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An Optimistic Method of Estimation and Minimization of Noise using Guided Filter

Mohamed Faizal .S, 2. Mohamed Ashraf .I, 3. Kamarunzaman .M and 4. Mohan .S.B
1.Finalyear ECE, 2. Finalyear ECE, 3.Finalyear ECE , and 4.Associate professor ECE.
Dhaanish Ahmed College of Engineering, Chennai

Abstract:

De-noising plays a vital role in removing the noise from the image. Captured Images usually have different types of noises. Estimation of noise in the captured image helps to use any of the algorithms in removing noise. Different techniques are available to estimate the noise present in the image. Various filtering techniques have been used previously but many of these algorithms remove the fine details and structure of the image in addition to the noise. We propose a technique which restricts the removal of fine image details. We propose Guided filter algorithm for noise removal, which is fast and non-approximate linear technique regardless of the kernel size and intensity range. We propose to develop a MATLAB code to sort out the difficulties like introduction of false edges in noise estimation and removal of fine details in noise removal.

I. INTRODUCTION

HIS document is a MOST applications in computer vision and Tcomputer graphics involve image filtering to suppress and/or extract content in images. Simple linear translation-invariant (LTI) filters with explicit kernels, such as the mean, Gaussian, Laplacian, and Sobel filters, have been widely used in image restoration, blurring/sharpening, edge detection, feature extraction, etc. Alternatively, LTI filters can be implicitly performed by solving a Poisson Equation as in high dynamic range (HDR) compression [3], image stitching [4], image matting [5], and gradient domain manipulation [6]. The filtering kernels are implicitly defined by the inverse of a homogenous Laplacian matrix. The LTI filtering kernels are spatially invariant and independent of image content. But usually one may want to consider additional information from a given guidance image. The pioneer work of anisotropic diffusion uses the gradients of the filteringimage itself to guide a diffusion process, avoiding smoothing edges. The weighted least squares (WLS) filter utilizes the filtering input (instead of intermediate results, as in [7]) as the guidance, and optimizes a quadratic function, which is equivalent to anisotropic diffusion with a nontrivial steady state. The guidance image can also be another image besides the filtering input in many applications. For example, in colorization [9] the chrominance channels should not bleed across luminance edges; in image matting [10] the alpha matte should capture the thin structures in a composite image; in haze removal [11] the depth layer should be consistent with the scene. In these cases, we regard the chrominance/alpha/depth layers as the image to be filtered, and the luminance/composite/scene as the guidance image, respectively. The filtering process in [9], [10], and [11] is achieved by optimizing a quadratic cost function weighted by the guidance image. The solution is given by solving a large sparse matrix which solely depends on the guide. This inhomogeneous matrix implicitly defines a translation-variant filtering kernel. While these optimization-based approaches [8], [9], [10], [11] often yield state-of-the-art quality, it comes with the price of expensive computational time. Another way to take advantage of the guidance image is to explicitly build it into the filter kernels. The bilateral filter, independently proposed in [12], [13], and [1] and later generalized in [14], is perhaps the most popular one of such explicit filters. Its output at a pixel is a weighted average of the nearby pixels, where the weights depend on the intensity/color similarities in the guidance image. The guidance image can be the filter input itself [1] or another image [14]. The bilateral filter can smooth small fluctuations and while preserving edges. Though this filter is effective in many situations, it may have unwanted gradient reversal artifacts [15], [16], [8] near edges (discussed in Section 3.4). The fast implementation of the bilateral filter is also a challenging problem. Recent techniques [17], [18], [19], [20], [21] rely on quantization methods to accelerate but may sacrifice accuracy.

II. NOISE IN AN IMAGE

Noise is a random variation of image Intensity and visible as grains in the image. It may arise in the image as effects of basic physics-like photon nature of light or thermal energy of heat inside the image sensors. It may produce at the time of capturing or image transmission. Noise means, the pixels in the image show different intensity values instead of true pixel values. Noise removal algorithm is the process of removing or reducing the

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noise from the image. The noiseremoval algorithms reduce or remove the visibility of noise by smoothing the entire image leaving areas near contrast boundaries. But these methods can obscure fine, low contrast details. The common types of noise that arises in the imageare a) Impulse noise, b) Additive noise [1], c) Multiplicative noise. Different noises have their own characteristics whichmake them distinguishable from others.

A. Gaussian noise

The term normal noise model is the synonym of Gaussian noise.This noise model is additive in nature [4] and follow Gaussian distribution. Meaning that each pixel in the noisy image is the sum of the true pixel value and a random, Gaussian distributed noise value. The noise is independent of intensity of pixel value at each point. The PDF of Gaussian random variable is given by:

B. Additive White Gaussian noise

The random nature of noise in time domain will, on occasions, because a transmitted symbol to be distorted such that the receiver interprets it as a different symbol in the modulation scheme alphabet.Under these circumstances, a given average level of AWGN introduces an average number of symbol errors where each symbol error causes one or more bit errors at output of the receiver. The errors maybe characterized by a bit error rate (BER)First, download basic and generally accepted model for thermal noise in communication channels, is the set of assumptions that the noise is additive, i.e., the received signal equals the transmit signal plus some noise, where the noise is statistically independent of the signal.

• The noise is white, i.e, the power spectral density is flat, and so the autocorrelation of the noise in time domain is zero for any non-zero time offset.

• The noise samples have a Gaussian distribution.

Mostly it is also assumed that the channel is Linear and Time Invariant. The most basic results further assume that it is also frequency non-selective. [6]Additive White Gaussian Noise (AWGN) is the statistically random radio noise characterized by a wide frequency range with regards to a signal in a communication channel.

White noise:

An infinite-bandwidth white noise signal is a purely theoretical construction. The bandwidth of white noise is limited in practice by the mechanism of noise generation, by the transmission medium and by finite observation capabilities. Thus, a random signal is considered "white noise" if it is observed to have a flat spectrum over the range of frequencies that is relevant to the context. For an audio signal, for example, the relevant range is the band of audible sound frequencies, between 20 to 20,000 Hz. Such a signal is heard as a hissing sound, resembling the /sh/ sound in "ash". In music and acoustics, the term "white noise" may be used for any signal that has a similar hissing sound.

Poisson noise

Photon noise, also known as Poisson noise, is a basic form of uncertainty associated with the measurement of light, inherent to the quantized nature of light and theindependence of photon detections. Its expected magnitude is signal-dependent and constitutes the dominant source of image noise except in low-light conditions .Image sensors measure scene irradiance by counting the number of discrete photons incident on the sensor over a given time interval. In digital sensors, the photoelectric effect is used to convert photons into electrons, whereas lm-based sensors rely on photo-sensitive chemical reactions. Christo Ananth et al. [2] discussed about Improved Particle Swarm Optimization. The fuzzy filter based on particle swarm optimization is used to remove the high density image impulse noise, which occur during the transmission, data acquisition and processing. The proposed system has a fuzzy filter which has the parallel fuzzy inference mechanism, fuzzy mean process, and a fuzzy composition process. In particular, by using no-reference Q metric, the particle swarm optimization learning is sufficient to optimize the parameter necessitated by the particle swarm optimization based fuzzy filter, therefore the proposed fuzzy filter can cope with particle situation where the assumption of existence of "ground-truth" reference does not hold. The merging of the particle swarm optimization with the fuzzy filter helps to build an auto tuning mechanism for the fuzzy filter without any prior knowledge regarding the noise and the true image. Thus the reference measures are not need for removing the noise and in restoring the image. The final output image (Restored image) confirm that the fuzzy filter based on particle swarm optimization attain the excellent quality of restored images in term of peak signal-to-noise ratio, mean absolute error and mean square error even when the noise rate is above 0.5 and without having any reference measures. This is a standard Poisson distributionwith a rate parameter t that corresponds to the expected incident photon count.The uncertainty described by this distribution is known as photon noise.

CURRENT TECHNIQUES:

A **bilateral filter** is a non-linear, edge-preserving and noise-reducing smoothing filter for images. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. This weight can be based on a Gaussian distribution. Crucially, the weightsdepend not only on Euclidean distance of pixels, but also on the radiometric differences (e.g. range differences, such as color intensity, depth distance, etc.). This preserves sharp edges by systematically looping through each pixel and adjusting weights to the adjacent pixels accordingly.

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The bilateral filter is defined as

$$I^{\text{filtered}}(x) = \frac{1}{W_p}\sum_{x_i\in\Omega} I(x_i) f_r(\|I(x_i)-I(x)\|) g_s(\|x_i - x\|),$$

where the normalization term

$$W_p = \sum_{x_i\in\Omega} f_r(\|I(x_i)-I(x)\|) g_s(\|x_i - x\|)$$

ensures that the filter preserves image energy and

- I^{filtered} is the filtered image;
- I is the original input image to be filtered;
- x are the coordinates of the current pixel to be filtered;
- Ω is the window centered in x;
- f_r is the range kernel for smoothing differences in intensities. This function can be a Gaussian function;
- g_s is the spatial kernel for smoothing differences in coordinates. This function can be a Gaussian function;

As mentioned above, the weight W_p is assigned using the spatial closeness and the intensity difference. Consider a pixel located at (i,j) which needs to be de-noised in image using its neighboring pixels and one of its neighboring pixels is located at (k,l). Then, the weight assigned for pixel (k,l) to denoise the pixel (i,j) is given by:

$$w(i,j,k,l) = e^{\left(-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2} - \frac{\|I(i,j)-I(k,l)\|^2}{2\sigma_r^2}\right)}$$

where σ_d and σ_r are smoothing parameters and I(i, j) and I(k, l) are the intensity of pixels (i,j) and (k,l) respectively. After calculating the weights, normalize them.

$$I_D(i,j) = \frac{\sum_{k,l} I(k,l) * w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)}$$

where I_D is the denoised intensity of pixel (i,j)

LIMITATIONS

The bilateral filter in its direct form can introduce several types of image artifacts:

- Staircase effect - intensity plateaus that lead to images appearing like cartoons
- Gradient reversal - introduction of false edges in the image

There exist several extensions to the filter that deal with these artifacts. Alternative filters, like the *guided filter* have also been proposed as an efficient alternative without these limitations.

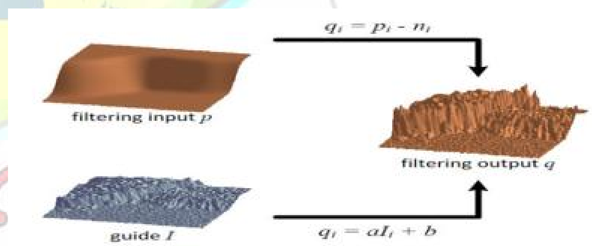
PROPOSED TECHNIQUE

There is lot ofprobability density functions are available to noise estimation and lot offilter techniques are available to removing the noise . the noise completely removing task is impossible but we can minimize the noise and will get good output. In current techniques consists of some limitations. To overcome that we proposed new techniques or noise estimation and denoising , Here we have to use Gaussian distribution function or noise estimation and guided filter is used or noise removal.

III. GUIDED FILTER

Guided filter produces filtered output ‘q’ by using guidance image ‘I’ and input image ‘p’. Based on the application, guidance image can be input image itself or different image. qi is a local linear transform of guidance image I in a window ωk centered at pixel k as shown in Fig. , which can be given as

$qi = akIi + bk, \forall i \in \omega k$ (1)



Where ak and bk are linear coefficients in a window ωk which is having radius r. Pixel i and windows ωi and ωk are shown in Fig.

Equation (1) is a local linear model which shows that q has an edge only if I has an edge, because ∇q=a∇I. He et al. [10] defined the following cost function in the window as

$(ak,bk) = \sum((akIi + bk - pi)2 + \varepsilon ak\ 2)\ i\in\omega k$ (2)

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Here ε is a regularization parameter which prevents ak from being too large. Solution of linear coefficients ak and bk for above cost function is given as

$ak = 1/|\omega| \sum Iipi - \mu k\overline{p}k i\in\omega k\sigma k\ 2 + \varepsilon$

(3) $bk = \overline{p}k - ak\mu k$ (4)

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Here µk and σk 2are mean and variance of I in ωk. |ω| is number of pixels in ωk. $\overline{pk}$ is the mean of p in ωk which is given as
$\overline{pk}$ =
1/ |ω|∑ $pki∈ωk$
(5)
For pixel i in the image, the value of qi is different for different windows as shown in Fig. 2. So simple strategy is to average the values of qi. So after computing linear coefficients for all windows ωk in the image, the filtered output is given as

qi =1/ |ω|∑ $(akIi + bk)$ k:$i∈ωk$ (6) = $\bar{a}iIi + \bar{b}i$ (7)

Now, edge preserving filtering for guided filter is explained. Consider the case I = p. If ε = 0 then solution to equation (2) is ak = 1 and bk = 0. If ε>0, two cases are formed: Case 1: "flat patch." if the image I is constant in ωk then we get ak = 0 and bk= $\bar{k}$. Case 2: "high variance." if the image I changes a lot in ωk then we get ak = 1 and bk = 0. ak, bk are averaged to get $\bar{a}i$ and $\bar{b}i$ and then filtered output is computed by using equation (7). If a pixel is in middle of a "flat patch" area then its value becomes the average of neighborhood pixels and if a pixel is in middle of a "high variance" area then its value is unchanged. This shows an edge preserving property of guided filter.

1.1 Guided filter algorithm

1. Read the image say I (color image) which acts as the guidance image.
2. Take p=I, where p is filtering image (color image).
3. Take the values for r and ε where r is radius of window and ε is regularization parameter.
4. Compute following mean values by applying averaging filter 'fmean': meanI = fmean(I) meanp = fmean(p) meanIp = fmean(I .* p) meanII = fmean(I .* I)
5. Compute covariance of (I,p) using formula: covIp = meanIp –meanI.* meanp
6. Compute variance using formula: varI = meanII –meanI.* meanI
7. Compute linear coefficients a and b as: a = covIp/ (varI + ε) b = meanp – a .* meanI
8. Compute mean of a and b as: meana = fmean(a) meanb = fmean(b)
9. Compute filtered output as: q = meana .* I + meanb

Block diagram

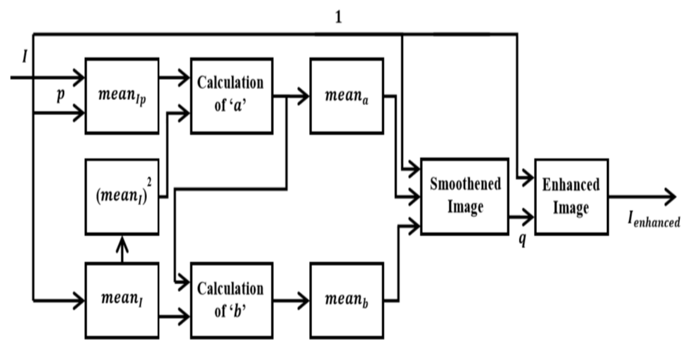

Fig. 5. Internal block diagram of guided filter block

Working

The data received in the input buffer is then used for detail enhancement by using guided filter. Based on the guided filter algorithm which is explained in section III, guided filter block gives the enhanced image as shown in Fig.
Guided filter block is applied separately on three different channels R, G and B. For detail enhancement application, input image p is used as guidance image. Guided filter takes input image from input buffer. The meanI block calculates mean of guidance image I. Mean of (I*p) is obtained by using meanIp block. In this block product of I and p is calculated and then its mean is calculated. The (meanI)2 block computes the square of mean of I by using output of meanI block. The calculation of 'a' block gives value of 'a' by using meanIp, (meanI)2 and ε values as per equation (3). The calculation of 'b' block gives value of 'b' by using a andmeanI values as per equation (4). The meana and meanb blocks are used for calculation of mean of a and mean of b respectively. Smoothened Image block is utilized to obtain smoothened image by using meana, meanb and I values as specified in equation (7). Then enhanced image is obtained by using the formula which is given as:
$Ienhanced = (I - q) * 4 + q$
The enhanced image is then stored into the output buffer's shared memory. Shared memory read interface is used to read data from output buffer for displaying it on display device.

ESTIMATED PARAMETERS:

Here we have estimated the amount of noise by the following parameters which fetches us effective analysis, through which we can easily say how much noise is present in an image.

1) Standard deviation;

The standard deviation (SD), also represented by the Greek letter sigma σ or *s*) is a measure that is used to quantify the amount of variation or dispersion of a set of data values.[1] A standard deviation close to 0 indicates that the data points tend to

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be very close to the mean(also called the expected value) of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values.

The standard deviation of a random variable, statistical population, data set, or probability distribution is the square root of its variance. It is algebraically simpler, though in practice less robust, than the average absolute deviation A useful property of the standard deviation is that, unlike the variance, it is expressed in the same units as the data. There are also other measures of deviation from the norm, including me

an absolute deviation, which provide different mathematical properties from standard deviation.

Original Image Image with Noise

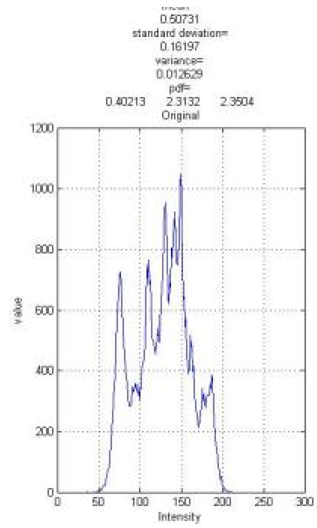
Denoised

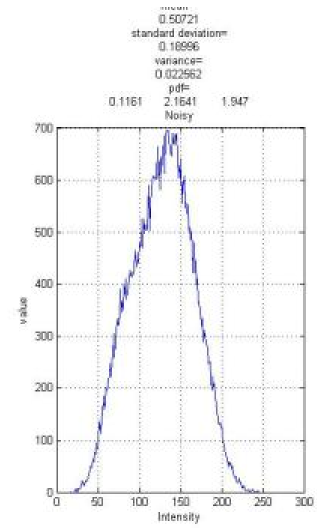
Relation between SD and noise:

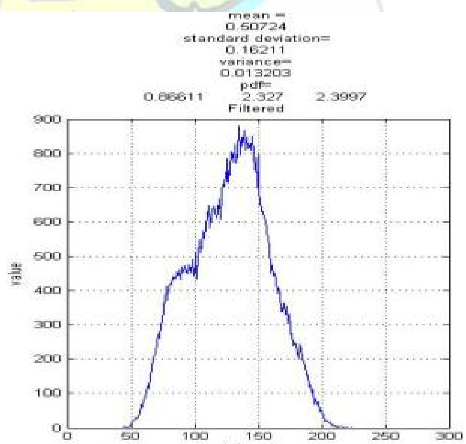
Signal-to-noise ratio (abbreviated **SNR** or *S/N*) is a measure used in science and engineering that compares the level of a desired signal to the level of background noise. It is defined as the ratio of signal power to the noise power, often expressed in decibels. A ratio higher than 1:1 (greater than 0 dB) indicates more signal than noise. While SNR is commonly quoted for electrical signals, it can be applied to any form of signal (such as isotope levels in an ice core or biochemical signaling between cells).

The signal-to-noise ratio, the bandwidth, and the channel capacity of a communication channel are connected by the Shannon–Hartley theorem.

Signal-to-noise ratio is sometimes used informally to refer to the ratio of useful information to false or irrelevant data in a conversation or exchange. For example, in online discussion forums and other online communities, off-topic posts and spam are regarded as "noise" that interferes with the "signal" of appropriate discussion







Signal-to-noise ratio is defined as the ratio of the power of a signal (meaningful information) and the power of background noise (unwanted signal):

$$\mathrm{SNR} = \frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}},$$

where *P* is average power. Both signal and noise power must be measured at the same or equivalent points in a system, and within the same system bandwidth.

If the variance of the signal and noise are known, and the signal is zero-mean

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$$\mathrm{SNR} = \frac{\sigma^2_{\mathrm{signal}}}{\sigma^2_{\mathrm{noise}}}.$$

If the signal and the noise are measured across the same impedance, then the SNR can be obtained by calculating the square of the amplitude ratio:

$$\mathrm{SNR} = \frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}} = \left(\frac{A_{\mathrm{signal}}}{A_{\mathrm{noise}}}\right)^2,$$

where *A* is root mean square (RMS) amplitude through this we can say, If the standard deviation is less the noise will be less. If the standard deviation is high the noise will be high. So the standard deviation is one of the essential factor for noise estimation

IV. Conclusion

We have shown our performance of noise estimation and denoising using guided filter technique.We shown our performance through the image and graph plot which above mention. Here we have using the standard image and also we analyze the noise using this techniques like Gaussian noise. The estimation of noise may be enhanced by studying fisher information matrix, least mean square error etc., which is in progress.

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