International Journal of Information Technology and Knowledge Management
July-December 2010, Volume 2, No. 2, pp. 601-604

# Robust Statistics based Filter to Remove Salt and Pepper Noise in Digital Images

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Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. This paper represents a robust statistics based filter to remove salt and pepper noise in digital images. The function of the algorithm is to detect the corrupted pixels first since the impulse noise only affect certain pixels in the image and the remaining pixels are uncorrupted. The corrupted pixels are replaced by an estimated value using the proposed robust statistics based filter. The proposed method perform well in removing low to medium density impulse noise with detail preservation upto a noise density of 70% compared to standard median filter, weighted median filter, recursive weighted median filter, progressive switching median filter, signal dependent rank ordered mean filter, adaptive median filter and recently proposed decision based algorithm.
Keywords: Image Denoising, Nonlinear Filter, Robust Statistics and Salt and Pepper Noise

## 1. Introduction

A very large portion of digital image processing is devoted to image restoration. This includes research in algorithm development and routine goal oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained [1]. Degradation comes from blurring as well as noise due to electronic and photometric sources. Blurring is a form of bandwidth reduction of the image caused by the imperfect image formation process such as relative motion between the camera and the original scene or by an optical system that is out of focus [2]. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contribute to the degradation. Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensate for distortion in the optical system of a telescope. Image denoising finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality [2].

Let us now consider the representation of a digital image. A 2-dimensional digital image can be represented as a 2-dimensional array of data s(x,y), where (x,y) represent the pixel location. The pixel value corresponds to the brightness of the image at location (x,y). Some of the most frequently used image types are binary, gray-scale and color images [3]. Binary images are the simplest type of images and can take only two discrete values, black and white. Black is represented with the value '0' while white with '1'.Note that a binary image is generally created from a gray-scale image. A binary image finds applications in computer vision areas where the general shape or outline information of the image is needed. They are also referred to as 1 bit/pixel images. Gray-scale images are known as monochrome or one-color images. The images used for experimentation purposes in this thesis are all gray-scale images. They contain no color information. They represent the brightness of the image. This image contains 8 bits/pixel data, which means it can have up to 256 (0-255) different brightness levels. A '0' represents black and '255' denotes white. In between values from 1 to 254 represent the different gray levels. As they contain the intensity information, they are also referred to as intensity images. Color images are considered as three band

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monochrome images, where each band is of a different color. Each band provides the brightness information of the corresponding spectral band. Typical color images are red, green and blue images and are also referred to as RGB images. This is a 24 bits/pixel image.

## 2. IMPULSE NOISE MODEL

The Salt and Pepper (SP) noise is also called as fixed valued impulse noise will take a gray level value either minimal (0) or maximal (255) (for 8-bit monochrome image) in the dynamic range (0-255) [4] [5] [6]. It is generated with the equal probability. In the case of salt and pepper noise, the image pixels are randomly corrupted by either 0 or 255. That is, for each image pixel at location (i, j) with intensity value Oi, j, the corresponding pixel of the noisy image will be Xi, j, in which the probability density function of Xi, j is

$$\rho(x) = \begin{cases} p/2 & \text{for } x = 0 \\ 1-p & \text{for } x = O_{i,j} \\ p/2 & \text{for } x = 255 \end{cases} \quad (1)$$

where p is the noise density.

## 3. ROBUST STATISTICS

In statistics, classical methods depend heavily on assumptions which are often not met in practice. Robust statistics seeks to provide methods that emulate classical methods, but which are not unduly affected by outliers or other small departures from model assumptions. Robust statistics have recently emerged as a family of theories and techniques for estimating the parameters while dealing with deviations from idealized assumptions.

The noise in an image is considered as a violation of the assumption of spatial coherence of the image intensities and is treated as an outlier random variable [7]. The linear filter estimation technique is designed under the assumption of wide-sense stationary signal and noise. For most of the natural images, this condition is not satisfied. In the past, many of the noise removing filters were designed with the stationarity assumption. These filters remove noise but tend to blur edges and fine details. Recently, nonlinear estimation techniques have been gaining popularity for the problem of image denoising. Based on non-stationary assumption, a noise adaptive soft switching algorithm [8] has been proposed to remove impulse noise in images. This algorithm fails to remove impulse noise in high frequency regions such as edges in the image.

To overcome these difficulties, a nonlinear estimation technique for the problem of image denoising has been developed, based on robust statistics. A robust parameter estimation algorithm [9] has been developed for the image model that contains a mixture of Gaussian and impulsive noise. Recently, some new filters [10], [11] and [12] have been proposed for removing mixed and heavy tailed noise based on robust statistics. In [13] and [14] Black et al have used Robust estimation to deal with intensity discontinuities in natural images and apply their robust formulation to smooth the noisy image while assuming that the only outliers in the image are those due to the intensity discontinuities. Recently, a robust estimation based filter [7] has been reported in the literature to remove low to medium density Gaussian noise in natural images with detail preservation.

## 4. M-ESTIMATORS

The M-estimators were initially proposed by Huber (1964) [15] as a generalization of the maximum likelihood estimator.The M- estimator addresses the problem of finding best fit to the model d = {d0, d1, d2,...,dS – 1} to another model e = {e0, e1, e2,...,eS – 1} in cases where the data differs statistically from the model assumptions [16]. It finds the value that minimizes the size of the residual errors between d and e. This minimization can be written as

$$\sum_{s\in S}^{\min} \rho((es - ds), \sigma) \quad (2)$$

where σ scale parameter that controls the outlier rejection is point, and ρ is M-estimator. Reducing ρ will cause the estimator to reject more measurements as outliers.To minimize above, it is necessary to solve the following equation

$$\sum_{s\in S} \psi((es - ds), \sigma) = 0 \quad (3)$$

$$\text{where } \psi(x, \sigma) = \frac{\partial \rho(x, \sigma)}{\partial x} \quad (4)$$

There are several types of M estimators available to solve equation (2); selection of estimator depends on measurement of robustness. Generally, robustness is measured using two parameters: influence function and breakdown point. The influence function gives the change in an estimate caused by insertion of outlying data as a function of the distance of the data from the (uncorrupted) estimate. Breakdown point is the largest percentage of outlier data points that will not cause a deviation in the solution. The least-squares approach has a breakdown value of 0%, because introducing a single outlier in the data sample will cause a deviation in the estimate from the desired solution. A robust estimator, however, may have a breakdown value of up to 50% [17]. To increase robustness, an estimator must be more forgiving about outlying measurements. In the proposed work, redescending estimators are considered for which the influence of outliers tends to zero with increasing distance [13]. Lorentzian estimator [18] [19] has an Influence function which tends to zero for increasing estimation distance and maximum breakdown value (shown in the Figure 1); therefore, it can be used to estimate the original image from noise corrupted image.

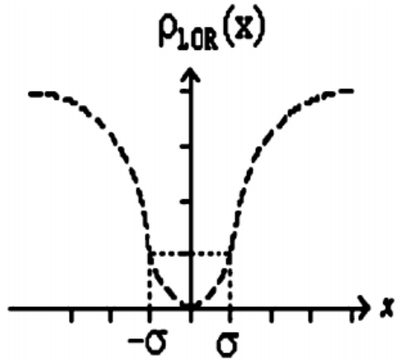


Fig. (a): Lorentzian Estimator

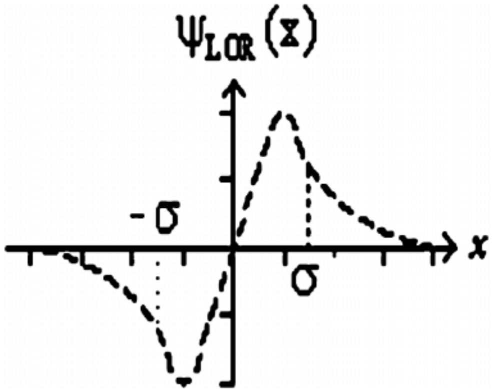


Fig. (b): Lorentzian Influence Fn

The Lorentzian estimator is defined by

$$\rho\,\mathrm{LOR}(x) \;=\; \log\left(1+\frac{x^2}{2\sigma^2}\right) \qquad (5)$$

and it is described by the influence function

$$\psi\,\mathrm{LOR}(x) \;=\; \rho'\,\mathrm{LOR}(x)=\frac{2x}{2\sigma^2+x^2} \qquad (6)$$

where x is the Lorentzian estimation distance and $\sigma$ is the breakdown point. Robust estimation based filter is applied to estimate image intensity values in image denoising. Image model is assumed as non stationary and, thus, the image pixels are taken from fixed windows and robust estimation algorithm is applied to each window.

## 5. CONCLUSION

The selection of the denoising technique is application dependent. So, it is necessary to learn and compare denoising techniques to select the technique that is apt for the application in which we are interested. By far there is no criterion of image quality evaluation that can be accepted generally by all. A technique to calculate the signal to noise ratio in images has been proposed which can be used with some approximation [St01]. This method assumes that the discontinuities in an image are only due to noise. For this reason, all the experiments are done on an image with very little variation in intensity. A test image where all pixel values having a magnitude of 100 is created and noise is added to it with the imnoise() function. Signal to Noise Ratio (SNR) for each of outputs is computed. A new robust statistics based filter to remove low to medium density salt and pepper noise with edge preservation in digital images is proposed in this paper. The proposed filter performs well for both gray scale and colour images. The proposed method restore the original image much better than standard non linear median-based filters and some of the recently proposed algorithms. The proposed filter requires less computation time compared to other methods. This filter can be further improved to apply for the images corrupted with high density impulse noise upto 90% and random valued impulse noise.

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