Modified and Improved JSM approach for Efficient Restoration of Images

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Abstract - Image Restoration gain popularity for every person deals with the images and want to recover from the corrupted images with different noises. These noises can be encountered during capturing faults or due to environmental effects. The restoration process having different stages of operation to recover information. This work is proposing a modified enhanced joint statistical model based method for efficient restoration of images. This work has experimented on the different images and found that the peak signal to noise ratio (PSNR) of the images is better compared to previous results. The experiments performed with the ratio of 50% and noise density of 10.

Keywords - Image Restoration, Modified JSM, Impainting, Denoising.

I. INTRODUCTION

In the past decade, there has been an exponential growth in the computing power of microprocessor chips. This combined with significant reduction in the cost of digital cameras have increased the amount of image data captured and processed on the computer. The advantage of digitizing an image is the access to several algorithms or image processing techniques that enhance the quality of the image. The term quality here and throughout the work refers to the perception of image quality to a human observer. A new field called computational photography is emerging that challenges the traditional boundaries of photography. New kinds of imaging devices are being developed that obtain a customized image (of a scene) after processing the raw image using a computer. In general, sophisticated algorithms are making novel and complex manipulations possible with imaging devices.

One such topic where computer processing is useful is restoration of images degraded by blur. This work focuses on algorithms that restore 2D and 3D blurred images (due to defocus) in a computationally efficient manner. Computational efficiency is achieved by using new models of image formation based on the physical properties of typical imaging systems. For example, in 2D, a concept called localization, which asserts that blurring is a local phenomenon is used to reduce computational complexity of image deblurring. In 3D image restoration, computational efficiency is achieved through deblurring in a new domain. These approaches also provide some new insight and perspectives to image restoration.

Images are ubiquitous and indispensable in modern science and everyday life. Mirroring the abilities of our own human visual system, it is natural to display observations of the world in graphical form. Images are obtained in areas ranging from everyday photography to astronomy, remote sensing, medical imaging and microscopy. In each case, there is an underlying object or scene we wish to observe; the image is a visual representation of these observations.

Yet imaging, just as any other observation process, is never perfect: uncertainty creeps into the measurements, occurring as blur, noise, and other degradations in the recorded images. The image is a projection of the real world onto the lower-dimensional imaging medium, a procedure that intrinsically discards information. Sometimes the information lost may contain things we are interested in: it can be beneficial to try to recover these hidden details, to infer what the underlying scene that generated these observations really was.

Recent signal processing techniques can provide a means to overcome some of the problems of the imperfect observation process, by post-processing these blurred and noisy images. By representing the observation process mathematically and applying prior knowledge of the types of images we expect to see, restoration methods such as JSM can be performed to recover detail and reduce image noise.

II. RESTORATION MODEL

The basic unit of a image is called a pixel or image element i.e. the image is divided into very small blocks called pixels. An image can be defined as a two dimensional function. the model has been demonstrated in Figure 2.1.

$$I = f(x, y) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 1.1$$

Where x and y are spatial coordinates. (x, y) represents a pixel. I is the intensity or grey level value which is the amplitude off at any point (x, y). If the values of the coordinates (spatial coordinates) and the amplitude are finite and discrete, then it is called digital image. The degraded image $g(x, y)$ can be represented as

$$g(x, y) = h(x, y) * f(x, y) + q(x, y) \ldots\ldots 1.2$$

Where $h(x, y)$ is the degradation function, $f(x, y)$ is the original image, the symbol * indicates convolution and n(x,y) is the additive noise.

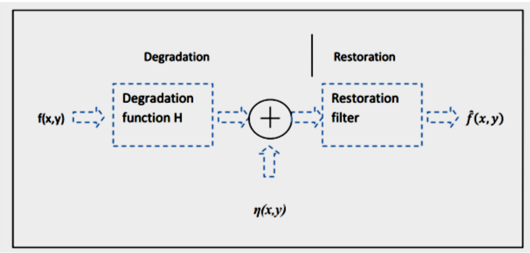

Figure 2.1 Image Degradation and Restoration Model.

III. PROPOSED METHODOLOGY

The proposed is based on the JSM Approach the most basic block representation of proposed work has been illustrated in Figure 3.1 a joint statistical modeling (JSM) in an adaptive hybrid space and transform domain, which offers a powerful mechanism of combining local smoothness and nonlocal self-similarity simultaneously to ensure a more reliable and robust estimation. Here, two types of popular image properties are considered, namely local smoothness and nonlocal self-similarity, the process of flow of working of proposed work has given in figure 3.2 the major steps are as follows.

1. Load Test image for experimental purpose.

2. Read Layers of Image.

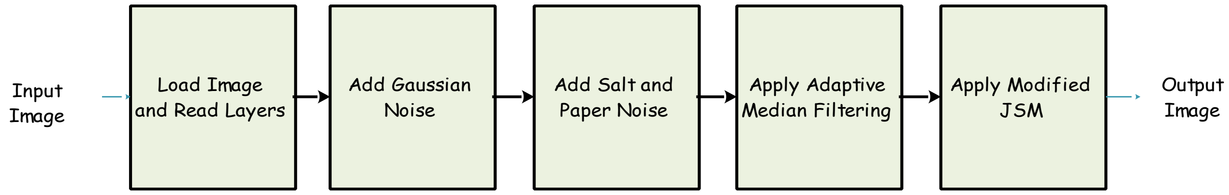

Figure 3.1 Block Representation of Proposed Model.

3. Add Gaussian noise in test image for experimental purpose.

4. Add additionally salt and Paper noise in test image for experimental purpose.

5. Apply Adaptive median filtering.

6. Apply proposed Modified JSM to Restore test image.

The proposed work has been implemented and simulated on Matlab Simulink ISE. the flow of simulation of proposed work has given in figure 3.2.

To star simulation first create simulation parameter in Matlab simulation environment. Browse image for process experiment. load input image and resize it to equalize its height and width ratio in square shape. Read layers of input image. Add certain noise for experimental purpose. Ally adaptive median filtering to eliminate noise from image An adaptive filter attempts to model the relationship between noise and signals in real time in an iterative manner. By choosing a particular adaptive filter structure, one specifies the number and type of parameters that can be adjusted. The adaptive algorithm used to update the parameter values of the image can take on a myriad of forms and is often derived as a form of optimization procedure that minimizes an error criterion that is useful for the task at hand. and apply modified joint statistical modeling. Calculate MSE and show Restored image.

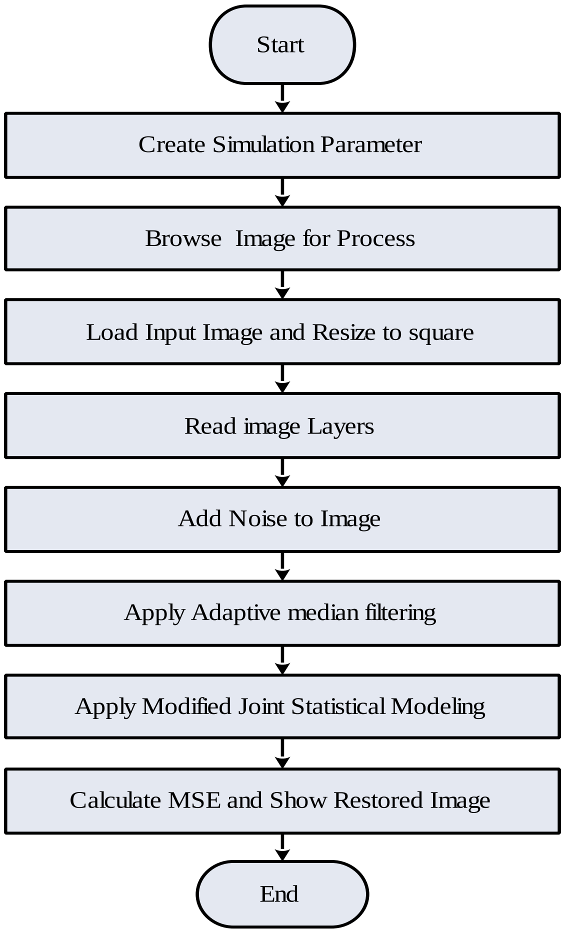

Figure 3.2 Flow of process.

IV. EXPERIMENTAL OUTCOMES

The experiment of proposed system explained previously is performed on the different images e.g. Lena, Barbara, Boat, House, Peppers etc. The images are first mixed with noises first with Gaussian Noise with $\sigma = 10$ density and salt and pepper noise with impulse ratio $r = 50\%$. The noisy image and restored images are shown below along with original image in below figures.

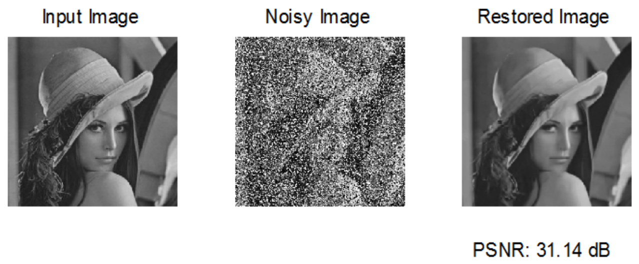

Fig. 4.1 Outcome of the Proposed Methodology with Lena Image

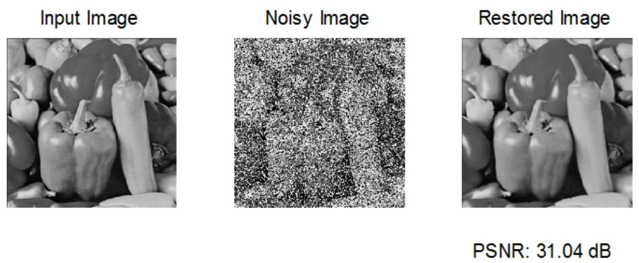

Fig. 4.2 Outcome of the Proposed Methodology with Peppers Image

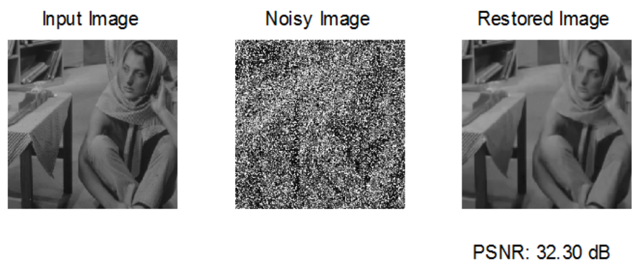

Fig. 4.3 Outcome of the Proposed Methodology with Barbara Image

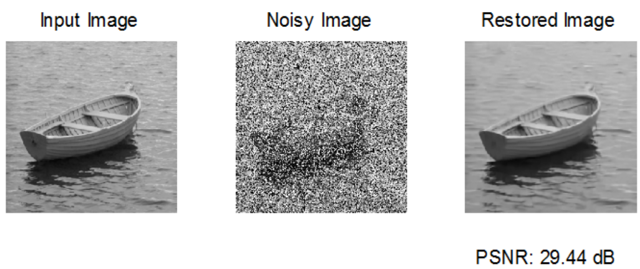

Fig. 4.4 Outcome of the Proposed Methodology with Boats Image

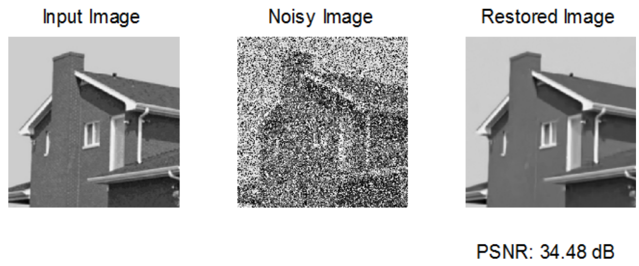

Fig. 4.5 Outcome of the Proposed Methodology with House Image

The peak signal to noise ratio(PSNR) is compared with the previous methodology and comparison table is shown below, which clearly indicated the efficiency of the proposed methdology

Table 1: Comparison of Peak Signal to Noise Ratio (PSNR) in dB with $r = 50\%$ and $\sigma = 10$.

Images	Previous Work	Proposed (Our) Work
Barbara	31.04	32.30
House	33.72	34.48
Boats	30.12	29.44
Lena	32.90	31.14
Peppers	-	31.04

V. CONCLUSION AND FUTURE SCOPE

This works shows the robust performance for image restoration by performing experiments on different images. The experimental comparison of peak signal to noise ratio (PSNR) for different images are shown in the table. The complexity of the algorithm is made lower as possible with the used of adaptive median filtering. The proposed algorithm is designed to work with the different noises densities. The future work can be integration of proposed method with enhancements with colour images and work with video restoration applications.

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