Reduction of Noise from Digital Image

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Abstract: Fundamental problem of image processing is to effectively remove noise from an image while keeping its features intact. The nature of problem depends on the type of noise added to the image. Fortunately two noise models adequately represent most noise added to the images: Gaussian noise and Impulse noise.A simpler, yet still quite effective solution to restore an image corrupted by mixed noise is to apply the trilateral filter.

In the system presented here we have introduced a local image statistics for identifying noise pixels in images corrupted with impulse noise of random values. The statistical values quantify how different the particular pixels in intensities are from there most similar neighbors. . A Trilateral filter is designed to remove Gaussian & Impulse noises effectively both in terms of quantitative measures of signals restoration and qualitative judgment of image quality. The approach is extended to remove the mix noise. Unlike bilateral filters or anisotropic diffusion methods that smooth towards piecewise constant solutions, the trilateral filter provides stronger noise reduction and better outlier rejection in high-gradient regions.

The trilateral filter has extensively tested for the noise removal capabilities and the results were compared with several existing filters.. It is found that the trilateral filters eliminate fair amount of noise while preserving edge boundaries and fine details. It also offers better performance for many visual applications including appearance-preserving contrast reduction problems for digital photography.

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I. INTRODUCTION

A frequent problem in image acquisition and transmission is corruption by noise, whose suppression is often required preprocessing stage. There are two types of noise Uniform noise and Impulse noise. Because of extremely non-linear nature of impulse noise, standard linear filtering techniques are unable to treat it in a proper way. Therefore a number of non-linear and /or adaptive algorithms for the impulse noise filtering have been proposed. There are two major impulse noise models used in contemporary literature:

1. **Salt-and-pepper Noise: -** Where noisy pixels have two highest and lowest values within the dynamic range.
2. **Uniform Noise: -** Where noisy pixels can have any value from dynamic range with equal probability.

One of the most common image processing tasks involves the removal of noise from images. Noise can be introduced during image capture, during transmission, or during storage. However, most images share characteristics with noise sources to a greater or lesser degree. Therefore, at its core, this task requires a balance between the improvement gained by a particular filter as noise is removed from an image and the degradation introduced by a particular filter as the noise-like components of the original image are also removed.

Conservative smoothing is a noise reduction technique that derives its name from the fact that it employs a simple, fast filtering algorithm that sacrifices noise suppression power in order to preserve the details (*e.g.* sharp edges) in an image. It is explicitly designed to remove *noise spikes i.e.* isolated pixels of exceptionally low or high pixel intensity (*e.g.* salt and pepper noise) and is, therefore, less effective at removing *additive noise* (*e.g.* Uniform noise) from an image.

Fundamental problem of image processing is to effectively remove noise from an image while keeping its features intact. The nature of problem depends on the type of noise added to the image. Fortunately two noise models adequately represent most noise added to the images: Uniform noise and Impulse noise. A simpler, yet still quite effective solution to restore an image corrupted by mixed noise is to apply the trilateral filter

In the system presented here we have introduced a local image statistics for identifying noise pixels in images corrupted with impulse noise of random values. The statistical values quantify how different the particular pixels in intensities are from there most similar neighbors. A Trilateral filter is designed to remove Uniform & Impulse noises effectively both in terms of quantitative measures of signals restoration and qualitative judgment of image quality. The approach is extended to remove the mix noise. Unlike bilateral filters or anisotropic diffusion methods that smooth towards piecewise constant solutions, the trilateral filter provides stronger noise reduction and better outlier rejection in high-gradient regions.

The trilateral filter has extensively tested for the noise removal capabilities and the results were compared with several existing filters.. It is found that the trilateral filters eliminate fair amount of noise while preserving edge boundaries and fine details. It also offers better performance for many visual applications including appearance-preserving contrast reduction problems for digital photography.

The proposed filter shows excellent performance in simultaneous removal of both salt & pepper noise and uniform noise. Therefore it can be regarded as the universal impulse noise filter.

II. LITERATURE REVIEW / SURVEY:

2.1 IMAGE PROCESSING:

A digital image is composed of *pixels* which can be thought of as small dots on the screen. A digital image is an instruction of how to color each pixel. In the general case we say that an image is of size *m*-by-*n* if it is composed of *m* pixels in the vertical direction and *n* pixels in the horizontal direction.

Image processing is in many cases concerned with taking one array of pixels as input and producing another array of pixels as output which in some way represents an improvement to the original array.

For example, this processing

- May remove noise,
- Improve the contrast of the image,
- Remove blurring caused by movement of the camera during image acquisition,
- It may correct for geometrical distortions caused by the lens.

2.2 NOISE:

Noise is a random signal. By this we mean that we cannot predict its value. We can only make statements about the probability of it taking a particular value, or range of values. Noise can be systematically introduced into images during acquisition and transmission. Noise plays a crucial role in communication systems. In theory, it determines the theoretical capacity of the channel. In practice it determines the number of errors occurring in a digital communication.

Images contain “noise”-pixels that aren’t what they suppose to be. The noise is nothing more than much localized high frequencies. Additive noise is often assumed to be impulse noise and Uniform noise. [9][3]

2.2.1 SALT AND PEPPER NOISE:

Impulse noise is isolated bad pixels. In a binary image this means that some black pixels become white and some white pixels become black. This noise is called as Salt and Pepper noise. Another common form of noise is *data drop-out* noise (commonly referred to *as* intensity spikes, speckle *or* salt and pepper noise). Here, the noise is caused by errors in the data transmission. The corrupted pixels are either set to the maximum value (which looks like snow in the image) or have single bits flipped over. In some cases, single pixels are set alternatively to zero or to the maximum value, giving the image a `salt and pepper' like appearance. Unaffected pixels always remain unchanged.. Noise can be systematically introduced into images during acquisition and transmission. [1][10][4].

The PDF (Probability Density Function) of (bipolar) impulse noise is given by,

$$P(z) = \begin{cases} P_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases}$$

If b>a, gray-level b will appear as a light dot in image. Conversely, level a will appear like a dark dot: If either Pa or Pb is zero, the impulse noise is called unipolar. If either probability is zero, & especially they are approximately equal , impulse noise values will resemble salt & pepper granules randomly distributed over the images. Bipolar impulse noise is called salt & pepper noise.[6]

Impulse noise is characterized by replacing a portion of an image’s pixel values with random values, leaving the remainder unchanged. Such noise can be introduced due to transmission errors.

2.2.2 Uniform Noise:

Additive zero- mean Uniform noise means that a value draw from a zero means Uniform probability density function is added to the true value of every pixel. Uniform noise can be reduced using a spatial filter.[6]
The PDF (Probability Density Function) is given by,

$$P(z) = \begin{cases} \dfrac{1}{b-a} & \text{If } a \le z \le b \\ 0 & \text{otherwise} \end{cases}$$

The mean of this density function is given by, μ=a+b/2 & its variance by,

$$\sigma^2 = \frac{(b-a)^2}{12}$$

2.3 FILTERING

The most effective basic spatial filtering techniques for noise removal include: mean filtering, median filtering. More sophisticated algorithms which utilize statistical properties of the image and/or noise fields exist for noise removal. For example, adaptive smoothing algorithms may be defined which adjust the filter response according to local variations in the statistical properties of the data.

Images contain features of different scales ranging from broad trends to fine textures. It is frequently useful to separate information on the basis of its spatial scale.

There are several techniques of digital image processing that can be used in the recovering of damaged graphical documents. The techniques presented are especially important when we try to recover ancient photographs or other ancient graphical documents. The materials used in these ancient graphical documents are degraded when time passes and a digital processing and storage allows a good conservation and a fast recovering process.

The most noticeable and least acceptable pixels in the noisy image are then those whose intensities are much different from their neighbours. However, it must be kept in mind that when smoothing an image, we reduce not only the noise, but also the fine-scaled image details because they also correspond to blocked high frequencies. Fig.2.1 shows the process of noise removal with noisy image and original image.

Figure 2.1(a) Original image (b) image with 20 % noise (c) Filtered image

2.3.1 Median Filter:

A median filter removes drop-out noise more efficiently and at the same time preserves the edges and small details in the image to better extent. Conservative smoothing can be used to obtain a result which preserves a great deal of high frequency detail, but is only effective at reducing low levels of noise.[9][3]

The median filter is normally used to reduce noise in an image, somewhat like the mean filter. The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the *mean* of neighboring pixel values, it replaces it with the *median* of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.)

Median filters are particularly effective in the presence of both bipolar and unipolar impulse noise.

One of the major problems with the median filter is that it is relatively expensive and complex to compute. To find the median it is necessary to sort all the values in the neighborhood into numerical order and this is relatively slow, even with fast sorting algorithms such as *quick sort*. A common technique is to notice that when the neighborhood window is slid across the image, many of the pixels in the window are the same from one step to the next, and the relative ordering of these with each other will obviously not have changed. [4][7]

2.3.2. Bilateral Filter

Bilateral filtering smoothes images while preserving edges, by means of a nonlinear combination of nearby image values. The method is non iterative, local, and simple. It combines gray levels or colors based on both their geometric closeness and their photometric similarity, and prefers near values to distant values in both domain and range.

Bilateral filtering produces no phantom colors along edges in color images, and reduces phantom colors where they appear in the original image. We propose a non iterative scheme for edge preserving smoothing that is non iterative and simple.

This is particularly important for filtering color images. If the three bands of color images are filtered separately from one another, colors are corrupted close to image edges. In fact, different bands have different levels of contrast, and they are smoothed differently. Separate smoothing perturbs the balance of colors, and unexpected color combinations appear. Bilateral filters, on the other hand, can operate on the three bands at once, and can be told explicitly, so to speak, which colors are similar and which are not. Only perceptually similar colors are then averaged together, and the artifacts mentioned above disappear. Two pixels can be *close* to one another, that is, occupy nearby spatial location, or they can be *similar* to one another, that is, have nearby values, possibly in a perceptually meaningful fashion. Traditional filtering is domain filtering, and enforces closeness by weighing pixel values with coefficients that fall off with distance.[8]

Similarly, we define range filtering, which averages image values with weights that decay with dissimilarity. Range filters are nonlinear because their weights depend on image intensity or color. Computationally, they are no more complex than standard non separable filters. Most importantly, they preserve edges. We then combine range and domain filtering, and show that the combination is much more interesting. We denote combined filtering as *bilateral* filtering. Bilateral filters can be applied to color images just as easily as they are applied to black-and-white ones.

A low-pass domain filter applied to image **f**(**x**) produces an output image defined as follows:

$$\mathbf{h}(\mathbf{x}) = k_d^{-1}(\mathbf{x}) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathbf{f}(\xi) c(\xi, \mathbf{x})\, d\xi \qquad (1)$$

Where, c(ξ, x)measures the *geometric* closeness between the neighborhood center **x** and a nearby point ξ. The bold font for **f** and **h** emphasizes the fact that both input and output images may be multiband.

If low-pass filtering is to preserve the dc component of low-pass signals we obtain

$$k_d(\mathbf{x}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\xi, \mathbf{x})\, d\xi \,. \qquad (2)$$

If the filter is shift-invariant c(ξ, x) is only a function of the vector difference ξ- **x**, and kd is constant.

Range filtering is similarly defined:

$$\mathbf{h}(\mathbf{x}) = k_r^{-1}(\mathbf{x}) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathbf{f}(\xi) s(\mathbf{f}(\xi), \mathbf{f}(\mathbf{x}))\, d\xi \qquad (3)$$

except that nows(**f**(ξ); **f**(**x**)) measures the *photometric* similarity between the pixel at the neighborhood center **x** and that of a nearby point . Thus, the similarity function s operates in the range of the image function **f**, while the closeness function c operates in the domain of **f**. The normalization constant (2) is replaced by

$$k_r(\mathbf{x}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} s(\mathbf{f}(\xi), \mathbf{f}(\mathbf{x}))\, d\xi \,. \qquad (4)$$

The spatial distribution of image intensities plays no role in range filtering taken by itself. Combining intensities from the entire image, however, makes little sense, since image values far away from **x** ought not to affect the final value at **x**. In addition, section 3 shows that range filtering by itself merely changes the color map of an image, and is therefore of little use. The appropriate solution is to combine domain and range filtering, thereby enforcing both geometric and photometric locality. Combined filtering can be described as follows:

$$\mathbf{h}(\mathbf{x}) = k^{-1}(\mathbf{x}) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathbf{f}(\xi) c(\xi, \mathbf{x}) s(\mathbf{f}(\xi), \mathbf{f}(\mathbf{x}))\, d\xi \quad (5)$$

with the normalization

$$k(\mathbf{x}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\xi, \mathbf{x}) s(\mathbf{f}(\xi), \mathbf{f}(\mathbf{x}))\, d\xi \,. \qquad (6)$$

Combined domain and range filtering will be denoted as *bilateral filtering*. It replaces the pixel value at **x** with an average of similar and nearby pixel values. In smooth regions, pixel values in a small neighborhood are similar to each other, and the normalized similarity function k_1s is close to one. As a consequence, the bilateral filter acts essentially as a standard domain filter, and averages away the small, weakly correlated differences between pixel values caused by noise.

2.3.3. TRILATERAL FILTER

2.3.3 A) DETECTING IMPULSES

Noise models

Let us consider the standard matrix notation for images. For example, when u is an image ,

$u_{i,j}$ will represent the intensity value of u at the pixel location (i, j) in the image domain. For the case of additive Uniform noise, the noisy image, u, is related to the original image, u^o, by $u_{i,j} = u^o_{i,j} + n_{i,j}$ where each noise value n is drawn from a zero-mean uniform distribution.

Impulse noise, denoted by n, is characterized by replacing a portion of the original pixel values of the image with intensity values drawn from some range. we consider the uniform noise distribution model, although the methods we discuss could be used without modification for the discrete model. Therefore, for images corrupted with impulse noise, the noisy
image u is related to the original image $\mathbf{u^0}$ by

$$u_{i,j} = \begin{cases} n_{i,j} & \text{with probability } p \\ u^0_{i,j} & \text{with probability } (1-p). \end{cases}$$

2.3.3 B) Detection scheme

The problem of deciding which pixels in an image are impulses is clearly not well-defined. Therefore we must be content with detecting pixels that are like impulses, that is, pixels that vary greatly in intensity from most surrounding pixels. Uncorrupted natural images rarely contain details isolated to a single pixel and generally have few impulse-like pixels. Impulse noise removal methods use many different techniques to determine whether a given pixel is an impulse in this sense.

The most basic impulse detectors are based on two-state methods that attempt to definitively characterize each image pixel as either an impulse or an unaffected pixel. The underlying goal of these two-state methods is to find pixels that are significant outliers when compared to their neighbors. One of the simplest and most intuitive methods is to compare a pixel's intensity with the median intensity in its neighborhood [5]. The advantage of these two-state methods is their simplicity, which makes them easily customizable. An additional concern with existing methods arises from the fact that when impulse noise is introduced to an image, a portion of the pixels will be replaced with intensities only slightly different from their original values. Two-state detectors, with or without training, will most likely fail to detect such small impulses since they look exclusively for large outliers. They remove the most conspicuous noise, but the lesser impulses remain, creating a grainy appearance. In response to this problem, we adopt a continuous function to represent how impulse-like a particular pixel may be.

2.4 ROAD(Rank Ordered Absolute Differences)

The ROAD statistic provides a measure of how close a pixel value is to its four most similar neighbors. The logic underlying the statistic is that unwanted impulses will vary greatly in intensity from most or all of their neighboring pixels, whereas most pixels composing the actual image should have at least half of their neighboring pixels of similar intensity, even pixels on an edge.

Let x = (x1; x2) be the location of the pixel under consideration, and let be the set of points in a (2N+1)X(2N+1) neighborhood centered at x for some positive integer N . In the following discussion, let us only consider N = 1, though the same procedure can be extended to any N > 1. Hence,

$$\Omega^o_x = \Omega_x(1) \setminus \{x\}$$

represents the set of points in a 3X 3 deleted neighborhood of x. For each point y $\varepsilon \Omega^O_X$, define dx;y as the absolute difference in intensity of the pixels between x and y, i.e.

$$d_{\mathbf{x},\mathbf{y}} = |u_{\mathbf{x}} - u_{\mathbf{y}}|.$$

Finally, sort the dx,y values in increasing order and define

$$ROAD_m(x) = \sum_{i=1}^{m} r_i(x),$$

$$where 2 \le m \le 7 and$$

$$ri(x) = ith \text{ smallest d x,y for } y \in \Omega^o_x$$

We call the statistic defined in (2) ROAD ("Rank-ordered Absolute Differences"). In this , we will consider m = 4 only, and set ROAD(x) = ROAD4(x). The ROAD statistic provides a measure of how close a pixel value is to its four most similar neighbors. The logic underlying the statistic is that unwanted impulses will vary greatly in intensity from most or all of their neighboring pixels, whereas most pixels composing the actual image should have at least half of their neighboring pixels of similar intensity, even pixels on an edge. Fig. shows examples from the Lena image comparing a typical impulse noise pixel to an edge pixel. Notice that the edge pixel has neighbors of similar intensity despite forming part of an edge, and thus has a significantly lower ROAD value.

Fig. demonstrates how the latter value was calculated. We illustrate numerically that the ROAD statistic is a good indicator of impulse noise. Ideally we want our statistic to be very high for impulse noise pixels and much lower for uncorrupted pixels. Fig. displays quantitative results from the Lena image. The upper dashed line represents the mean ROAD value for noise pixels as a function of the amount of impulse noise added, and the lower dashed line represents the mean ROAD value for uncorrupted pixels. The noise pixels consistently have much higher mean ROAD values than the uncorrupted pixels, whose mean ROAD values remain nearly constant even with very large amounts of noise.

Figure 2.2: ROAD of impulse: 525; ROAD of edge pixel: 88.

$$\begin{pmatrix} 213 & 171 & 88 \\ 216 & 186 & 107 \\ 218 & 202 & 139 \end{pmatrix} \longrightarrow \begin{pmatrix} 27 & 15 & 98 \\ 30 & - & 79 \\ 32 & 16 & 47 \end{pmatrix}$$

Original Neighborhood Absolute Differences

$r_1 = 15, r_2 = 16$ $$ROAD = \sum_{r=1}^{4} r_i$$

$r_3 = 27, r_4 = 30$ $\longrightarrow$ 15+16+27+30=88

Figure 2.3 demonstrating how to calculate ROAD

2.5 THE ROAD AND TRILATERAL FILTER

We are introducing the ROAD statistic into many existing filtering techniques, allowing them to detect and properly handle impulse-like pixels in a noisy image. Below we describe how one might extend the bilateral filter to create a filter capable of removing both impulse and additive Uniform noise from images. We begin with a brief introduction to the bilateral filter and then we are adding a weighting function to bilateral filter to get a newer filter say, Trilateral Filter which is capable enough to remove both Uniform and Impulse noise as well as Mixed Noise.

2.5.1 Bilateral Filter

The bilateral filter, as described in [2], applies a nonlinear filter to u to remove Uniform noise while retaining the sharpness of edges. Each pixel is replaced by a weighted average of the intensities in a (2N+1)X(2N+1) neighborhood. The weighting function is designed to smooth in regions of similar intensity while keeping edges intact, by heavily weighting those pixels that are both near the central pixel spatially and similar to the central pixel radiometrically.

More precisely, let x be the location of the pixel under consideration, and let

$$\Omega = \Omega_x(N) \qquad (3)$$

be the pixels in a (2N + 1) X (2N + 1) neighborhood of x. The weight of each y ε Ω with respect to x is the product of two components, one spatial and one radiometric:

$$w(x, y) = w_S(x, y) w_R(x, y), \qquad (4)$$

Where,

$$w_S(x, y) = e^{-\frac{|x-y|^2}{2\sigma_s^2}} \quad \ldots\ldots\ldots\ldots\ldots \ (5)$$

and,

$$w_R(x, y) = e^{-\frac{|u_x - u_y|}{2\sigma_R^2}} \quad \ldots\ldots\ldots \ (6)$$

The weights must be normalized, so the restored pixel $\bar{u}_x$ is given by

$$\bar{u}_x = \frac{\sum_{y \in \Omega} \omega(x, y) u_y}{\sum_{y \in \Omega} \omega(x, y)} \quad \ldots\ldots\ldots\ldots (7)$$

The w_S weighting function decreases as the spatial distance between x and y increases, and the w_R weighting function decreases as the radiometric "distance" between the intensities u_x and u_y increases. The spatial component of the weight decreases the influence of pixels far away from x to generally reduce blurring, while the radiometric component diminishes the influence of pixels with significantly different intensities to keep the edges of distinct image regions sharp. Notice that the w_S and w_R weighting functions need not be Uniforms—any suitable nonnegative functions that decrease to zero may be used instead.

In our particular weighting functions, the parameters σS and σR control the behavior of the weights. They are the values at which the respective Uniform weighting functions take their maximum derivatives, so they serve as rough thresholds for identifying pixels sufficiently close spatially or radiometrically. Note, in particular, that as σR →∞ and radiometric differences are rendered irrelevant by this high threshold, the bilateral filter approaches a Uniform filter of standard deviation σS. As both σR, σS → ∞ so that all neighboring pixels easily meet both thresholds, the bilateral filter approaches the mean filter.

2.5.2 Weighting function

We incorporate the ROAD statistic into the bilateral filtering framework by introducing a third weighting function influenced by how impulse-like each pixel of the image is. The "impulsive" weight, w_I , at a point x is given by:

$$w_I(x) = e^{-\frac{\mathrm{ROAD}(x)^2}{2\sigma_I^2}}. \quad (8)$$

The σI parameter determines the approximate threshold above which to penalize high ROAD values. We would like to integrate this impulsive component into a nonlinear filter designed to weight pixels based on their spatial, radiometric, and impulsive properties. Unfortunately, the impulsive component is not directly compatible with the radiometric component already present in the bilateral filter. The radiometric weight works contrary to our goal because it was not designed to remove impulse noise. However, if used selectively, the radiometric weight can still be helpful for removing impulse noise.

It can help smooth impulses that are only slightly different from their surrounding pixels without blurring edges, while the impulsive weight works to remove the larger outliers. If we can use the radiometric component for only small impulses, we can improve upon the common two-state methods for impulse noise removal by not only removing the larger outliers, but also smoothing away smaller impulses. To add the impulsive weight while still retaining the radiometric component of the bilateral filter, we introduce a switch to determine how much to use the radiometric component in the presence of impulse noise. If x is the central pixel under consideration, and y ε Ω_X (N) is a pixel in the neighborhood of x, we define the "joint impulsivity" J of y with respect to x as

$$J(x,y) = 1 - e^{-\left(\frac{\mathrm{ROAD}(x)+\mathrm{ROAD}(y)}{2}\right)^2 / 2\sigma_J^2}.$$

(9)

The J(x; y) function assumes values in [0; 1]. The σJ. parameter controls the shape of the function. Again, any suitably nonnegative function that decreases to zero may be used in place of the Uniform. If *at least one* of **x** or **y** is impulse-like and has a high ROAD value with respect to σJ, then J(x; y) ≈ 1. If neither pixel is impulse-like, and thus neither has a high ROAD value, then J(x; y) ≈ 0. We would like to use the radiometric weight more heavily when J(x; y) ≈ 0 to smooth regions without large impulses and less heavily when J(x; y) ≈ 1, because if either pixel is an impulse, the radiometric weight fails to function correctly as illustrated above. Conversely, we would like to use the impulsive weight less heavily when J(x; y) ≈ 0 and more heavily when J(x; y) ≈ 1, to suppress large impulses. With this in mind, we define the final, "trilateral" weight of y with respect to the central point x as:

$$w(x,y) = w_S(x,y)w_R(x,y)^{1-J(x,y)}w_I(y)^{J(x,y)}. \quad (10)$$

Referring to the Uniform forms of wR and wI , we see that raising these functions to the specified exponents has the effect of modifying their effective standard deviations or "thresholds". When J(x; y) ¼ 1 so that 1 ¡ J(x; y) ¼ 0, the radiometric threshold becomes very large so that radiometric differences become irrelevant, while the impulsive weight is unaffected. When J(x; y) ¼ 0, the opposite happens and only the radiometric weight is used to distinguish pixels because the effective impulsive threshold is so high. In this way, the appropriate weighting function is applied on a pixel-by-pixel basis. We will call the nonlinear filter of form (7) with the weighting function w(x; y) given in (10) the "trilateral filter," since it combines three different measures of neighboring pixels in determining its weights.

In general, the trilateral weighting function works well to remove impulse noise without compromising the bilateral filter's ability to remove Gaussian noise. For images with no impulse noise and thus few points with high ROAD values–

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the J(x; y) term in (10) effectively "shuts off" the impulsive component of the weight and only uses the radiometric and spatial weights. Essentially, the trilateral filter reverts to the bilateral filter when processing images without impulse noise.

2.5.3 Removing Mixed Uniform and Impulse Noise

The trilateral filter can be easily extended to remove any mixture of Uniform and impulse noise. The ideal solution would be to locally vary parameters so that they are finely tuned to remove the precise amount and type of noise present in each section of the image. A simpler, yet still quite effective solution to restore an image corrupted by mixed noise is to apply the trilateral filter twice with two different values of ¾S—once with a smaller value of ¾S, to remove the impulse noise, and another time with a larger value of ¾S, to smooth the remaining Our implementation of the trilateral filter used a 5 £ 5 window size and performed multiple iterations when it provided better results (for p > 25%). Image boundaries were handled by assuming symmetric boundary conditions. Our first goal was to ensure that our approach provides visually pleasing output. The trilateral filter can restore images corrupted with low to moderate levels of impulse noise (p >25%) with virtually unblemished results. Fig. shows the Lena image corrupted with 20% impulse noise and the result after trilateral filtering.

Comparing with the original, it is clear that the trilateral filter can eliminate a fair amount of noise while preserving edge boundaries and fine details. We also verified that the trilateral filter retains the ability to remove Uniform noise and that it can effectively remove mixed noise. The trilateral filter continues to adequately suppress Uniform noise, even after the introduction of the impulsive weight and the joint impulsivity function.

2.6 Signal Restoration

Once the visual quality of images restored by the trilateral filter had been confirmed, we concentrated on directly comparable, quantitative measures of signal restoration. In particular, we measured the peak signal-to-noise ratio (PSNR). If u0 is the original m £ n image and ~u is a restored image of u0, the PSNR of ~u is given by:

$$\mathrm{PSNR}(\tilde{u}) = 10\log_{10}\left(\frac{\sum_{i,j=1}^{m,n} 255^2}{\sum_{i,j=1}^{m,n}(\tilde{u}_{i,j} - u^0_{i,j})^2}\right). \qquad (11)$$

Larger PSNR values signify better signal restoration. the trilateral filter provided results with higher PSNR values than the results of the other methods tested, especially for very high levels of noise. In particular, for the Lena image with 50% noise, the trilateral filter produces PSNR values almost a full three decibels higher than the closes competing method.

III. SYSTEM DESIGN

The first stage of any vision system is the image acquisition stage. After the image has been obtained, various methods of processing can be applied to the image**.** In next stage as images contains various types of noise while they got transmitted this can be reduced or minimized with the help of different filters.

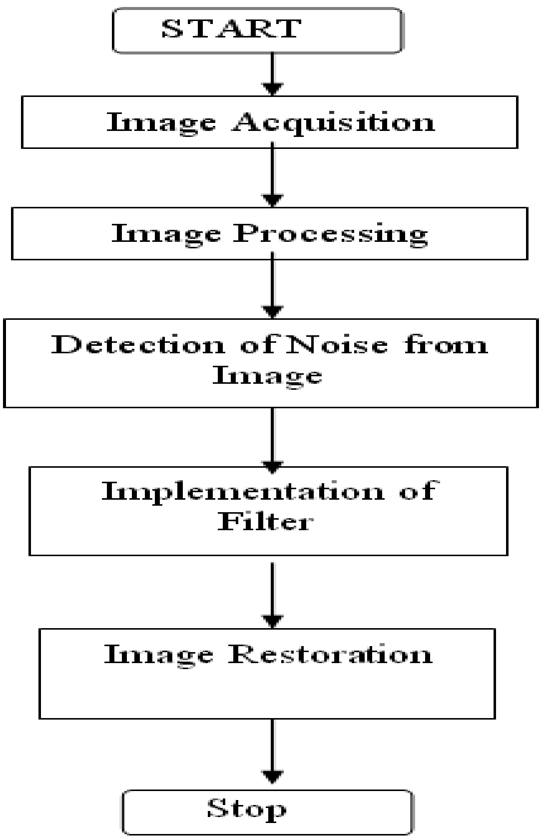

Fig 4.1: Image Processing Flow Diagram

There are various types of noises such as uniform noise, impulse noise etc. After detecting the noise from an image we go for filtering that image to reduce the noise from an image by using filters. There are various types of filters such as Median filter bilateral filter, trilateral filter. After filtering the image by using filter we have to restore the image as a filtered output image or a denoised image.

Project Flow:

First it opens the image for further processing. After opening image it calculates ROAD value of image. By selecting, desired noise is added in image and then detecting processing is carried out. Now at next stage we removed noise from image using Filter. Last steps we compared filtered image with original image

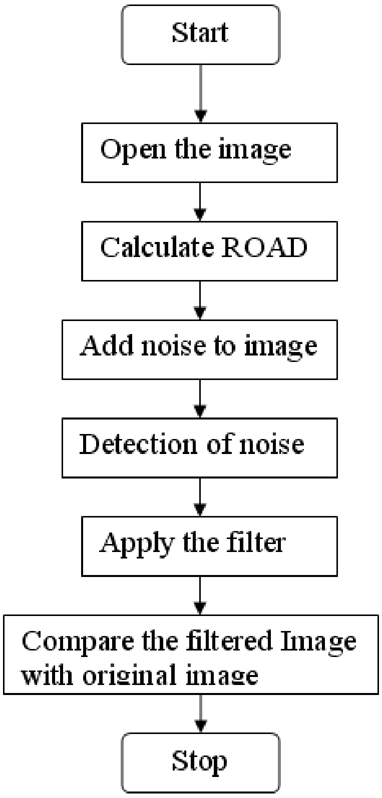

Fig 4.2: Project flow diagram

Here we have developed a Trilateral filter with reference to Bilateral filter. Bilateral filter smooth images while preserving edges. We have referred to Noise model. Let when u is an image ,

$u_{i,j}$ represent the intensity value of u at the pixel location (i, j) in the image domain. For the case of additive Uniform noise, the noisy image, u, is related to the original image, u^o , by

$$u_{i,j} = u^o_{i,j} + n_{i,j}$$

Where , nij = Noise in the pixel location(i,j)

For images corrupted with impulse noise, the noisy image u is related to the original image $\mathbf{u}^0$ by

$$u_{i,j} = \begin{cases} n_{i,j} & \text{with probability } p \\ u^0_{i,j} & \text{with probability } (1-p). \end{cases}$$

For detection of noise we use ROAD.

ROAD(Rank Ordered Absolute Differences) statistic provides a measure of how close a pixel value is to the four most neighbors.

$$ROAD_m(x) = \sum_{i=1}^{m} r_i(x),$$

$$where 2 \le m \le 7 and$$

$ri(x) = ith$ smallest dx,y for $y \in \Omega^o_x$

The mean for ROAD is calculated. The ROAD for corrupted pixels & the value of ROAD for uncorrupted pixels are calculated. The noise pixels have higher mean ROAD values than the uncorrupted pixels. ROAD of Impulse & ROAD of edge pixel is calculated.

The weight of each y ε Ω with respect to x is the product of two components, one spatial and one radiometric:

$$w(x, y) = w_S(x, y) w_R(x, y),$$

Where,

$$w_S(x, y) = e^{-\frac{|x-y|^2}{2\sigma_s^2}}$$

and,

$$w_R(x, y) = e^{-\frac{|u_x - u_y|}{2\sigma_R^2}}$$

The restored pixel $\bar{u}_x$ is given by,

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$$\bar{u}_x = \frac{\sum_{y\in\Omega} \omega(x,y) u_y}{\sum_{y\in\Omega} \omega(x,y)}$$

Impulsive weight, w_I , at a point x is given by:

$$w_I(x) = e^{-\frac{ROAD(x)^2}{2\sigma_I^2}}.$$

Trilateral weight of y with respect to the central point x as:

$$w(x,y) = w_S(x,y) w_R(x,y)^{1-J(x,y)} w_I(y)^{J(x,y)}. \quad (10)$$

The trilateral filter can be easily extended to remove any mixture of Uniform and Impulse noise. The Trilateral filter can restore images corrupted with how to moderate levels of impulse noise(p>25%)

IV. SYSTEM TESTING

As fig 6.1 shows that we have filtered noisy image having mixed noise(Impulse noise and Uniform noise). After filtering the noisy image , we see that the filtered image is approximately equal to the original image.

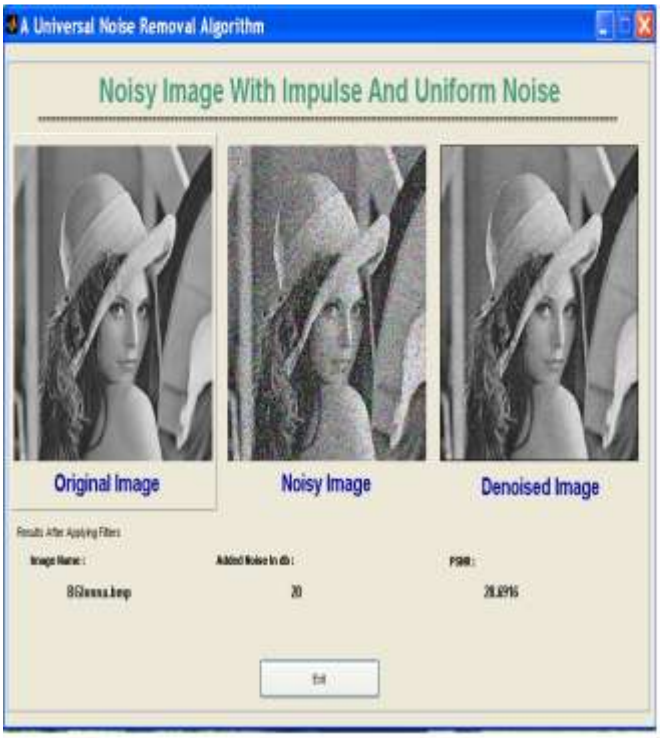

Fig 6.1: Filtered Image of Mixed Noise Using Trilateral Filter

Here we have added 20% of mixed noise(10% Impulse noise and 10% Uniform noise). We get the filtered image with the PSNR of 28.6916.

V. CONCLUSION

Comparing with the original, it is clear that the trilateral filter can eliminate a fair amount of noise while preserving edge boundaries and fine details. We also verified that the trilateral filter retains the ability to remove Uniform noise and that it can effectively remove mixed noise. The trilateral filter continues to adequately suppress Uniform noise & Impulse noise.

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