Robust Image Denoising using Total Variation and Unsharp Masking

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Abstract: ***Evolution of imaging devices has changed the world to see it from personal perspective. Camera is in every hand around the world and the capturing the every moment of life and places they visit. This ease increased the expectation for quality of images should be captured in each and every situation. In this row image denoising algorithms and techniques are being adopted to make noises reduced in the picture captures in dusty or in noisy environment. In this paper a robust image denoising algorithm is proposed to reduce the effect of gaussian noise. The proposed algorithm utilizes the Total Variation (TV) method and improvement in algorithm is further achieved by using Unsharp masking (USM). The results show that it will give better than the previous techniques.***

Keywords: Image Denoising, Total Variation (TV), Unsharp Masking (USM), and Gaussian Noise etc.

1. Introduction

Image denoising is the trouble of finding a clean image, given a noisy one. In the majority of cases, it is assumed that the noisy image is the sum of an underlying clean image and a noise component, the image denoising is a decomposition problem: The task is to decompose a noisy image into a clean image and a noise component. Since an infinite number of such decompositions exist, for finding that a plausible clean image, given a noisy one. The notion of plausibility is not clearly defined, but the idea is that the denoised image should look like an image, where the noise component should look noisy. The notion of plausibility therefore involves prior knowledge: One knows something about images and about the noise. Without having prior knowledge, image denoising would be impossible.

An image is a point lying in a high-dimensional space. Hence, image denoising involves moving from one point in a high-dimensional space (the noisy image), to a different point in the same space (the clean image) which is unknown a priori. Usually, it is impossible to find the clean image exactly. Therefore we interested in finding an image that is close to the clean image. We discuss several measures of closeness. In Figure 1, the denoising problem is illustrated using the 2-norm as a measure of closeness.

In the figure, each point represents an image. Each and every image lying on the circle around the clean image has the same `2-distance to the clean image. However, some images on the circle are more desirable than others: The image lying on the straight line between the noisy image and clean image is the most desirable because it contains no new artifacts (i.e. no artifacts that are not contained in the noisy image). This is due to the fact that the noise is assumed to be additive. All additional points on the circle contain some new artifacts. Usually, it is impossible to find a point lying exactly on the line between the noisy image and clean image. Hence, denoised images almost invariably contain artifacts not contained in the noisy image. During denoising, one can ideally seek to introduce artifacts that are the least visually annoying. Though, it is not clear how to define a measure or visual annoyance".

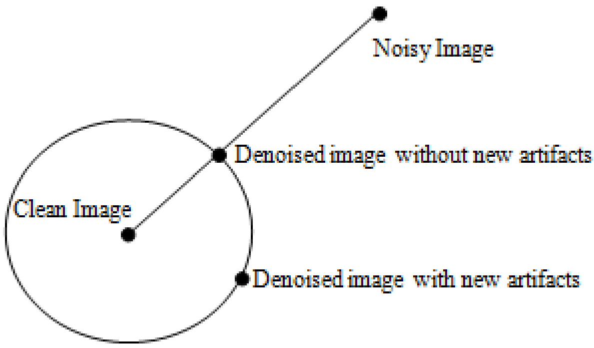

Figure 1.1: Two-dimensional figure of the denoising problem. The two denoised images have the same l2-distance to the clean image, but just the denoised image lying on the path between the noisy image and the clean image contains no new artifacts.

During any physical measurement, it is possible that the signal acquisition process is corrupted by few amount of noise. The sources and various types of noise depend on physical size. Noise frequently comes from a source that is different from the one to be measured (e.g. read-out noise in digital cameras), but sometime is due to the measurement process itself (e.g. photon shot noise). Some of the time, noise might be due to the mathematical manipulation of a signal, as it is the case in image deconvolution or image compression. Often, a measurement is corrupted by several sources of noise and it is usually difficult to fully characterize all of them. In every case, noise is the undesirable part of the signal. Preferably, one can seek to reduce noise by manipulating the signal acquisition process, but when such a modification is not possible, denoising algorithms are necessary.

2. Various Image Noises

The characteristics of the noise depend on the signal acquisition process. Images can be acquired in a number of ways, including, but not limited to: Digital and analog cameras of various kinds (e.g. for visible or infra-red light), magnetic resonance imaging (MRI), computed tomography (CT), positron-emission tomography (PET), ultra sonography, electron microscopy and radar imagery such as synthetic aperture radar (SAR). The following is a list of possible types of noise. Additive white Gaussian noise: In image denoising, the most common setting is to use black-and-white images corrupted with additive white Gaussian (AWG) noise. For each pixel, a random value drawn from a normal distribution is added to the clean pixel value. The distribution is same for every pixel (i.e. the mean and variance are the same) and the noise samples are drawn independently of each other. The read-out (or amplifier") noise of digital cameras is often approximately AWG. An example of an image corrupted with AWG noise has been shown in Figure 2.1.

2.1 Additive white Gaussian Noise

In image denoising, the most common setting is to use black-and-white images corrupted with additive white Gaussian (AWG) noise. For each pixel, a random value drawn from a normal distribution is added to the clean pixel value. The distribution is same for the every pixel (i.e. the mean and variance are the same) and the noise samples are drawn independently of each other. The read-out (or \amplifier") noise of digital cameras is often approximately AWG.

Salt-and-pepper noise: Salt-and-pepper noise is a type of noise where the image contains a certain percentage of noisy pixels, whereas the noisy pixels are at random either completely dark (pixel value zero) or saturated (highest possible pixel value). The value of the noisy pixels is therefore completely uncorrelated with the value of the same pixels in the clean image, which is different from e.g. AWG or Poisson noise. Salt-and-pepper noise can arise due to errors during transmission of an image.

2.2 Additive and Multiplicative Noises:

The noise commonly present in an image. It may be noticed that noise is undesired information that contaminates the image. In image denoising technique, information about the type of noise present in the original image plays an important role. Generally images are corrupted with noise modeled with either a Gaussian, uniform, salt or pepper distribution. Another noise is a speckle noise, which is multiplicative in nature. Noise is present in an image either in an additive or multiplicative form .
An additive noise follows the rule

$$w(x, y) = s(x, y) + n(x, y)\ ,$$

While the multiplicative noises satisfy

$$w(x, y) = s(x, y) \times n(x, y)\ ,$$

where $s(x,y)$ is the original signal, $n(x,y)$ signifies the noise introduced into the signal to produce the corrupted image $w(x,y)$, and (x,y) represents the pixel location. The above image algebra has been done at the pixel level. Image addition as well determines applications in image morphing [Um98]. By image multiplication, we mean the brightness of the image is varied.

The digital image acquisition process converts an optical image into a continuous electrical signal that is, then, sampled [Um98]. At every step in the process there are fluctuations caused by natural phenomena, adding a random values to the correct brightness value for a given pixel.

2.3 Gaussian Noise

Gaussian noise is evenly distributed on the signal. That means each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As suggested the name indicates, this type of noise has a Gaussian distribution, which have a bell shaped probability distribution function given by,

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2}$$

Where, g represents the gray level, m is the mean and average of the function, and σ is standard deviation of the given noise. Graphically, it is presented as shown in Fig. 2.1. When introduced into an image, Gaussian noise with the zero mean and variance as 0.05 would look as in Fig. 2.1. Fig. 2.2 illustrates the Gaussian noise with mean (variance) as 1.5 (10) on a base image with a constant pixels value of 100.

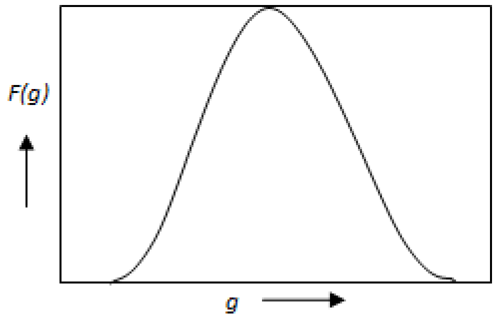

Figure 2.1: Gaussian distribution

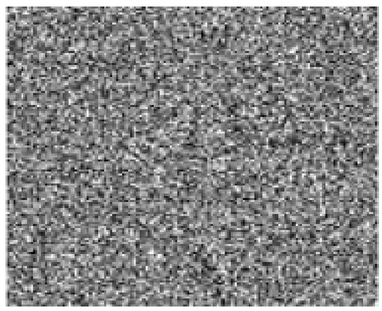

Figure 2.2: Gaussian noise (mean=0 and variance 0.05)

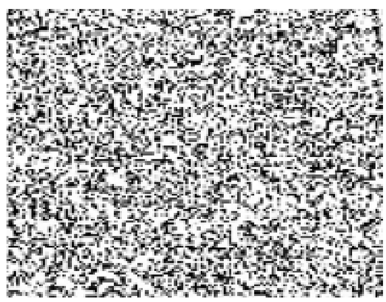

Figure 2.3: Gaussian noise (mean=1.5 and variance 10)

2.3 Salt and Pepper Noise

Salt and pepper noise is an impulse kind of noise; this is also referred to intensity spikes. This is caused normally due to errors in data transmission. It has only two probable values, *a* and *b*. The probability of each is typically a lesser amount of 0.1. The corrupted pixels have been set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" such appearance. Unaffected pixels remain as it is. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255.

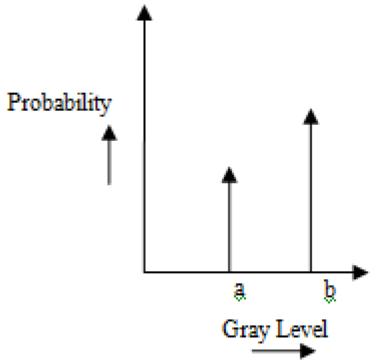

Figure 2.4: PDF for salt and pepper noise

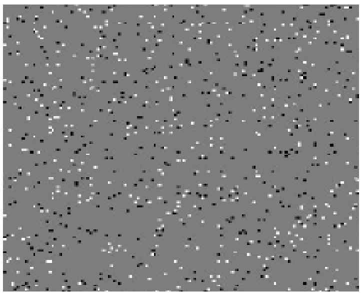

Figure 2.5: Salt and Pepper noise

The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, timing errors or faulty memory locations, in the digitization process. Whereas the probability density function for this type of noise is shown in Fig. 2.4. Salt and pepper noise with a variance of 0.05 is shown in Fig. 2.5.

PROPOSED METHODOLOGY

The block diagram of the Proposed Methodology has been given here in this very firstly the original image is being processed then noise is added with is for analysis purpose after this the Total Variation Methods (TV) is used with the combination of Un-sharp Masking Filtering (USM) both gives the better results than previous.

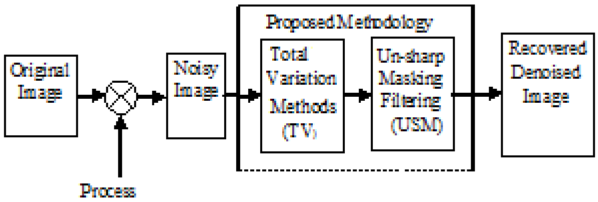

Figure 3.1: Block Diagram of Proposed Methodology

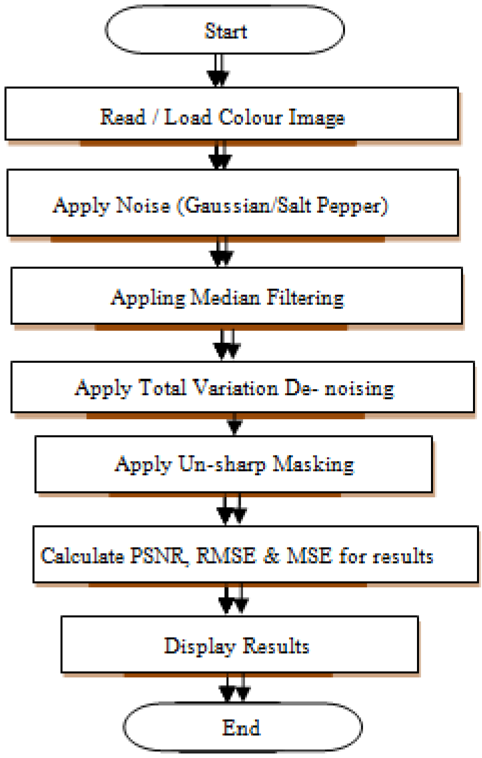

Figure 3.2: Flow Graph of Proposed Methodology

Above flow graph shows the complete simulation process of Proposed Methodology in this firstly, the colour Image is taken for loading then Gaussian or Salt Pepper noise is added for analysis purpose after that Median Filtering is applied then Total Variation De-noising is applied then the Un-sharp Masking is adopted to reduce the noise level and then the Calculations of PSNR, RMSE & MSE have been done, at the last outcomes have been displayed.

3. Simulation Results

In the previous section proposed methodology for image denoising is explained with flow chart and block diagram. The simulation done on various image is shown in this section. Here we have taken five different images for performing denoising experiments. First we have attacked images with gaussian noise and then applied the denoising algorithm. In below table comparison of original image, noisy image and denoised image is shown.

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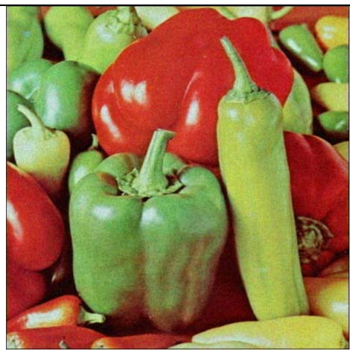
Table 1: Noisy and Denoised Images affected by Gaussian Noise

Original Image	Noisy Image	Denoised Image
		
		
		
		
		

The robustness and performance of the proposed approach is checked with calculation if parameters i.e. figure of merit like peak signal to noise ratio(PSNR), root mean square error(RMSE) and mean square error(MSE). The comparison of values of PSNR, RMSE and MSE for all images is shown in table 2. The robustness is clearly visible from the PSNR values calculated before and after denoising and denoising PSNR is quite improved.

Table 2: Performance Proposed Algorithm of PSNR, RMSE and MSE for Gaussian Noised Images

Image		PSNR	RMSE	MSE
India Gate	Noisy Image	24.732 dB	14.847	220.437
	Denoised Image	25.426 dB	13.708	187.898
Kalam	Noisy Image	24.759 dB	14.801	219.080
	Denoised Image	35.103 dB	4.499	20.238
Lena	Noisy Image	24.500 dB	15.250	232.555
	Denoised Image	30.453 dB	7.684	59.044
Rose	Noisy Image	25.925 dB	12.942	167.487
	Denoised Image	32.223 dB	6.267	39.278
Peppers	Noisy Image	24.673 dB	14.948	223.436
	Denoised Image	31.453 dB	6.848	46.898

4. Conclusion and Future Scope

Image denoising algorithm is applied on gaussian noise attacked images and robustness is calculated before and after denoising. From the simulation results it can be conclude that proposed methodology giving better performance for gaussian noised images. In future addition of other method can enhances the performance of the denoising algorithm. These is also improvement in the proposed methodology also increase the performance of technique.

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