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RESEARCH ARTICLE

Comparative Analysis of Non-Local Means and Hybrid Median Bilateral Filtering for Mobile Image Denoising

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Abstract: Image denoising is an important step in many computer vision applications, including but not limited to intelligent transportation systems, mobile robotics, remote sensing, autonomous driving, and surveillance. In wearable devices such as smart glasses, wearable health monitoring devices, and other body-mounted devices, the image quality suffers due to non-uniform illumination, motion, occlusions, etc. The image denoising is required prior to image analysis for many computer vision tasks. Many computer vision algorithms perform well when the images are captured using high-resolution cameras under controlled conditions. However, the performance of these methods degrades when images are captured using low-resolution mobile phone cameras or when the images suffer from environmental noise. The images captured using mobile phones act as a proxy for many wearable devices to a reasonable extent because of the similarity in the size of sensors used and the imaging conditions. In this paper, the images captured by a mobile phone are subjected to Gaussian noise. Two different methods, namely, the non-local means denoising method and the hybrid median bilateral method, are used for denoising the images. The performance evaluation of the two methods is done using metrics, namely, peak signal-to-noise ratio and structural similarity index. It is observed that the non-local means denoising method performs better than the hybrid median bilateral denoising method. The method is useful in many image analysis tasks for images captured with smart wearable devices.

Keywords: image denoising, hybrid filtering, PSNR, SSIM, non-local denoising

1. Introduction

A digital image is buried with noise due to several factors. These factors may be internal or external factors. The noise can enter a digital image during acquisition, transmission, or data processing. One of the major causes of noise in an image is sensor noise. The sensor noise may be thermal noise, which occurs due to heat produced in sensors. Another form of sensor noise is shot noise, which arises due to the random movement of photons in the sensor. The electrical disturbance occurring near the camera may introduce noise in the digital image. During transmission of images over a network, missing data may cause noise in the image. Environmental factors such as fog and rain also contribute to noise in digital images. Denoising is an important preprocessing step in computer vision algorithms as the performance of many sophisticated models relies on the input data. Many object detection methods suffer in low-resolution scenarios, giving degraded performance in tasks such as road object detection in intelligent transportation systems.

The various image denoising methods are used for denoising the images depending on the type of image and the type of noise. The enhancement of social media images is done using frequency-based methods in [1]. The PET images are denoised using a non-local mean filter in [2]. The method performed better than the conventional denoising methods in terms of Signal-to-Noise Ratio (SNR). The performance of the method is compared to traditional denoising methods using mean squared error (MSE) and peak signal-to-noise ratio (PSNR). The non-local means filter is used for denoising, and PSNR is evaluated in [3]. The denoising for multispectral images is done using a method that combines non-local rank tensor decomposition with a bilateral filter in [4]. The denoising of ultrasound images using the modified Perona–Malik model is discussed in [5]. The evaluation metrics used are PSNR and structural similarity index (SSIM). The combination of median filter, bilateral filter, and Gaussian filter is used for denoising images in [6]. The method is evaluated with the BSDS500 dataset images using performance metrics PSNR and SSIM. A review of various denoising techniques based on traditional methods and deep learning techniques is done in [7]. The images used are X-ray images, and the noise added to the images is Gaussian noise and Poisson noise. A framework for the removal of speckle noise in medical images is proposed in [8]. The performance method is evaluated with metrics PSNR and SSIM. A wavelet-based approach is used for denoising images in [9]. An inverse Gaussian filter is introduced for denoising images in [10]. The method outperforms many spatial domain methods in terms of PSNR and SSIM. The continuum topological

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derivative technique is used for denoising the MRI images, Gaussian noise, and Rayleigh noise in [11]. The non-local means filtering method for denoising medical images with varying noise levels is analyzed in [12]. The non-local means technique of denoising the MRI images and Computed Tomography images is done in [13]. A non-local means denoising combined with a feature extraction method is proposed in [14]. The performance of the method is evaluated with PSNR and SSIM. A deep-learning technique for denoising heritage images is used in [15]. The non-local means filtering is combined with histogram-based multi-thresholding for denoising images [16]. Spatial binary filtering is combined with wavelet thresholding for denoising medical images with Gaussian noise in [17]. The medical image denoising is done using deep residual networks in [18]. The evaluation of the method is done using PSNR and SSIM.

For wearable devices, such as smart glasses, smart watches, health monitoring devices, and other body-mounted devices, the cameras used are often small in size, which are prone to image deterioration due to non-uniform illumination, motion artifacts, and sensor noise [19]. The denoising methods for many computer vision tasks to work effectively need to be robust for images captured using smart wearable devices. The methods discussed in the paper are useful for denoising images captured by cameras used in smart wearable devices. The denoising of medical images is done in [20]. The method uses a three-stage approach, which combines adaptive Kalman filtering, followed by nonlinear means filtering, and then median filtering. The parameters of the filters are optimized to retain the diagnostic details in the images. The method is evaluated using performance metrics PSNR and SSIM. A Field-Programmable Gate Array (FPGA)-based filter is implemented for image denoising for embedded system applications in [21]. The method is reconfigurable to adapt to the dynamic imaging conditions. The noisy pixels are detected in the image using AI techniques and are replaced for image denoising. The noisy pixels are considered for processing instead of considering all the image pixels in order to save computational cost. A deep learning model for the recognition of bionic hand movements is discussed in [22]. The method tackles the problem of image recognition due to noise captured in biosignals. Signal denoising is achieved using a gradient-enhanced bilateral median filter. The segmentation of biosignals is achieved using modifies UNet3++ model. The model efficiency is improved using an AI-based optimization technique. A virtual assistant system for visually impaired people is proposed in [23] to recognize patterns in fabric. A bilateral filter is used for image denoising, and histogram equalization is used for contrast enhancement. The pattern classification is done using a hybrid Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN)-based deep learning model. The motion artifacts are removed from smartwatch photoplethysmography data in [24]. The method uses a convolutional denoising autoencoder for reconstructing clean data from noisy data. Image denoising in Wireless Sensor Network (WSN) is discussed in [25]. The method reduces noise in an image while preserving the fine details in the image. The method uses a fast non-local means filtering technique along with a wavelet-based denoising technique. A spatial field binary filter is used for image denoising in [26]. The method is tested on various types of images such as MRI, ultrasound, and X-ray images. The performance of the method is evaluated using PSNR and MSE. The denoising of medical images using a deep learning model is done in [27]. A vectorial total variation method is used for refining image quality. The noisy images exist not only in medical image datasets but also in the agriculture domain, where images are captured using unmanned aerial vehicles. The deep learning–based denoising methods require high computational power, which may not be suitable for many real-time applications on mobile or wearable devices. Therefore, in this study, the filtering methods such as non-local means, median, and bilateral filtering techniques, which require less computational power for noise removal, are used. The paper is organized as follows. The methodology is given in Section 2. The experimental results and discussion are given in Section 3. Section 4 concludes the work.

2. Methodology

A digital image I captured by a camera often suffers from various types of noise, which degrades the image quality. It occurs during the image acquisition by the digital camera in a mobile phone or one mounted on a smart wearable device. The image degradation also occurs during image transmission. The noise is introduced in a digital image due to several factors such as the nonlinear behavior of various components of the imaging device, electronic fluctuations, environmental factors, etc. Out of many noise models, the Gaussian noise model is commonly used in image analysis as Gaussian noise is commonly introduced in the digital image, which causes image degradation. A digital image I when deteriorated with Gaussian noise N having mean value of zero with standard deviation σ, a noisy image I_n is obtained as given in equation 1.

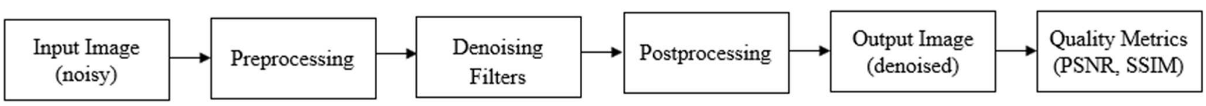
$$I_n = I + N(0,\ \sigma^2) \tag{1}$$

The noise strength is defined by the standard deviation. The fine details in the image are blurred in the presence of Gaussian noise. The block diagram of the image denoising framework is given in Figure 1. In the absence of fine details contained in an image, object detection becomes a challenging task in computer vision algorithms. The noise is introduced during image acquisition by the imaging system. The algorithm for denoising the image is given in Algorithm 1.

Algorithm 1: Image Denoising

Read input image I
Apply non-local means filtering with the following parameters:
    Patch size = 7 × 7
    Search window = 21 × 21
    Filtering parameter h = 10
Apply a median filter of window size 3 × 3

Figure 1
Block diagram of the image denoising framework



7: Apply a bilateral filter with parameters:
8: $\sigma_{spatial} = 3$
9: Return denoised image D

2.1. Non-local means denoising

The non-local means denoising method eliminates noise in a digital image based on the concept that similar image patches are not present locally in the image but at different locations in the image [28]. It works by extracting image patches around every pixel in the image. A search window is used to search for similar patches in the image. The weights are assigned based on how similar patches are in the image [29]. All the patches that are similar are used to calculate the new pixel value. The non-local means denoising method can mathematically be represented using equation 2:

$$\hat{I}(x) = \sum_{i \in \Omega} w(x, i) I_n(i) \tag{2}$$

where w(x, i) is the weight based on the similarity of patches in the image. The focus of this study is on algorithmic behavior and not on the deployment. The computational cost of non-local means filtering can be estimated in terms of memory complexity. It has complexity of $O(N \cdot P^2 \cdot W^2)$, where N is the number of pixels, P is the patch size, and W is the size of the search window.

2.2. Median and bilateral filter

The median filter used for denoising is a filter that is nonlinear filter, which replaces the pixel of an image by its median value calculated from the pixel values of neighborhood pixels to that pixel [30]. A window of size 3 × 3 or 5 × 5 is usually taken for the purpose. The median filtering technique is commonly used for removing the salt and pepper noise [31]. Bilateral filters are also nonlinear filters that smooth an image. A bilateral filter is a filter that combines two Gaussian filters. One filter is in the spatial domain, and another is in the intensity domain [32]. A bilateral filter is commonly used for denoising images with Gaussian noise. In this work, median filtering is applied, followed by bilateral filtering as given in equation 3:

$$\hat{I}(x) = \frac{1}{W} \sum_{i \in \Omega} G_s(||x - i||) G_r(|I_m(x) - I_m(i)|) I_m(i) \tag{3}$$

where I_m is the median of $I_n$and G_s and G_r are the spatial and range Gaussian functions, respectively. Given h as the filtering parameter, i indexing pixels in the search window of x, and W(x) as the normalization constant, the non-local means weight function w(x, i) is defined in equation 4.

$$w(x, i) = \frac{1}{W(x)} \exp\left(-\frac{||I_m(x) - I_m(i)||^2}{h^2}\right) \tag{4}$$

3. Experimental Results and Discussion

An experimental evaluation is performed to evaluate the performance of non-local means filtering and hybrid median bilateral filtering for denoising the images captured using a mobile phone. The images captured by mobile phones and the noise introduced are similar to those of smart wearable devices as the sensors used in both cases are small in size and sensor characteristics are also usually similar. The original image captured using a mobile phone is shown in Figure 2. The image is of size 389 × 405 pixels. The images captured with a mobile phone for experiments resemble the images captured with cameras mounted on smart wearable devices. The noise present in the captured images is similar to that present in images captured with smart wearable devices due to the similarity of sensor characteristics. The images are subjected to Gaussian noise, which deteriorates the clean image. The Gaussian noise N of zero mean and $\sigma = 0.05$ standard deviation is added to image I. This noise is similar to the noise that is added to images captured by cameras mounted on smart wearable devices. The non-local mean filtering is applied to the noisy image. The method works on self-similarity, in which each pixel of the image is replaced by a weighted average of pixel intensities in the similar patches occurring in the search window. The weight assigned depends on the structural and texture information in the search window. All experiments were implemented in Python using OpenCV on a Windows-based system with an Intel i7 processor and 16 GB RAM.

Figure 2
Original image

The addition of noise is done to the original image. The noisy image is shown in Figure 3.

The non-local mean filtering is applied to the noisy image. The image after denoising is shown in Figure 4.

The output image after applying non-local means filtering preserves the edge information while reducing the noise. The texture information is also retained in the output image. The noisy image is also given to a hybrid median bilateral filter, and the denoised image obtained using this method is shown in Figure 5.

The method combines median filtering with bilateral filtering for denoising images. The median filtering is robust to impulsive noise, while the bilateral filtering preserves the edges. The output image reduces the noise, but the texture information is lost to some extent. The evaluation of the two methods for denoising the images is done using assessment metrics commonly used for image denoising methods.

Figure 3
Noisy image

Figure 4
Non-local means filtering

The parameter settings used in the experiments are given in Table 1. The objective of this experiment is to illustrate the qualitative behavior of different denoising filters and not to provide large-scale statistical benchmarking.

Quality Metrics: The PSNR and SSIM were used to evaluate denoising performance. PSNR was calculated as given in equation 5:

$$PSNR = 10 \cdot \log_{10}\left(\frac{L^2}{MSE}\right) \tag{5}$$

where L is the dynamic range of pixel values and MSE is the mean squared error between the denoised and reference images. The PSNR and SSIM are evaluated for both methods, namely, non-local mean filtering and hybrid median bilateral filtering. PSNR gives an estimate of reconstruction fidelity for input and denoised image pixel intensities. SSIM considers structural information in the images. A comparison of the two methods is given in Table 2.

Figure 5
Hybrid median bilateral filtering

Table 1
Parameters

Method	Parameter	Value
Non-local means	Patch size	7×7
Median filtering	Window size	3×3
Bilateral filtering	σ spatial	3

From Table 2, it is observed that the non-local median filtering performs better, giving a higher PSNR than hybrid median bilateral filtering. It can be said that the non-local median filtering method removes noise from mobile phone cameras better than the hybrid median bilateral filtering method. The same can also be stated for images captured using cameras mounted on smart wearable devices due to the similarity in the cameras used. Apart from the image quality of the denoised image for smart wearable devices, the processing time is also an important aspect. As a nonlinear median filtering method works by considering patches

Table 2
Performance comparison of non-local mean filtering and hybrid median bilateral filtering

Method	PSNR (dB)	SSIM	No. of images, trials
Non-local mean filtering	9.13	0.43	1 image, 3 trials
Hybrid median bilateral filtering	8.84	0.34	1 image, 3 trials

in the image, the method may be computationally expensive. The optimization of nonlinear median filtering may be adopted for real-time image denoising in smart wearable devices. The PSNR values are low because the experiment was performed on small, single-instance data to illustrate qualitative differences between filters. The mean and standard deviation values can be reported with larger datasets for statistical generalization. As the objective of this paper is to compare the performance of different filtering techniques rather than performing large-scale benchmarking, the denoising methods such as BM3D, wavelet-based denoising, and deep learning–based approaches are not used.

4. Conclusion

The denoising of images captured by a phone is done using two methods, namely, non-local mean filtering and hybrid median bilateral filtering. The original image is subjected to Gaussian noise. The noisy image is denoised using two methods. The performance of both methods is compared by evaluation metrics PSNR and SSIM. It is observed that non-local mean filtering performs better than the hybrid median bilateral filtering method in terms of PSNR and SSIM. Due to the similarity of images captured by mobile phones and those captured by smart wearable devices, non-local filtering methods could be an effective preprocessing method for image analysis in smart wearable devices. The lightweight AI models can be combined with non-local means filtering for real-time deployment in mobile devices.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Ashwani Kumar Aggarwal: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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