Development of Efficient Image Denoising Method Using Gaussian Low Pass Filter and Total Variation Scheme

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Abstract - Image denoising is the fascinating research area among researchers due to applications of the images in everywhere, social networking sites, High Definition videos and stills. The need of it is to enhance the facility to imaging devices and the processing devices for denoising and enhancement of images. In this paper, Total Variation (TV) regularization is used to allow for accurate registration near such boundaries. We propose a novel formulation of TV-regularization for parametric displacement fields and Gaussian Low Pass Filter to enhance or denoising of images. The proposed methodology's performance are usually compared in terms of peak-signal-to-noise ratio (PSNR). These are simply mathematically defined image metrics that take care of noise power level in the whole image.

Keywords - PSNR, Image Denoising, TV, Gaussian Low Pass Filter.

I. INTRODUCTION

Image denoising is the trouble of finding a clean image, given a noisy one. In most 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, one is interested in finding 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, whereas the noise component should look noisy. The notion of plausibility therefore involves prior knowledge: One knows something about images and about the noise. Without 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. One is therefore interested in finding an image that is close to the clean image.

All the images lying on the circle around the clean image have 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 other 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 ideally seeks to introduce artifacts that are the least visually annoying. However, it is not clear how to define a measure or visual annoyance".

During any physical measurement, it is likely that the signal acquisition process is corrupted by some amount of noise. The sources and types of noise depend on the physical measurement. Noise often comes from a source that is different from the one to be measured (e.g. read-out noise in digital cameras), but sometimes is due to the measurement process itself (e.g. photon shot noise). Sometimes, noise might be due to the mathematical manipulation of a signal, as 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 all cases, noise is the undesirable part of the signal. Ideally, one seeks to reduce noise by manipulating the signal acquisition process, but when such a modification is impossible, denoising algorithms are required.

II. VARIOUS 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 the 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 is shown in Figure 2.1.

Additive white Gaussian Noise:

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Salt-and-pepper noise: Salt-and-pepper noise is a type of noise where the image contains a certain percentage of noisy pixels, where the noisy pixels are randomly 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.

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 the image denoising process, information about the type of noise present in the original image plays a significant role. Typical images are corrupted with noise modeled with either a Gaussian, uniform, or salt and pepper distribution. Another typical 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 noise satisfies

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

where $s\,(x,y)$ is the original signal, $n\,(x,y)$ denotes 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 is done at pixel level. Image addition also finds 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 value to the exact brightness value for a given pixel.

Gaussian Noise:

Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has 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 or average of the function, and σ is the standard deviation of the noise. Graphically, it is represented as shown in Fig. 2.1. When introduced into an image, Gaussian noise with 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) over a base image with a constant pixel value of 100.

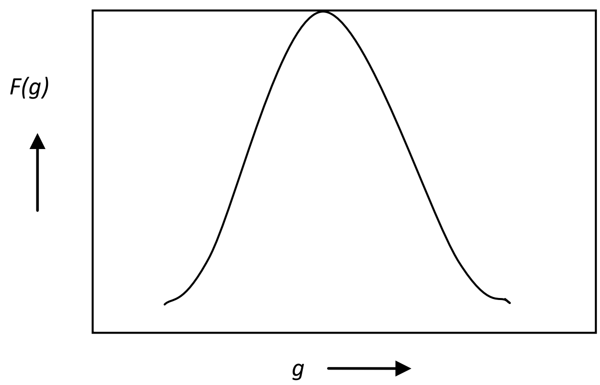


Fig. 2.1: Gaussian distribution

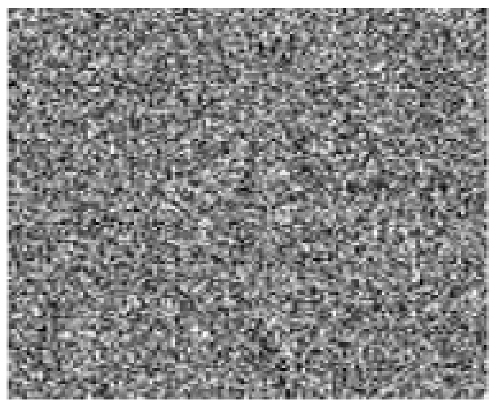


Fig. 2.2: Gaussian noise(mean=0, variance 0.05)

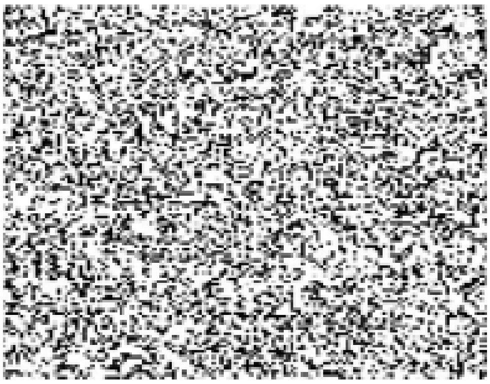


Fig. 2.3: Gaussian noise(mean=1.5, variance 10)

III. PROBLEM FORMULATION

- Previous work performed on the four different images of same extension not different extension.
- The PSNR calculated is lower and there is scope and need to improve increase it to enhance the quality of images.
- Previous methodology is utilizing DWT which works after transforming in frequency domain, and little bit complex process.

IV. 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 Gaussian Low pass Filtering both gives the better results than previous.

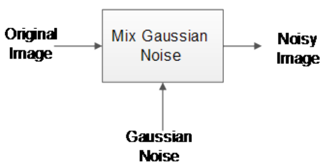


Fig. 3.1 Denoising Process

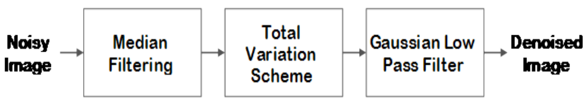


Fig. 3.2 Block Diagram of Proposed Methodology

The flow graph shows the complete simulation process of Proposed Methodology in this firstly, the color 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 low pass filtering is adopted to reduce the noise level and then the Calculations of PSNR, and RMSE have been done, at the last outcomes have been displayed.

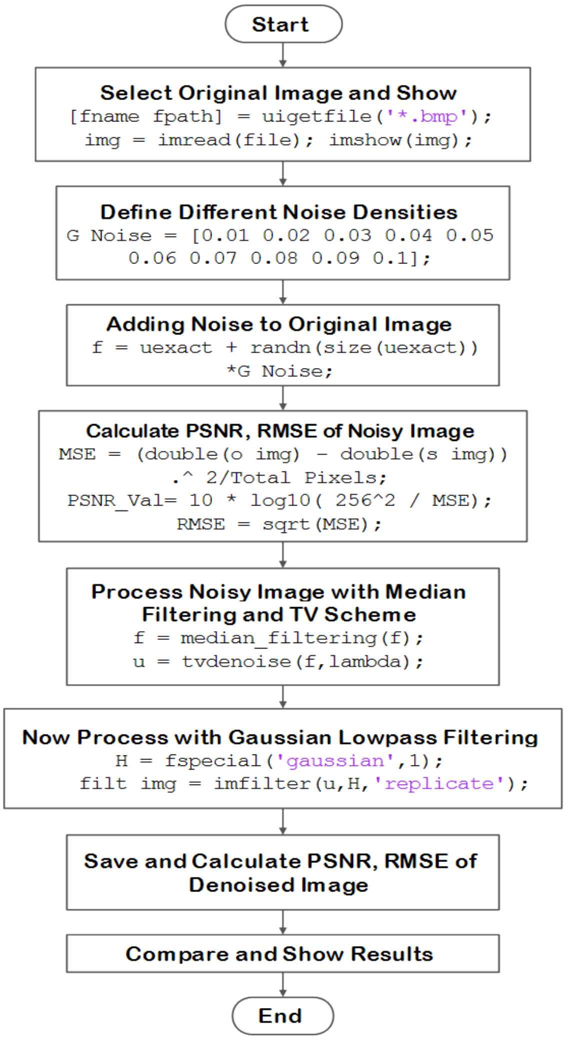
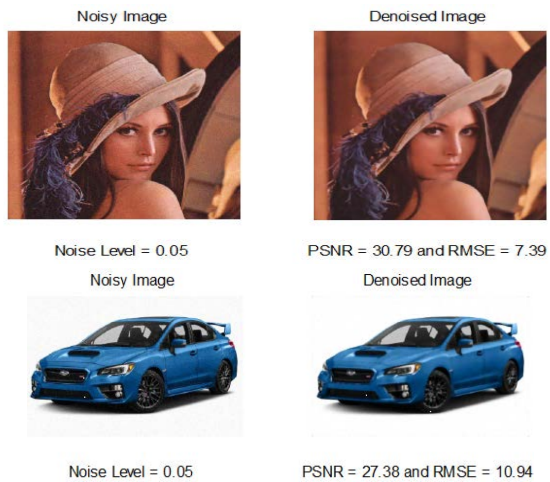


Fig. 3.3 Flow chart of Proposed Methodology

V. SIMULATION OUTCOMES

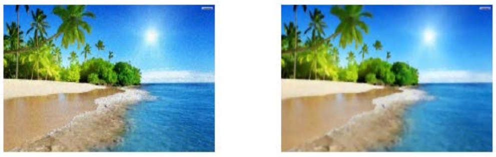
In the previous section proposed methodology for image denoising is explained with flow chart and block diagram. The simulation done on various image is shown in this section. Here we have taken different noise densities for performing denoising experiments.



Noisy Image | Denoised Image

Noise Level = 0.05 | PSNR = 29.27 and RMSE = 8.81

Noisy Image | Denoised Image



Noise Level = 0.05 | PSNR = 26.73 and RMSE = 11.80

Noisy Image | Denoised Image

Noise Level = 0.01 | PSNR = 31.40 and RMSE = 6.89

Noise Level = 0.02 | PSNR = 31.30 and RMSE = 6.97

Noise Level = 0.03 | PSNR = 31.14 and RMSE = 7.10

Noise Level = 0.04 | PSNR = 31.00 and RMSE = 7.22

Noise Level = 0.05 | PSNR = 30.79 and RMSE = 7.39

Noise Level = 0.06 | PSNR = 30.53 and RMSE = 7.61

Noise Level = 0.07 | PSNR = 30.30 and RMSE = 7.82

Noise Level = 0.08 | PSNR = 29.99 and RMSE = 8.10

Noise Level = 0.09 | PSNR = 29.58 and RMSE = 8.49

Fig. 4.1 Lena Image Outcomes of Different Noise densities left (Noisy Image), Right (Denoised Image and PSNR of it.

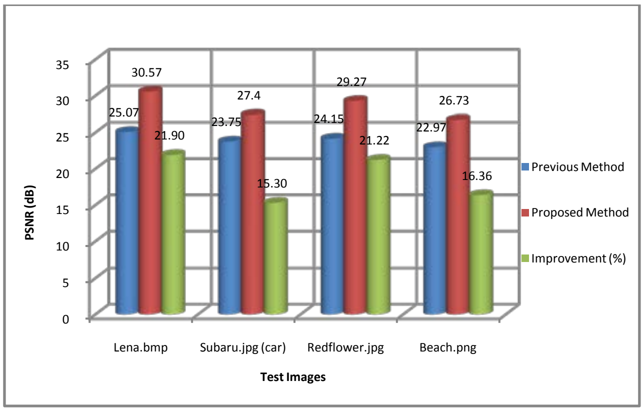


Fig 4.2 Comparison of PSNR between Previous and Proposed Methodology with Improvements

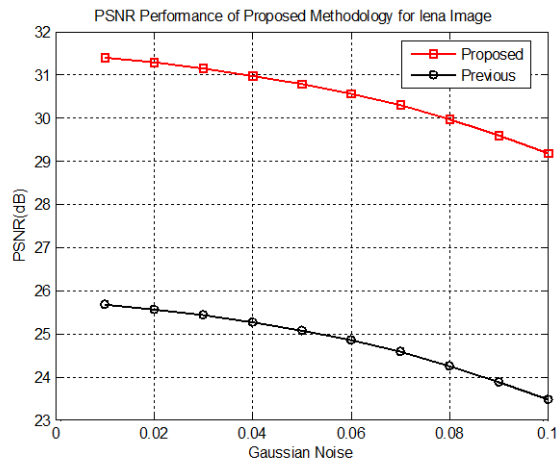


Fig. 4.3 Comparison of PSNR with Previous Methodology

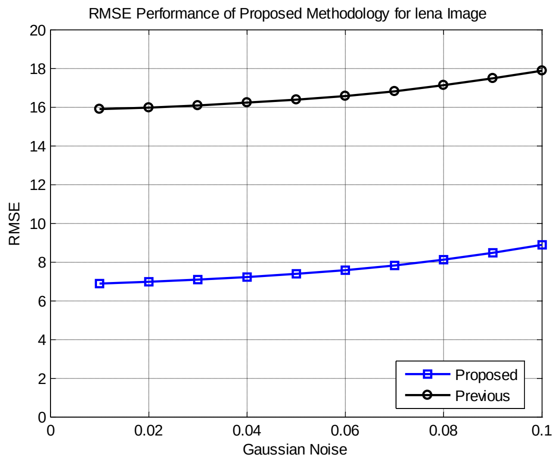


Fig. 4.4 RMSE Curve of Lena Image for Different Noise Levels

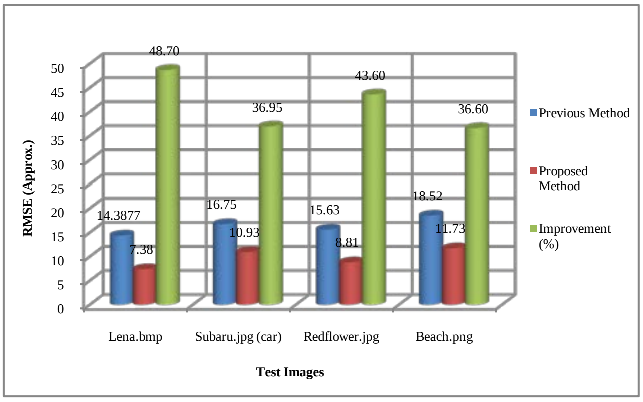


Fig. 4.5 Comparison of RMSE (Approx.) Between Previous and Proposed Methodology with Improvements

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) and root mean square error (RMSE). The graph of values of PSNR and RMSE for all images is shown in above figures. The robustness is clearly visible from the PSNR values calculated before and after denoising and denoising PSNR is quite improved.

V. CONCLUSION AND FUTURE SCOPES

The image denoising approach shown in this paper is proved efficient for various images and also for various noise densities of Gaussian Noise. The Effectiveness of the proposed approach is compared with the existing work in terms of Peak Signal to Noise Ratio (PSNR) and Root Mean Square Error (RMSE). The average percentage improvement from previous work is about 5% and such performance is appreciable. The Gaussian Low Pass Filter utilized in proposed algorithms can be more efficient with other filters like Daubechies, Symlet, Haar and Bi-Orthogonal filters with different thresholding and filter levels. From the comparison of simulations results with previous methodology an analysis clearly shows the proposed methodology for denoising of images is better because of PSNR calculated with our approach is quite better for the images with different extensions. The increased PSNR shows better enhancement in quality of image than existing work. Our methodology is less complex than the previous approach because we no need to utilize transform domain to process denoising of images.

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