

Read image

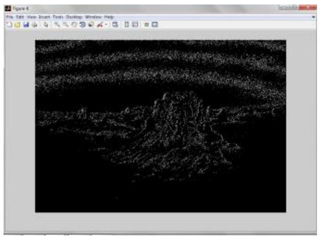
RGB into gray



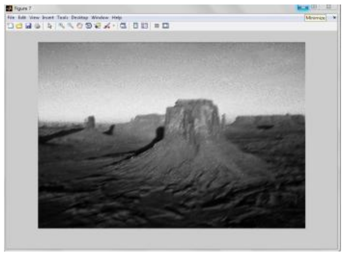
Generate cluster



spline control points



Restored image



VI. CONCLUSION

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This paper, presents an efficient method for MAP estimation of images in the presence of blur and noise. The method uses a piecewise stationary Gaussian prior. It also uses the concept of the extension of a region to overcome the difficulties inherent in LSI filtering while maintaining most of the computational simplicity of the filtering approach. The method maybe considered a generalization of Wiener and inverse filtering,as the segmentation varies from the whole image being a single region (Wiener filtering) to every pixel being in its own region(inverse filtering). It uses wavelet based methods for image denoising.

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