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IMAGE DE-BLURRING AND DE-NOISING USING WIENER -ANISOTROPIC DIFFUSION WITH NLM FILTER

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Abstract: Photographs are a common type of signal used in digital communication. Images are widely disseminated throughout many social media platforms. However, there are a variety of factors, such as compression methods and other variables, that might cause an uploaded image to become fuzzy and introduce noise into the picture. Methods for deblurring and denoising images are demonstrated using a Wiener filter, anisotropic diffusion filter, and non-local mean filter. The Wiener filter is a linear and time-invariant filter that is used to estimate a desired picture or random process from observations of noise. This is done on the assumption that the signal and noise spectra are stationary, and that the additive noise is also known. The most common application of non-local filters is noise reduction, namely the elimination of Gaussian and speckle noise. The probability density function of Gaussian noise is normally distributed, making it a type of statistical noise. Additive white noise is its most common application; when combined with other forms of additive white noise, it produces additive white Gaussian noise. There is an improving pattern in the MSE and PSNR measurements taken from the anisotropic diffusion technique with wiener filter and NLM filter.

Index Terms – NLM, Deblurring, Denoising, MATLAB, Image Processing

I. INTRODUCTION

Image processing is a practise that entails converting an image into digital format and then performing certain operations on it in order to create a better image or extract useful data. Picture processing seeks to improve or extract information from an image. The act of converting an analogue picture to its digital counterpart is another definition of "image processing." It is one of the technologies that is expanding rapidly in the modern world, and it has applications in a range of business-related fields [1-4]. This topic of study also contributes to the growth of the academic disciplines of engineering and computer science's core research domain. An image is a two-dimensional representation that has the same look as its subject, which is often a real-world object or a living person. Photography is the medium for creating pictures [5]. Images may be two-dimensional, such as photographs or screen displays, or three-dimensional, such as statues. Both forms of representations are regarded as examples of images. In this larger meaning, images may be formed manually, such as by drawing, painting, or carving; rendered mechanically, such as by printing or computer graphics technology; or constructed using a combination of techniques, as in the case of a pseudo-photograph. Drawing, painting, and carving are all instances of manual processes. Printing and computer graphics technologies are examples of automated processes. These tactics may be shown by examples such as: A pixel grid, which is a grid of squares, is used to generate a picture. It is possible to determine both its height and breadth based on its pixel count[6-8].

Blurring is the most common kind of image degradation that may be caused by everyday actions such as blurring the focus or shaking the camera. The human eye is especially sensitive to this form of picture deterioration. The previously discussed image enhancement techniques are incapable of resolving all blurring issues, which are often resolved by image deblurring techniques. The technique of eliminating blur from a picture is one of the most basic issues involved with image restoration, and it has attracted a great deal of academic interest [9].

Noise and blurring are the most typical forms of picture degradation seen in the field of short videos and public monitoring. There have been several advancements in the field of image restoration over the course of the previous few decades. Regularization technique, which entails adding suitable constraints to an originally ill-conditioned issue in order to make it more susceptible to image restoration, has been largely responsible for these developments. This technology has enabled the great bulk of these advancements. The TV regularisation approach and the wavelet-based regularisation method are examples of regularisation techniques. The performance of the image denoising method tends to approach its limit, in contrast to the problems associated with many other types of image restoration [10].

Image restoration in the presence of Poisson noise is crucial for a broad variety of applications, such as astronomical observation, medical imaging, and similar applications [11,12]. Different from additive noise such as Gaussian noise or salt and pepper noise, Poisson noise is a signal-dependent noise. As a result, the value of each pixel is subject to a Poisson distribution, and the mean of the Poisson distribution is equal to the noise-free picture value at that pixel. The value of the noiseless image at a pixel is equal to the pixel's value. This indicates that a Poisson distribution is being applied to each pixel's stored value. As a result, the intensity of the Poisson noise, also known as the peak value, is commonly characterised using the pixel value that corresponds to the greatest possible value inside a picture. When examining the peak value, a bigger value suggests less noise intensity, whilst a lower value indicates the reverse. Even the process of picture restoration using Poisson noise becomes more difficult to execute as blurring develops [13]. This occurs when, for instance, a patient is undergoing a medical imaging procedure and the subject moves, causing the blur effect to occur. This might also occur if the individual is attempting to avoid being photographed during the process [14-16].

When there is little available light, it may be difficult to take photographs with your hands. Since there is less available light, longer exposure periods are required; nevertheless, without a tripod, the camera is more prone to wobble, resulting in poor images. By increasing the camera's light sensitivity, which is more often referred to as utilising a higher ISO setting, the exposure time may be shortened, which is of tremendous assistance [17]. In contrast, this will increase the overall amount of background noise. In addition, this is often insufficient, and the exposure time remains too lengthy for handheld photography; as a result, many of the taken images are blurry and noisy. In recent decades, several possible solutions to the problem of camera shaking have been presented; nevertheless, the bulk of these solutions depend on the lack of background noise. In the course of our study, we do not make this assumption; rather, our goal is to produce a clear picture from one that was initially foggy and noisy[18].

In recent years, High Dynamic Range Imaging, sometimes known as HDR Imaging, has been an important subject of study in the fields of vision and graphics. Debevec and Malik, whose work in the field is now well-known in the industry, were the ones who devised the method of creating an HDR image by combining a number of photographs with varying exposures. This method is most successful when used to earlier digital camera models, which typically have an analog-to-digital conversion with a resolution of just 8 bits (ADC). The majority of digital single-lens reflex (DSLR) cameras and machine vision cameras on the market today are equipped with a higher-resolution analog-to-digital converter. The Canon EOS 7D and the Point Grey Grasshopper both have ADCs with 14 bits, whereas the vast majority of other cameras have ADCs with at least 12 bits. Using modern cameras equipped with high-resolution analogue-to-digital converters, we present a practical method for extending the dynamic range of HDR photography in this article. This method is made feasible by the use of HDR photography [19-20].

II. IMPLEMENTATION

The suggested approach explains how to deblur and denoise pictures using a Wiener filter in conjunction with an anisotropic diffusion filter that utilises the NLM filter. The Wiener filter is intended to reduce the mean square error between the estimated random process and the planned process as much as possible. Using a technique based on components separation and wavelet reduction, it also removes Gaussian noise from pictures. This ensures that no information is lost while the image's quality is maintained.

When we blur a picture, we simply blur the image. If we can exactly identify every item and its form inside a shot, the image will seem more clear and distinct. When we can discern facial characteristics such as the eyes, ears, nose, mouth, and forehead, we perceive a picture of a face to be distinct. The edges of an item contribute to the formation of its shape. To blur an image, reduce the amount of information at the image's borders and ensure that the transition from one colour to the next is relatively smooth.

Using the non-local means procedure, the value of a pixel is replaced with the average of the values of a selection of other pixels. Small patches centred on other pixels are compared to the patch centred on the pixel of interest, and the average is determined solely for pixels with patches that are near to the present patch. As a result, the approach is able to maintain textures that would become fuzzy if handled by a different denoising algorithm.

Widespread application of the non-local mean filtering approach has been seen in the denoising of both natural and medical images (NLM). The NLM filter utilises the redundant information available in the target image to identify the underlying structures and signals from the noise. This redundant data may take the form of repeated patterns or textures.

In signal processing, the Wiener filter is used to estimate a desired or target random process via linear time-invariant (LTI) filtering of an observed noisy process. Under the premise that stationary signal and noise spectra as well as additive noise are known, this is performed. The Wiener filter is meant to decrease the mean square error as much as feasible when comparing the estimated random process to the planned process.

The Wiener filter is meant to perform the job of generating a statistical estimate of an unknown signal by accepting as input a signal that is related to the unknown signal and then filtering the known signal to get the estimate. For example, the known signal may be a previously unknown signal of interest that has been contaminated by additive noise. Thus, the transmission would become unreliable. To acquire an estimate of the signal of interest that lies underneath the damaged signal, the Wiener filter may be used to eliminate the noise caused by the signal corruption. The Wiener filter is based on a statistical approach, and an article named "minimum mean square error estimator" (MMSE estimator article) offers a more accurate statistical explanation of the concept.

Throughout the design phase, the frequency response of a typical deterministic filter is optimised. The Wiener filter, on the other hand, is developed with a distinct technique in mind. It is assumed that the individual is acquainted with the spectral properties of both the original signal and the noise. Next, one looks for a linear time-invariant filter whose output is as physically close to the original signal as possible. Listed below are criteria that identify Wiener filters:

1. It is assumed that both the signal and (additive) noise are stationary linear stochastic processes with established spectral characteristics, autocorrelation, and cross-correlation.
2. Prerequisite: the filter must be realisable or induced by the real world (this requirement can be dropped, resulting in a non-causal solution)
3. Performance criterion: minimum mean-square error (MMSE).

Anisotropic diffusion is a method used in image processing and computer vision to minimise visual noise without destroying substantial image information. Typically, these key aspects of the image's content include borders, lines, or other characteristics that are essential to the image's interpretation. Perona–Malik diffusion is another name for anisotropic diffusion. The creation of a scale space is analogous to anisotropic diffusion. Based on a diffusion process, one picture is used to produce a parameterized family of ever blurrier images. Each of the final pictures generated by this family is represented as the convolution between the original image and a 2D isotropic Gaussian filter, with the filter's width growing as the parameter is raised. This type of diffusion produces an image that has undergone a linear and space-invariant alteration. This diffusion mechanism is generalised by anisotropic diffusion. Each final picture is a mix of the original image and a filter that is depending on the local content of the original image. A family of parameterized pictures is generated using anisotropic diffusion. As a direct result of this, anisotropic diffusion is a nonlinear and space-variant change of the starting picture.

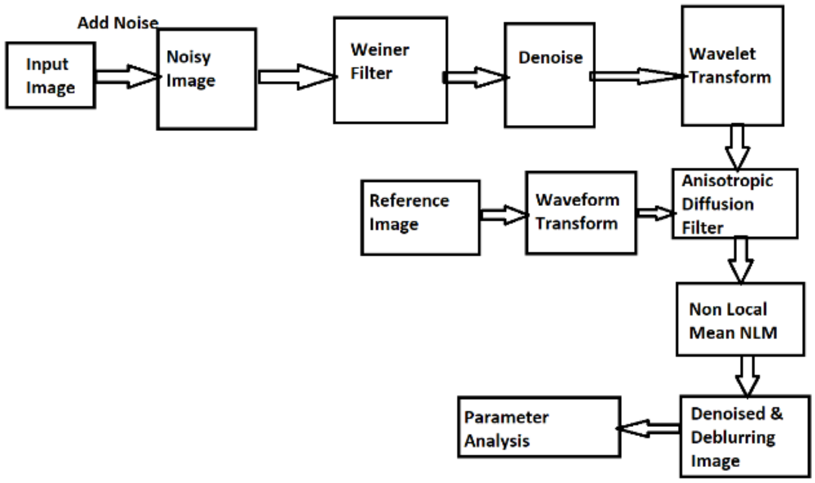

Fig. 1 Block Diagram

The block diagram of image denoising and deblurring using a Wiener filter, Wavelet transform, and Anisotropic Diffusion Filter in conjunction with the NLM Filter is displayed in Fig. 1.

III. Results

This section shows the implementation result outputs.

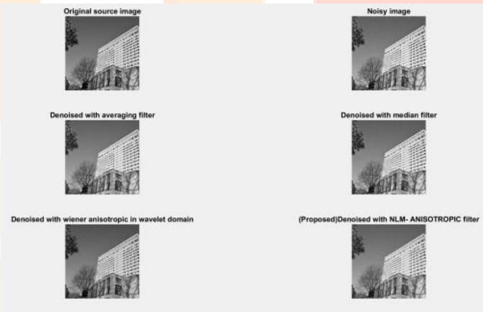

Fig. 2: Image 1 Output

Fig. 2 shows output for image 1, and Fig. 3 and Fig. 4 show better PSNR and MSE in proposed method.

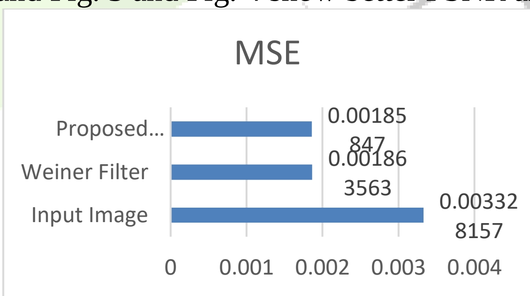

Fig. 3: MSE Input Image 1

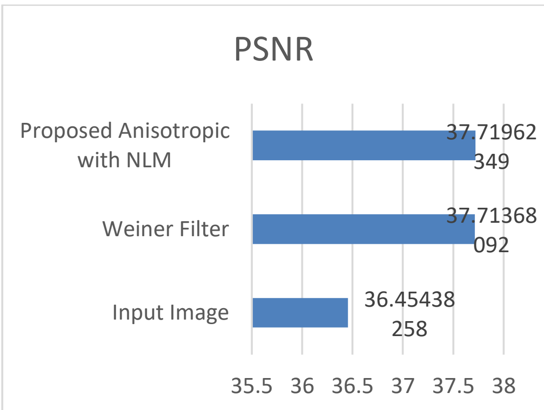

Fig. 4: PSNR Input Image 1

Fig. 5 Input Image 2 Output

Fig. 5 displays the results obtained for picture 2, and Figures 4.6 and 4.7 illustrate how the suggested technique achieves superior PSNR and MSE values.

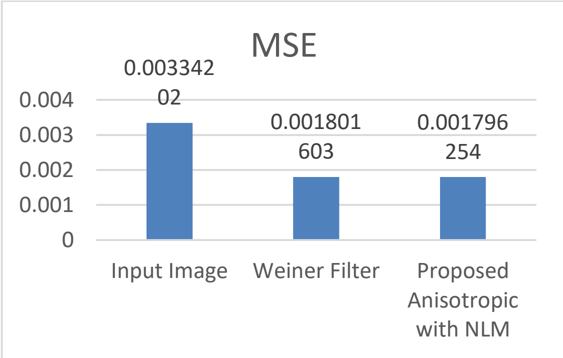

Fig. 6: MSE Input Image 2

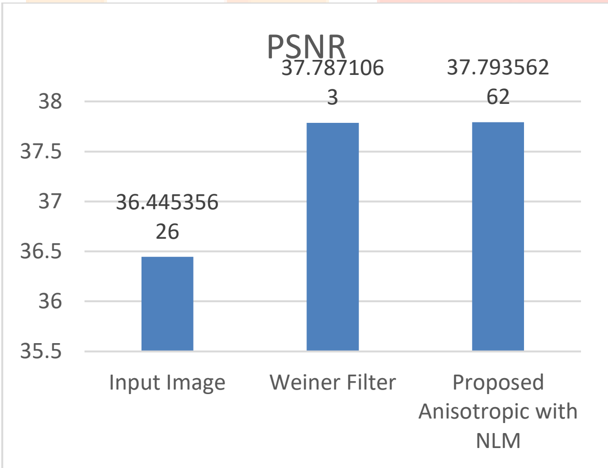

Fig. 7: PSNR Input Image 2

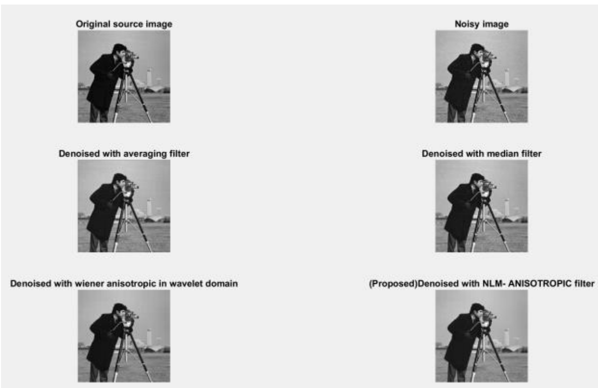

Fig. 8 Input Image 3 Output

The findings that were obtained for image 3 are shown in Fig. 8, and Figures 4.9 and 4.10 show how the recommended approach generates improved PSNR and MSE values.

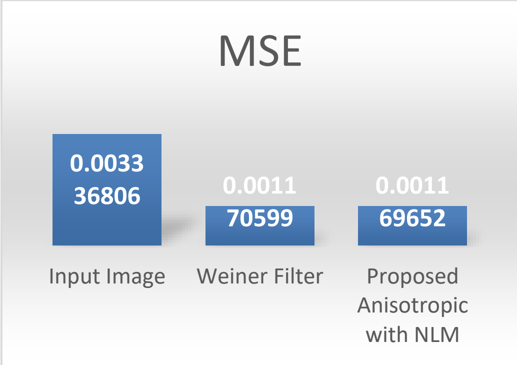

Fig. 9: MSE Input Image 3

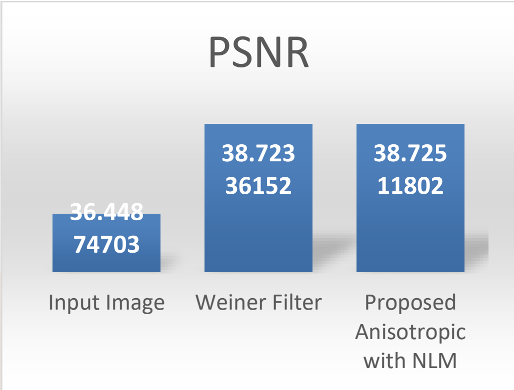

Fig. 10: PSNR Input Image 3

Fig. 11 Input Image 4 Output

The results that were obtained for picture 4 are shown in Fig. 11, and Figures 4.12 and 4.13 demonstrate how the strategy that was proposed yields better PSNR and MSE values respectively.

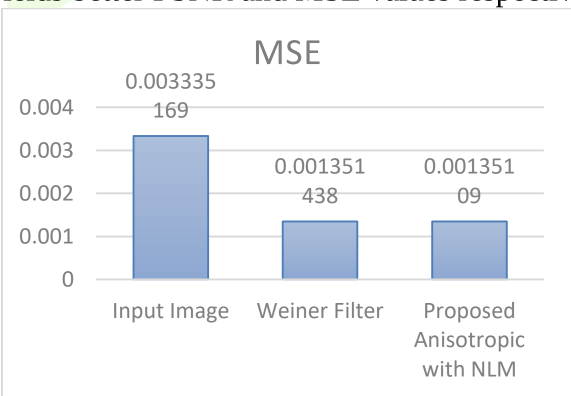

Fig. 12: MSE Input Image 4

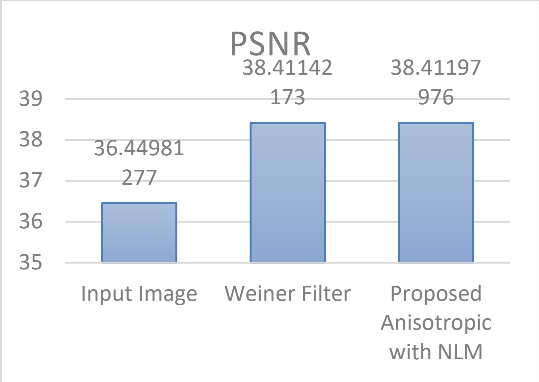

Fig. 13: PSNR Input Image 4

The tabular results are given in table 1, shows better proposed method anisotropic with NLM outputs.

Table 1: Results Comparison

Image 1	Input Image	Weiner Filter	Proposed Anisotropic with NLM
MSE	0.003328157	0.001863563	0.00185847
PSNR	36.45438258	37.71368092	37.71962349
Image 2	Input Image	Weiner Filter	Proposed Anisotropic with NLM
MSE	0.00334202	0.001801603	0.001796254
PSNR	36.44535626	37.7871063	37.79356262
Image 3	Input Image	Weiner Filter	Proposed Anisotropic with NLM
MSE	0.003336806	0.001170599	0.001169652
PSNR	36.44874703	38.72336152	38.72511802
Image 4	Input Image	Weiner Filter	Proposed Anisotropic with NLM
MSE	0.003335169	0.001351438	0.00135109
PSNR	36.44981277	38.41142173	38.41197976

IV. Conclusion

Using a Wiener filter in conjunction with an anisotropic diffusion filter that combines with a non-local mean filter, the suggested approach efficiently deblurs and denoises photos. The basic purpose of the Wiener filter is to estimate a desired image or random process by linearly and time-invariantly filtering an observed noisy process. This is performed by targeting a random process using the Wiener filter. To do this, it is required to assume that the stationary signal and noise spectra, as well as the additive noise spectrum, are already known. It is well accepted that the non-local means (NLM) noise reduction algorithm is an effective method for decreasing noise in magnetic resonance (MR) images in order to improve diagnostic accuracy. This is achieved by using a mix of several strategies. Within the purpose of this study, a thorough literature search was conducted to assess the performance of the NLM noise reduction approach in MR imaging. Using the Wiener filter in conjunction with the NLM Filter, the wavelet transform, and anisotropic diffusion, the original image was cleaned up and sharpened, resulting in a realistic depiction of the original. The picture attributes are scrutinised with great accuracy.

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