Image Restoration using Higher Order Statistics

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ABSTRACT
Most of the techniques for image restoration are based on some known degradation models. But in many situations it is difficult to accurately measure the degradation factors or noise type that is the real motivation behind the use of blind deconvolution technique for image restoration. Here the observed degraded image is restored without having any prior knowledge about the noise type. Most of the existing blind deconvolution methods for images apply for the restoration of grey scale images. In this paper a blind deconvolution technique using higher order statistics is applied for colour image restoration. Selective filtering is repeatedly applied for better results.

General Terms
image processing, image restoration

Keywords
blind deconvolution, Higher order statistics

1. INTRODUCTION
The field of image restoration is very broad with an over 30 year long history. Since it has many applications and has a simple mathematical formulation it has attracted strong research interest. It is a classical inverse problem for which good solutions are not easily obtained. The objective of image restoration, is to estimate an image from a given corrupted version, using an inverse operation like a linear filter [4, 10]. Optimal linear filter known as minimum mean square error filter or nonlinear filter are very useful in image restoration from corrupted images. Images may be corrupted by both positive and negative impulse noise. Non linear mean filter cannot remove such positive and negative impulse noise simultaneously but the median filter performs quite well in such cases [2,5,10]. But as the probability of impulse noise occurrence becomes high it fails. To overcome this situation two new algorithms for adaptive median filters are proposed in [3]. Prior information is used in usual restoration approaches to restrict the number of possible solutions. Such prior knowledge can be stochastic or deterministic in nature. In many situations it is difficult to accurately measure the degradation factors or noise type, which is the real motivation behind the use of blind deconvolution technique for image restoration. The concept of deconvolution finds many applications in signal processing and image processing in many scientific and engineering disciplines, especially in fields such as astronomical imaging, medical imaging, and remote sensing, etc. The objective of the blind image restoration is to reconstruct the original image from a degraded observation without the knowledge of either the true image or the degradation process.

D. Kundur and D. Hatzinakos give a detailed review of existing blind image deconvolution techniques in [6]. Here the degraded image is restored without having any prior information about the degradation model and noise type. Learning-based algorithms for image restoration and blind image restoration are proposed in [7], which addresses linear degradation systems which are spatially invariant, and has typically low-pass characteristics. In [9] blind deconvolution was applied to deblurr the images. In [8] the degraded images are restored using blind deconvolution algorithm with canny edge detector. Objective of this paper is to restore degraded images without having any prior knowledge about the noise type. Here the blind source separation technique using Higher Order Statistics with selective filtering is applied to restore degraded images by unknown models. The quality of the images seems to improve in successive iterations.

2. METHODOLOGY
Here the observed degraded image is restored without having any prior knowledge about the noise type. Noise pixels are identified by applying Higher-order statistics such as skewness and kurtosis. Then selective filtering is applied to restore the image.

2.1 Higher Order Statistics
Higher Order Statistics (HOS) measures are extensions of second-order measures to higher orders. The second-order measures work fine if the signal has a Gaussian probability density function. Any Gaussian signal is completely characterized by its mean and variance. Consequently the HOS of Gaussian signals are either zero or contain redundant information. Many signals encountered in practice have non-zero HOS, and many measurement noises are Gaussian, and so in principle the HOS are less affected by Gaussian background noise than the 2nd order measures.

Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable. The skewness value can be positive or negative, or even undefined. A negative skew indicates that the left side of probability density function is longer than the right side and the bulk of the values including the median lie to the right of the mean. A positive skew indicates that the tail on the right side is longer than the left side and the bulk of the values lie to the left of the mean. A zero value indicates that the values are relatively evenly distributed on both sides of the mean, typically but not necessarily implying a symmetric distribution.

For a sample of n values the sample skewness is

$$g1 = \frac{m_3}{m_2^{3/2}} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^3}{\left(\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2\right)^{3/2}}$$

Where, $\bar{x}$ is the sample mean, m_3 is the sample third central moment, and m_2 is the sample variance. The normal distribution has a skewness of zero and a nonzero skewness of the dataset indicates whether deviations from the mean are going to be positive or negative.

Kurtosis is a measure of the peakedness of the probability distribution of a real-valued random variable. Higher kurtosis means more of the variance is the result of infrequent extreme deviations. Kurtosis is equal to the fourth moment around the mean divided by the square of the variance of the probability distribution minus 3. For a sample of n values the sample kurtosis is

$$g_2 = \frac{m_4}{m_2^2} - 3 = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^4}{\left(\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2\right)^2} - 3$$

Where, m_4 is the fourth sample moment about the mean, m_2 is the second sample moment about the mean or the sample variance x_i is the i^{th} value, and is the sample mean.

2.2 Restoration Technique used

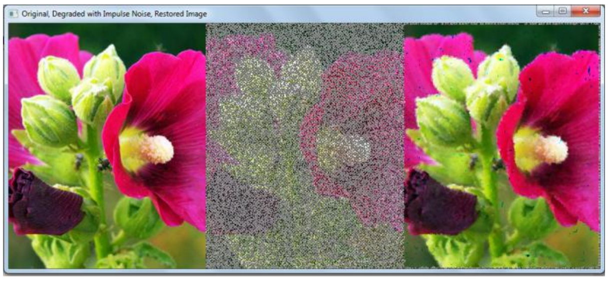
In general, the objective of deconvolution is to find the solution of a convolution equation of the form: $f * g = h$.. Usually, h is the signal received, and f is the original signal which has been affected by some other signal g before we received it. To recover the original image from the received degraded image we should know g in advance, but in many situations it is not possible. In such situations we need some other techniques to recover the original image. In this work we use the local behavior of the image to identify the noise pixels. Noise pixels are separated by computing the skewness and Kurtosis of random samples around the pixels. If the count of nonzero skewness and Kurtosis of random samples around exceed a specific threshold, such pixels are identified and marked as noise pixels. Then the possible original pixel values are estimated by considering the local neighbourhood of such pixels. In order to avoid the influence of noise pixels in the local neighbourhood while estimating the possible value, we use a selective median filtering.

3. RESULTS

The algorithm is implemented in IDL. In order to test the algorithm original images are first degraded by applying impulse noise and Gaussian noise. The results obtained for Gaussian noise are not much better than that for impulse noise. In both cases successive iterations improved the quality of restored image. Using this method impulse noise can be eliminated effectively. The main results obtained are given below in figures 1 to 3. Table 1 shows the PSNR obtained as impulse noise varies from 10 to 90 percentages.

4. CONCLUSION

Blind deconvolution technique is used for restoring color images. Since the Higher Order Statistics are less affected by the background than the 2nd order measures, here Higher Order Statistics are measured around random samples of each pixel to identify the noise pixels. Better results can be achieved by preprocessing the degraded observed image using Nonlocal Image Averaging before applying the higher order statistics.



(a) (b) (c)

Figure 1 (a) Original (b) Degraded with 90% Impulse Noise (c) Restored Image

Table1. PSNR as Impulse Noise varies from 10 to 90 percentage

Impulse Noise %	PSNR
10	34.8667
20	34.9478
30	34.9472
40	34.9344
50	34.9957
60	34.6309
70	34.5560
80	33.7829
90	32.7834

(a) (b) (c)

Figure 2 (a) Original (b) Degraded by Gaussian noise with variance 50 (c) Restored Image

(a) (b) (c)

Figure 3 (a) Original (b) Image degraded by both impulse and Gaussian noise (c) Restored Image

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