Image Restoration

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Abstract: Image restoration refers to the procedure of retrieving the original image by eliminating both noise and blur from the image. Image blurring is a challenge encountered in various scenarios, such as in photography, where motion blur can result from camera shake, or in radar imaging, where it may be induced by the image system's response. On the other hand, image noise represents unwanted signals that find their way into images through sensors like thermal or electrical signals and external factors like rain or snow. Researchers have put forth numerous approaches in addressing this issue, and in this paper, we will explore and engage in discussions pertaining to various noise and blur models as well as restoration methods.

Keywords: Real time, surveillance, pedestrian detection, Convolution Neural Networks.

1. Introduction

Image restoration involves The process of recovering the clean, original version of an image from a distorted or noisy state involves addressing various types of corruption, including effects like motion blur and noise, and camera misfocus. The process of image restoration involves reversing the distortions that led to image blurriness. This is accomplished by capturing an image of a point source and using the resultant image of the point source, referred to as the Point Spread Function (PSF), to retrieve the image details that were degraded as a result of the blurring. It's important to note that image restoration differs from image enhancement, which aims to highlight certain features in the image to make it more visually appealing to the viewer, without necessarily producing scientifically accurate data.

2. Digital Image Processing

Digital image processing involves the use of digital computers and algorithms to manipulate digital images. Situated within the domain of digital signal processing, it offers several benefits when compared to analog image processing. It grants the ability to employ a wider range of algorithms on the input data while also addressing concerns like the accumulation of noise and distortion during the processing phase. As images are characterized in two or more dimensions, digital image processing can be envisioned as a type of multidimensional system.

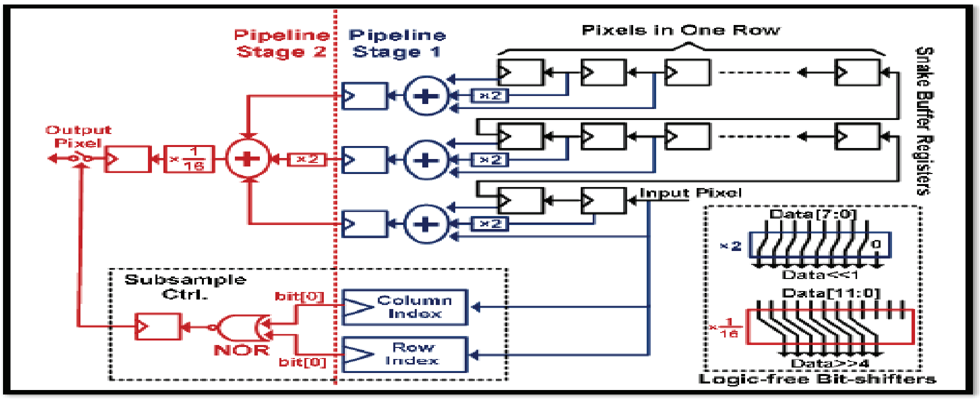
Three primary factors have a major impact on the development and advancement of digital image processing. Firstly, the advancement of computers plays a pivotal role. Secondly, the development of mathematics, particularly the creation and enhancement of The advancement of discrete mathematics theory plays a substantial role in promoting its development. Furthermore, its expansion is propelled by a growing demand for a wide range of applications spanning various fields such as environmental science, agriculture, military, industry, and medical science.

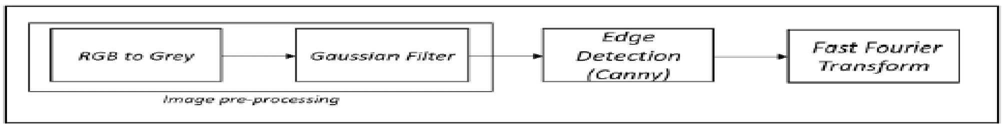
2.1. Gaussian Filtering

In the domain of electronics and signal processing, especially in the realm of digital signal processing, a Gaussian filter is distinguished by an impulse response that closely resembles a Gaussian function or a close approximation of it. It's worth noting that a genuine Gaussian response would result in an infinite impulse response. Gaussian filters possess distinct attributes, including the absence of overshooting when subjected to a step function input, all the while minimizing the time it takes for the signal to rise and fall. This behavior is intricately tied to the fact that Gaussian filters exhibit the smallest possible group delay. Essentially, a Gaussian filter offers an optimal balance between suppressing high-frequency components and minimizing spatial dispersion, which aligns with the fundamental principles of the uncertainty principle.

These attributes have considerable importance in a range of applications, such as in oscilloscopes and digital telecommunication systems. Additionally, a Gaussian filter functions as a low-pass filter, effectively attenuating noise, which corresponds to high-frequency components, and introducing a smoothing effect in specific parts of an image. Typically, it is realized as an asymmetric kernel with an odd size, which can be envisioned as a matrix within the realm of digital image processing. This kernel is applied to each pixel within the Region of Interest to achieve the intended filtering outcome.

Working Diagram of Gaussian filter





Results Of Gaussian Filter

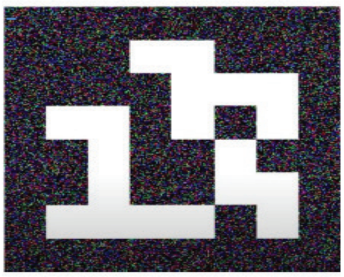


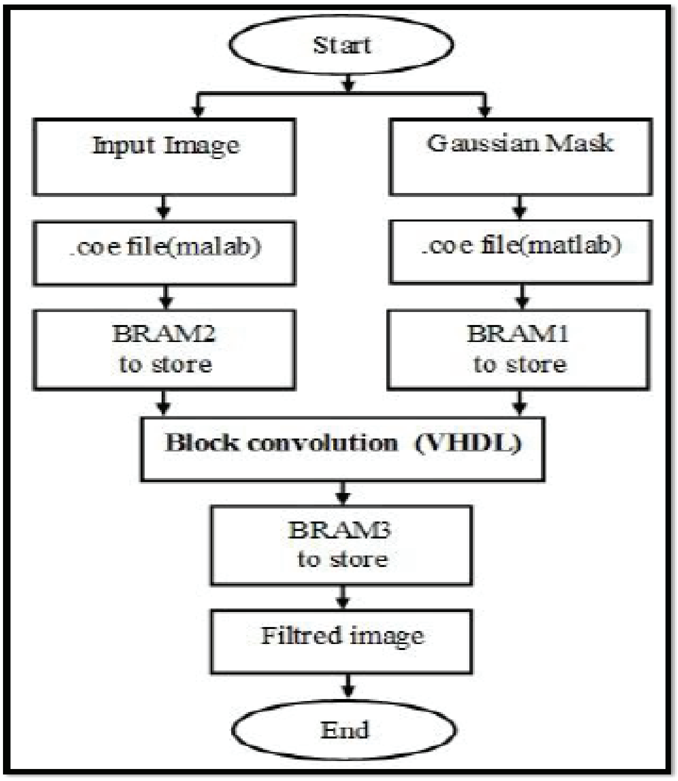
Fig.1

Fig.2

In this context, Figure 1 represents the initial noisy image, while Figure 2 illustrates the image subsequent to the application of a Gaussian filter. It is evident that the Gaussian filter effectively diminishes the noise, albeit at the cost of reducing the image's sharpness. To address this trade-off, a superior alternative in the form of the Bilateral Filter is available.

2.2. Dealing with a noisy image using LOG

The logarithmic transformation of an image is a grayscale image manipulation technique. When we apply a log transformation to an image, we substitute each pixel's original value with its corresponding logarithmic value. This log transformation is employed for image enhancement, primarily to amplify the brightness of darker pixels in the image in contrast to those with higher pixel values.



Block Diagram for Image Filtering

2.3. Bilateral Filtering

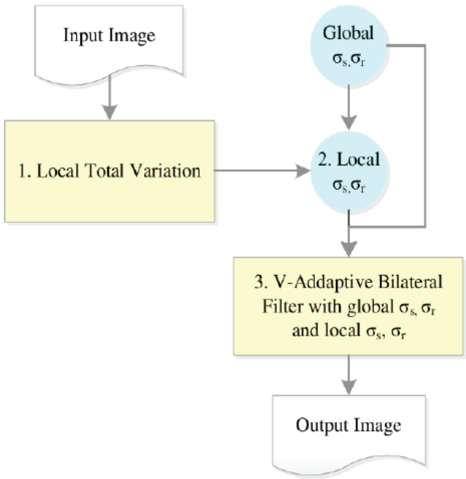
The Bilateral Filter is a filter designed for images that aims to provide non-linear processing, all while safeguarding the sharpness of edges and diminishing noise. It accomplishes this by substituting the intensity value of each pixel with a weighted average derived from the Pixel values in close proximity. These weights are typically derived from a Gaussian distribution. Importantly, the Bilateral Filter's weights consider not only the spatial separation between pixels (measured in Euclidean distance) but also the differences in radiometric properties, such as color intensity, depth, and more. This unique approach ensures that sharp edges within the image are retained.

2.4. Edge-preserving Filtering with the Bilateral Filter

The bilateral filter can be described as a weighted average of neighboring pixels, similar to the principles of Gaussian convolution. What distinguishes it is its capacity to consider variations in pixel values while preserving the sharpness of edges when performing the smoothing operation. Fundamentally, the bilateral filter functions based on the concept that for one pixel to influence another, they should not only be physically close but also share a degree of similarity in their values.

This concept has been established and explored in academic literature by various researchers, including Yaroslavsky, Aurich and Weule, Smith and Brady, as well as Tomasi and Manduchi.

The bilateral filter, represented as BF[·], is formally defined as follows:



Working Diagram of Bilateral Filter

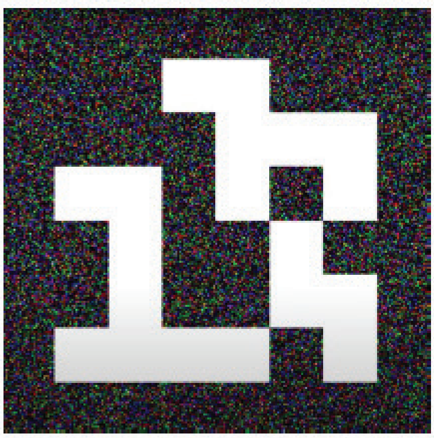


Fig.1

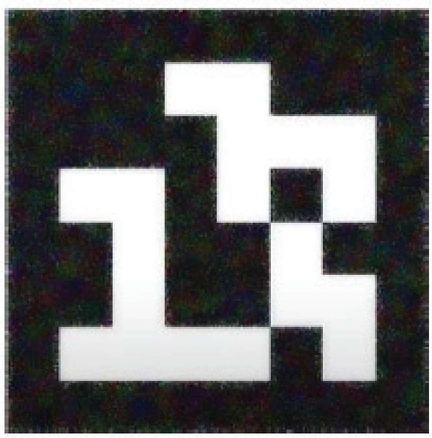


Fig.2

In this context, Figure 1 represents the original noisy image, while Figure 2 displays the image after the application of a Gaussian filter. As observed, the Gaussian filter effectively eliminates noise, yet it does not compromise the sharpness of the image, which is an advantage compared to Gaussian filtering.

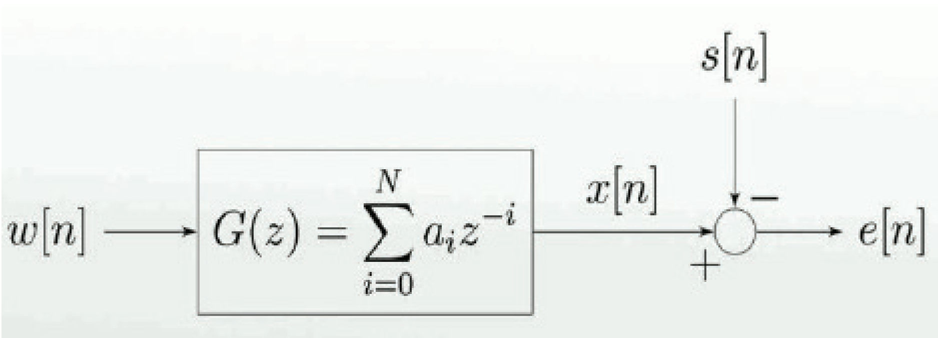
Bilateral filtering stands as an enhanced iteration of Gaussian blurring. While standard blurring operations tend to eliminate both noise and smooth edges, bilateral filtering distinguishes itself by retaining sharp edges while reducing noise. This is accomplished by incorporating Gaussian-distributed values that consider both the spatial separation between pixels and the differences in pixel values, resulting in a more sophisticated approach to reducing noise.

2.5. Deblur Images Using a Wiener Filter

The Wiener filter is recognized as the most effective stationary linear filter for minimizing Mean Square Error (MSE) in images affected by both additive noise and blurring. The computation of the Wiener filter relies on the assumption that both the signal and noise processes demonstrate second-order stationarity in the context of random processes. For the purpose of this explanation, we will focus on noise processes with a zero mean, which is a common and general assumption.

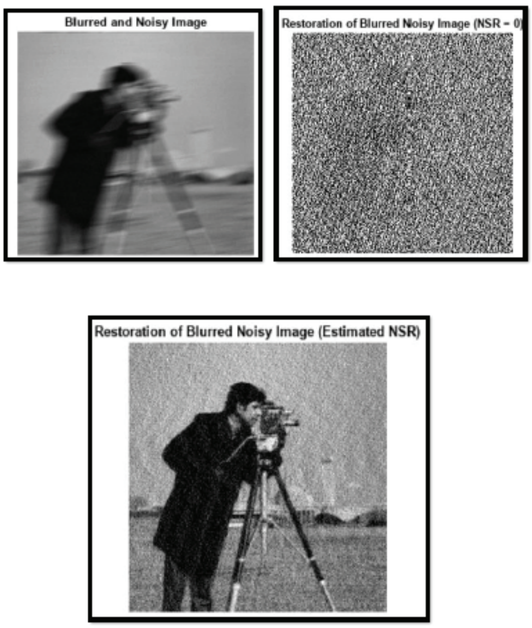
Typically, Wiener filters are employed in the frequency domain. To apply a Wiener filter, the process commences with a degraded image, denoted as x(n,m), and proceeds to calculate its Discrete Fourier Transform (DFT) to obtain X(u,v). The spectral characteristics of the original image are estimated by multiplying X(u,v) with the Wiener filter, represented as G(u,v):

$$\hat{S}(u,v) = G(u,v)X(u,v)$$



Working Diagram of Weiner Filter

Results of Weiner Filter



Results of Weiner Filter

Results of Weiner Filter

2.6. Advantage of Bilateral filtering over Gaussian Filtering

Bilateral Filtering can be seen as an improved iteration of Gaussian blurring since it goes beyond typical blurring methods, which often lead to not only noise reduction but also the blurring of distinct edges. In contrast, the bilateral filter excels in preserving the sharpness of edges while effectively eliminating noise. It achieves this by employing Gaussian-distributed values and simultaneously considering both the spatial distance between pixels and the differences in pixel values.

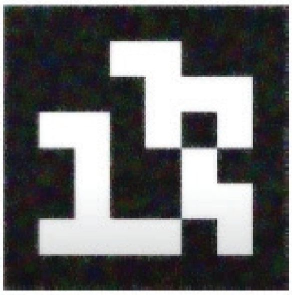


Fig.1

Fig.2

In this context, Figure 1 exhibits the outcome of the Bilateral Filter, while Figure 2 illustrates the result obtained using the Gaussian filter. It is evident that the Gaussian filter tends to excessively blur the image, leading to a loss of sharpness. Conversely, Bilateral filtering effectively maintains the sharpness of edges while primarily blurring the noisy regions and not impacting the edges.

3. Results

Numerous deblurring methods are available, and a comprehensive review of Diverse image deblurring techniques Suggested by various scholars has been conducted. The task of restoring or deblurring blurred images is known to be a challenging problem. Among the surveyed techniques, it has been determined that the Lucy and Wiener filters consistently yield superior results when compared to other methods. To further advance this research, neural networks are being explored as an additional approach to enhance these techniques.These conclusions are drawn from the evaluation of metrics such as Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR).

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