

# A Novel Hybrid Image Denoising Technique based on Trilateral Filtering and Gaussian Condition Random Field Model

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**Abstract** - In digital imaging systems it is found that the acquisition methods and hardware systems adds various types of noises and artifacts. So denoising becomes more important in comparison to other processed involved in image processing as well as in applications. Saving the data or information of an image and eliminating the random noise is the final aim of image denoising systems. Not only the noisy image originates the undesirable visual quality but even downgrades the visibility of dim contrast entities and objects. Gaussian noise is normal form of noise which gets added up in the digital images through the digital systems. Some known techniques improved the visual quality of image by degrading the noise level. But sometimes in an image the noise levels are not same at all regions. Also some techniques perform blurring as well as remove the details present in the image. So there is a need of filtering technique that can remove the Gaussian noise as well as keep the detail present in the image. In this research work, an interactive hybrid Gaussian image denoising technique which is based on trilateral filtering and Gaussian condition random field approach is proposed. The trilateral filter is edge preserving Gaussian filter and Gaussian condition random field use deep neural network to deal with different noise levels. This dissertation provides the improvements to the existing algorithms of denoising in digital images to obtain better results. The proposed algorithm will be compared with the existing state of art Gaussian image denoising methods. The parameters for objective evaluation are peak signal to noise ratio, mean square error of the digital images. For subjective evaluation graph of these parameters will be observed for both input and output images.

**Key Words:** *image processing, denoising, filtering, trilateral filter, Gaussian condition random field.*

## 1. INTRODUCTION

Digital images performs a vital part in everybody normal routine for example images are utilized in television, traffic controlling as well as monitoring, handwriting verification or signature validations on checks, different resonance imaging and also in verities of research and technology like land information systems as well as in astronomy. In digital imaging systems it is found that the acquisition methods and hardware systems adds various types of noises and artifacts. So denoising becomes more important in comparison to other processed involved in image processing as well as in applications. Saving the data or information of an image and eliminating the random noise is the final aim of image denoising systems. Not only the noisy image originates the undesirable visual quality but even downgrades the visibility of dim contrast entities and objects. Therefore noise elimination is very much important in different digital imaging processes as well as in applications to find the fine details that are not easily visible in the raw data.

## 2. LITERATURE SURVEY

B. S. Thakre et al. [1] improved the image denoising performances by developing an image denoising application. To overcome noise, first of all pixel classification is applied utilizing multinomial logistic regression (MLR) for classification and then Gaussian Conditional Random Field is further used for denoising. It had generated efficient performance for image denoising applications. Proposed work comprised of two procedures such as: (i) parameter generation by considering multinomial logistic regression (MLR) based on input noisy image and (ii) designing an inference network whose layer performed the computations which are tangled in GCRF formulation.

Traditional learning techniques such as a posteriori (MAP), maximum likelihood and large margin criterion were not good to provide efficient optimization according to noise variations due to that performance was degraded in terms of average accuracy or error rates. Various performance measurement parameters were considered here for showing the comparison analysis. Parameters were Peak Signal to noise ratio, Mean Squared Error, Structural Similarity (SSIM) index. Authors experiment showed that proposed approach performed nicely when compared with Median filtering, Weiner filtering, SWT (stationary Wavelet) and Discrete Wavelet transform methods and could performed for both grayscale as well as for color images.

R. Vemulapalli et al. [2] proposed deep network architecture for image denoising based on a Gaussian Conditional Random Field (GCRF) model which was trainable. In comparison to the known discriminative denoising techniques that trained a different model for each individual noise level, the supposed deep network modeled the input noise variance. So model was capable of handling different noise levels. Proposed network based on two sub-networks. First one was a parameter generation mesh that generated the pairwise potential parameters based on the noisy input image. Other was an inference network whose layers performed the computations processed in an iterative GCRF inference procedure. Author trained two deep GCRF networks where each network operated over a range of noise levels. First one was for low input noise levels and second one was for high input noise levels. Both were supposed to maximize the peak signal-to-noise ratio measure.

Authors trained network using a dataset of 400 images where 200 images were taken from BSD300 training set and 200 images were taken from PASCALVOC 2012 dataset and evaluated it using a dataset of 300 images where 100 images are taken from BSD300 test set and 200 images were taken from PASCALVOC 2012 dataset. Authors utilized white Gaussian noise of various standard deviations. For performing real checking, every image was quantized to 0-255 range after adding the noise. Authors achieved results on par with the state-of-the-art by training two deep GCRF networks, for both low and high input noise levels.

T. Rahman et al. [4] proposed a modified fuzzy filter for reduction of Gaussian noise. Known function used a  $3 \times 3$  filtering window that had 8 neighboring pixels. In the concept of filter  $F_p$  was taken as the general 8-neighbour function which was calculated for the filtering window. To find the degree of corruption of each pixel authors had incorporated a condition of modification to divide the  $F_p$  by number 8. In addition, as the image intensity was represented utilizing the range of 0 to 255. So if the intensity was either 0 or 255 authors had taken the membership value and for other intensity values authors had calculated membership value also.

The proposed algorithm was applied on different standard grayscale as well as color images of order of  $512 \times 512$  pixels. The performance of the proposed algorithm was tested for different level of noise corruption and compared with standard filters known as mean, wiener filter, geometric mean, harmonic mean and existing fuzzy filter. Each time the test image was corrupted by Gaussian noise with zero mean and different variance from 0.01 to 0.05. Proposed method had implemented using Matlab Version R2009b. Peak signal to noise ratio and computation time of the proposed fuzzy method was also found reasonable.

M. Wang et al. [5] proposed a new image denoising method based on Gaussian filter and Non-local means filter. The new algorithm was designed for dealing with the image noise learned from the weighted average thoughts of particle filter. Authors analyzed the difference amid the proposed method and other two algorithms then performed multi-group experiments to compare the denoising effect of these methods, and evaluated their performance mainly through visual effect and peak signal-to noise ratio.

In the first step the grey mean and variance of the original image was found and then selected parts of pixels that were near around the current pixel's neighborhood to find current point's grey value. It was found that both the proposed and as well as NLmeans filtering could keep enough edge details. In comparison, the denoising effect of NL-means filter was not good as proposed method, but it could keep better detail texture in comparison to proposed method. Proposed method could make a good compromise amid get rid of noises and reserve details. It could get a good denoising effect when dealing with the noises that were obey to normal distribution, but the result was not that good when facing with other types of noises, so there was need to use different denoising methods for different noise images as to get a better denoising effect.

A. Sharma et al. [6] used objective evaluation methods to judge the efficiency of different types of spatial domain filters applied to different noise models with a quantitative approach. Performance of each filter is compared as they were applied on images affected by a wide variety of noise models. Conclusions were drawn in the end, about which filter is best suited for a number of noise models individually induced in an image, according to the experimental data obtained. The tests were conducted on several other benchmark images to validate experimental conclusions. Minimum and maximum filters in the case of Salt & Pepper noise was used in conjunction. First minimum filter was applied, followed by maximum filter. For Gaussian, Salt & Pepper, Poisson and Gamma Noise best filter was Median Filter. Uniform noise and Rayleigh Noise was corrected best by Minimum filter and for Exponential Noise. Best filter was found to be Harmonic Mean Filter.

### 3. PROPOSED TECHNIQUES AND RESEARCH METHODOLOGY

#### 1. Trilateral Filter

The trilateral filter [7] was proposed as an averages or means to limit impulse noise in digital images. The basic idea of the filter was relied on the functioning of bilateral filter [8] which is famous for its feature of an edge preserving using Gaussian filtering. The trilateral filter was extended to be a gradient-preserving filter, including the local image gradient into the filtering process.

This filter has the added benefit that it requires only one user-set parameter and the rest are self-tuning to the image. Authors showed that filter could also be utilized for 2D image which is effective in reducing the contrast of digital images and make them suitable to a user. Also the filter can also be effective in that the filter could be used to denoise 3D images quite accurately. Recent applications of trilateral filtering have shown that it also very applicable to biomedical imaging. It decreases noise while still preserving image details. The trilateral filter has also been utilized to create residual images while illumination invariant images to increase the quality of optical flow and stereo matching. Using only one pass produces sufficient results.

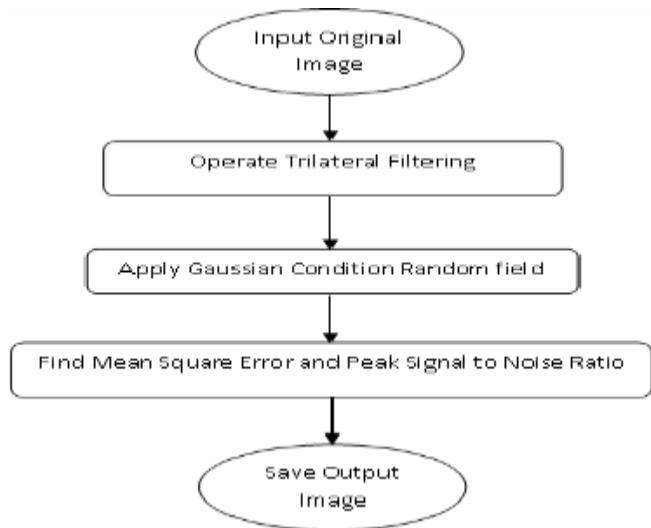
## 2. Gaussian Condition Random Field

GCRFs were first proposed in [3] where authors modeled the parameters of the conditional distribution of output given input as a function of the input image. The precision matrix associated with each image patch was modeled as a linear combination of twelve derivative filter-based matrices. The combination weights were chosen as a parametric function of the responses of the input image to a set of oriented edge and bar filters, and the parameters were learned using discriminative training. Image denoising utilizing a GCRF prototype have two steps. First one is a parameter selection step. Here the potential function parameters are selected which are relied on the digital input image, and an inference step in which energy minimization is performed for the chosen parameters.

## 3. Proposed Technique

The hybrid algorithm includes fusion of trilateral filter and Gaussian condition random field. The specific process is as follows:

- (1) Smoothing the image using trilateral filtering
- (2) Use Gaussian condition random field on smoothed image.
- (3) Perform the objective parameter evaluation for original and proposed images.



**Fig. 1: Proposed Technique**

## 4. Research Methodology

**Step 1:** Implement the trilateral filter and Gaussian condition random field approach technique and design the new algorithm for image denoising.

**Step 2:** Select simulation parameters like mean square error rate and peak signal to noise ratio.

**Step 3:** Compare the results for different types of digital images.

**Step 4:** Draw the conclusion from simulation results.

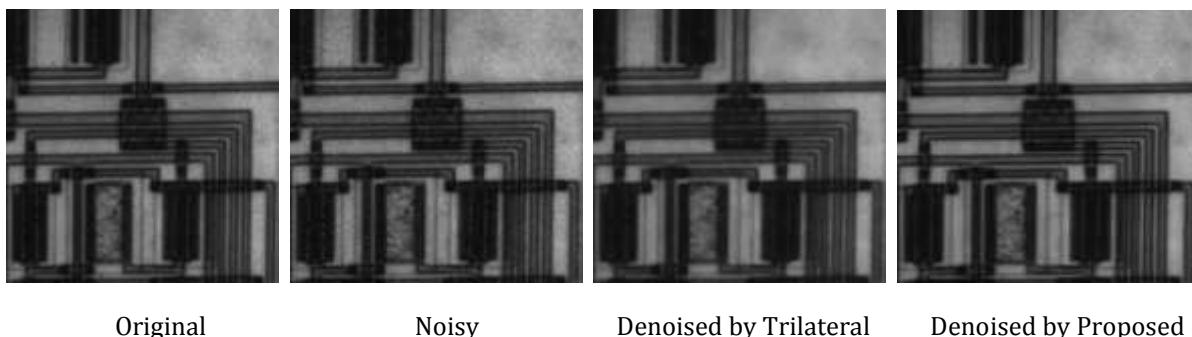
## RESULTS



**Fig. 4.1: Original, Noisy, Trilateral and Proposed Method filtered Images of Cameraman**

**Table 4.1: Objective parameter values of difference of different gray scale images with  $\lambda = 0.08$ , standard deviation,  $\sigma = 10$  of cameraman**

|      | Noisy - Original | Trilateral Denoised-Original | Proposed Denoised - Original |
|------|------------------|------------------------------|------------------------------|
| RMSE | 9.84             | 5.78                         | 3.97                         |
| PSNR | 28.27            | 32.89                        | 36.15                        |



Original                          Noisy                          Denoised by Trilateral                          Denoised by Proposed

**Fig. 4.2: Original, Noisy, Trilateral and Proposed Method filtered Images of Circuit**

**Table 4.2: Objective parameter values of difference of different gray scale images with  $\lambda = 0.08$ , standard deviation,  $\sigma = 10$  of circuit**

|      | Noisy - Original | Trilateral Denoised-Original | Proposed Denoised - Original |
|------|------------------|------------------------------|------------------------------|
| RMSE | 9.94             | 5.03                         | 3.23                         |
| PSNR | 28.19            | 34.09                        | 37.96                        |



Original

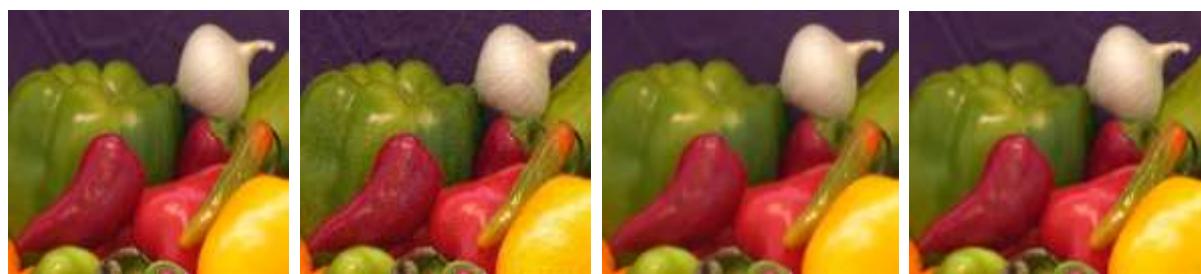
Noisy

Denoised by Trilateral

Denoised by Proposed

**Fig. 4.3: Original, Noisy, Trilateral and Proposed Method filtered Images of Moon****Table 4.3: Objective parameter values of difference of different gray scale images with  $\lambda = 0.08$ , standard deviation,  $\sigma = 10$  of moon**

|             | Noisy - Original | Trilateral Denoised-Original | Proposed Denoised - Original |
|-------------|------------------|------------------------------|------------------------------|
| <b>RMSE</b> | 8.36             | 3.14                         | 2.59                         |
| <b>PSNR</b> | 29.68            | 38.18                        | 39.95                        |



Original

Noisy

Denoised by Trilateral

Denoised by Proposed

**Fig. 4.4: Original, Noisy, Trilateral and Proposed Method filtered Images of Vegetables****Table 4.4: Objective parameter values of difference of different gray scale images with  $\lambda = 0.08$ , standard deviation,  $\sigma = 10$** 

|             | Noisy - Original | Trilateral Denoised-Original | Proposed Denoised - Original |
|-------------|------------------|------------------------------|------------------------------|
| <b>RMSE</b> | 9.72             | 4.78                         | 4.74                         |
| <b>PSNR</b> | 28.37            | 34.55                        | 34.61                        |



Original

Noisy

Denoised by Trilateral

Denoised by Proposed

**Fig. 4.5: Original, Noisy, Trilateral and Proposed Method filtered Images of Kid**

**Table 4.5: Objective parameter values of difference of different gray scale images with  $\lambda = 0.08$ , standard deviation,  $\sigma = 10$  of kid**

|      | Noisy - Original | Trilateral Denoised-Original | Proposed Denoised - Original |
|------|------------------|------------------------------|------------------------------|
| RMSE | 9.99             | 3.21                         | 2.52                         |
| PSNR | 28.14            | 38.01                        | 40.10                        |

### 3. CONCLUSIONS

From the results it is cleared that mean square difference is least and peak signal to noise ratio is maximum for proposed filter which out performs trilateral filter for Gaussian image denoising of digital images.

The outcomes of the proposed filter have refined edges and not remove any detail present in the image. While the other denoising methods usually out perform under some condition. So the proposed technique is better in comparison to trilateral filter technique for denoising of digital images.

In the future work different techniques can be combined to retrieve other better outcomes in comparison to the proposed techniques. Other objective parameters like correlation, entropy can also be taken in consideration so that more denoising factor can be achieved in the digital images.

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The authors can acknowledge any person/authorities in this section. This is not mandatory.

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