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Hybrid Smoothing and Sharpening Filters Using the Spatial Domain: Literature Review

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***Abstract* - This study explores the field of image processing, emphasizing the difficulty presented by exterior artefacts on film, such as scratches, bruises, and cracks. Due to the limitations of mathematical analysis, unlike homogeneous noise, the shape and location of these faults must be determined manually during picture processing. The tight balance between retaining minute details and removing undesirable effects like noise makes the search for a universal filtering algorithm ongoing. The proposed work presents the enhancing through removing noises by applying proposed smoothing technique in order to eliminate these noises, this step leads to the blurring case, so for removing this blurring case, the output of this step is considered as an input to the next step through applying a proposed sharpening algorithm in the field of spatial domain, the final step is grouping all the processed frames for retrieving the processed video segment, in order to measure the performance of the proposed work, we compare the proposed work with others through some determined metrics.**

Keywords: Image Processing, Image Enhancement, Contrast Enhancement, Noise Reduction, Filtering Methods.

I. INTRODUCTION

In the realm of image processing, the presence of external artifacts, such as cracks, scratches, and bruises on film, poses a unique challenge. Unlike noise with a uniform structure, the determination of the shape and location of these defects often exceeds the capabilities of mathematical analysis. Consequently, manual image processing becomes a necessity to address these non-uniform artifacts, a consideration that lies beyond the scope of the present work [1].

While numerous methods exist for removing noise from images, ranging from specialized processing programs to applications in photo and video cameras [2], the quest for a universal filtering algorithm persists. The complexity arises from the inherent trade-offs in image processing – the delicate balance between preserving small details, such as size, and eliminating unwanted effects like noise. Even with a plethora of filtering algorithms, there is no one-size-fits-all solution, as the choice between detail preservation and noise elimination remains an ongoing challenge [3].

One fundamental approach to noise removal involves averaging pixel values over a spatial neighborhood. This concept relies on the cancellation of noise from adjacent pixels when added, given the individual variability of noise from pixel to pixel [4]. The process entails overlaying a rectangular window on each pixel, and the central pixel's value is determined by analyzing all neighboring pixels within the window area. Adjusting the size of the window directly impacts the degree of blurring, with larger windows resulting in more pronounced blurring effects [5].

In its simplest form, the analysis of neighboring pixels involves finding their arithmetic mean [6]. To mitigate the influence of pixels from different areas, a numerical threshold can be introduced, considering only the difference of neighbors within a certain limit. This threshold-driven approach allows for more nuanced noise reduction, particularly in scenarios with contrasting pixel values, such as dark outlines on light backgrounds. Moreover, introducing weighted coefficients for each neighboring pixel, based on their distance from the center of the considered area, enhances the sophistication of this method [7].

While this approach can extend into the time domain by averaging pixels over adjacent frames in a video stream, it often falls short of producing optimal results, leading to significant blurring of image details. Alternatively, the Gaussian filter operates on a similar principle of averaging pixels and their neighbors but introduces a Gaussian function to dictate the filtering process [8]. Unlike linear averaging filters, the Gaussian filter considers a region of a certain radius, selectively including points based on a predetermined value (threshold). This selective approach minimizes blurring in areas of sharp edges, preserving fine details while effectively reducing noise in the image [5]. Additionally, a low-pass filtering technique, such as applying a Gaussian filter to blur the original image, can yield an approximate representation of illumination [9].

In this exploration of noise removal techniques, the intricate balance between preserving image details and

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mitigating unwanted effects unfolds, offering insights into the nuanced world of image processing.

II. DIGITAL NOISE

Digital noise, often called picture noise or electronic noise, is a typical distortion seen in digital photos. It appears as erratic changes in color and brightness that are introduced during the image acquisition, transmission, or processing process rather than being innate to the scene being photographed. Numerous factors, such as sensor limits, ambient conditions, and electronic components, might cause this undesired interference. The effects of digital noise are more noticeable in low light or at higher ISO levels, which makes it more difficult to take detailed and crisp pictures [10].

Digital noise can severely impair the quality of photos or movies, so controlling it are essential to image processing. Diverse methods of noise reduction, including filtering algorithms and post-processing tools, are utilized to reduce digital noise while maintaining crucial features, guaranteeing the creation of accurate and aesthetically pleasing representations [11].

In the realm of image processing, "noise" refers to the arbitrary fluctuations in intensity levels that introduce interference to the visual data. An extra layer of unwanted information is applied to the pixels as a result of this phenomena, creating a noisy image. Because of the introduction of unnecessary information that distorts the true values of the pixels, some pixels in this context might not accurately represent the true values of the scene. Additive and multiplicative are the two basic mathematical models that are used to describe noise.

According to the additive noise concept, a noise signal that is additive is added to the original signal. The outcome of this process is the creation of a corrupted signal, which contributes to the overall loss of image fidelity by combining the original signal with the additive noise signal in a certain way [7].

$$w(x,y) = s(x,y) + n(x,y) \quad (1)$$

The multiplicative noise model is a unique method in which the original signal is multiplied by the noise signal. The multiplicative noise model adds variations by multiplying the original signal by the noise component, in contrast to additive noise, which is characterized by the addition of noise to the original signal.

The way the multiplicative noise signal interacts with the original signal is governed by a set of rules that this model follows. This multiplication process results in a distorted signal that captures the effects of both the doubled noise and the original information. Comprehending the workings of the multiplicative noise model is essential to the development of efficient image processing techniques that reduce noise and improve the overall precision and quality of the visual input.

$$w(x,y) = s(x,y) \times n(x,y) \quad (2)$$

When it comes to image processing, the original image's density is represented by the variable s(x, y), and the presence of a noisy and corrupted signal at a pixel location (x, y) is indicated by s(x, y). In the realm of image processing, noise is classified into several kinds; additive, multiplicative, and impulsive noise is prominent examples. One sort of noise in particular is called impulse noise, which is defined by pixel values changing randomly.

Within the imaging process, impulse noise is further classified into static and dynamic (random) noise in Figure 1, as illustrated in the discussion. By helping to differentiate between the various forms of impulse noise, this classification offers important information for creating strategies for reducing noise and improving the overall integrity and quality of the processed images. It is crucial to comprehend the nature and traits of different noise kinds in order to apply focused strategies to deal with particular issues related to image deterioration [7].

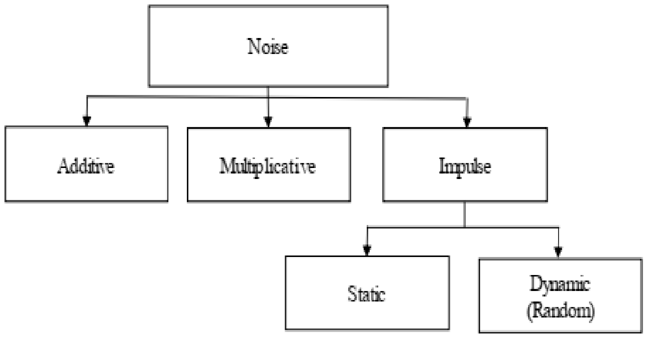

Figure 1: Noise in image processing

III. TYPE OF NOISE

Digital picture integrity and clarity can be jeopardized in the field of image processing by a variety of noise forms. Gaussian noise, impulse noise, poison noise, and speckle noise are four common forms of noise that are frequently encountered [12]. Comprehending the attributes of every kind is essential for formulating efficacious noise mitigation tactics customized for particular situations. An overview of different noise kinds is given in this introduction, along with information on their unique characteristics and image processing ramifications [13] (Table 1).

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Table 1: Type of Noise

Noise Type	Characteristics	Source of Noise	Impact on Image
Gaussian Noise [14]	Follows a Gaussian distribution; adds random variations to pixel values, creating a smooth, continuous effect.	Sensor limitations, transmission errors, or electronic interference.	Blurs image details, affecting overall sharpness.
Impulse Noise [15]	Manifests as sudden, isolated spikes in pixel values; disrupts specific pixels randomly.	Often caused by hardware malfunctions or data transmission errors.	Creates localized distortions; may lead to significant artifacts.
Poisson Noise [16]	Follows a Poisson distribution; common in low-light conditions and sparse photon events.	Inherent in the process of photon counting, prevalent in low-light imaging.	Particularly pronounced in low-light scenarios; impacts image contrast.
Speckle Noise [17]	Results in granular patterns resembling grains or speckles; introduced during image acquisition.	Arises from reflective surfaces, textured backgrounds, or uneven lighting.	Distorts image textures; challenges accurate feature extraction.

IV. CLASSIFICATION OF DE-NOISING TECHNIQUES

Image de-noising is a broad field with a variety of methods, each tailored to solve particular problems caused by noise deterioration in digital image processing [18]. The main objective is to lower noise without sacrificing important aspects of the image, like corners, edges, and other sharp structures. The next subchapter explores a variety of de-noising methods, each with a special use in image processing [19].

With an emphasis on spatial filters, their subcategories, and the consequences of their use. Linear filters and non-linear filters are the two main types that are covered; each has unique benefits and things to keep in mind when it comes to noise reduction. The analysis that follows explores how these filters are applied and offers insights into their advantages and disadvantages, especially when it comes to reducing additive noise [20].

Table 2: Classification of De-Noising Techniques

De-Noising Technique	Characteristics	Advantages	Limitations
Spatial Filter[21]	- Classified into Linear and Non-Linear Filters	- Effective for additive noise reduction	- Tends to blur images; may impact fine details
	- Linear filters, such as Mean and Wiener, suitable for Gaussian noise	- Preserves general image features	- Wiener filter requires knowledge of noise and original signal spectra
	- Non-Linear filters, like Median, adept at multiplicative noise	- Non-linear filters preserve edges	- Median filter may result in loss of fine details
Transform Domain [22]	- Utilizes basis functions in transform domain	- Offers simultaneous temporal and frequency localization	- Complexity increases with data-adaptive transformations
Filtering [23]	- Non-data adaptive functions (Spatial Frequency and Wavelet)	- Wavelet approaches provide energy concentration	- Wavelet domain limitations based on wavelet base selection

In terms of image de-noising, this comparison table offers a thorough rundown of the traits, benefits, and drawbacks of both spatial filtering and transform domain filtering methods. The subtleties indicated in this table help practitioners and researchers choose the best de-noising method depending on the unique properties of the noise and the intended results for the processed images.

V. IMAGE SMOOTHING

Image filtering is a crucial technique in image processing, aiming to enhance image quality, reduce noise, and extract relevant information. Among various filtering methods, mean filtering, median filtering, adaptive median filtering, Gaussian filtering, and bilateral filtering are commonly employed. Each method has its unique approach and characteristics in addressing specific challenges associated with image processing (Table 3) [24].

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1) Mean Filtering Method: Mean filtering is a simple spatial domain processing technique that replaces each pixel in an image with the average value of its neighboring pixels within a specified template. While effective in reducing noise, mean filtering tends to blur the image, especially in areas with edges and details. Weighted domain average methods are often employed to mitigate this blurring effect [25].
2) Median Filtering Method: The median filtering method is a non-linear approach that replaces a pixel's gray value with the median value of its surrounding pixels. This method excels in removing noise while preserving edges. However, for certain image elements like points, lines, and top details, a weighted median filtering algorithm may be necessary to improve processing efficiency. Adaptive Median Filtering Method: An enhancement of the median filter, the adaptive median filtering algorithm adjusts the size of the filter window dynamically based on predetermined conditions. It effectively handles impulse noise and maintains more image details compared to traditional median filtering [26].
3) Gaussian Filtering Method: Gaussian filtering employs a weighted average based on the Gaussian function, effectively suppressing noise following a normal distribution. While it is efficient in smoothing images, Gaussian filtering may lead to blurring of edges and details. It is often used in the preprocessing stage of computer vision algorithms to enhance images of different scales [27].
4) Bilateral Filtering Method: The bilateral filter, an anisotropic filter, considers both spatial and value domains, allowing it to retain image edges while filtering noise. The output pixel value is a locally weighted average of the input image. Bilateral filtering is effective in smoothing images without sacrificing edge information [28].

Table 3: Image Filtering Methods Comparison [24]

Method	Advantages	Disadvantages
Mean Filtering	Simple, effective noise reduction	Blurs edges and details
Median Filtering	Removes noise, preserves edges	Inefficient for certain image elements
Adaptive Median Filtering	Dynamically adjusts filter window	Complexity increases with dynamic adjustments
Gaussian Filtering	Efficient noise suppression, suitable for preprocessing	May blur edges and details
Bilateral Filtering	Retains edges, effective noise reduction	Computationally intensive, may not handle all types of noise effectively

VI. IMAGE SHARPENING

Edge sharpening is a technique in Table (4) used in image processing to enhance the clarity and definition of edges in a two-dimensional image. It's commonly employed to make images appear more visually appealing or to highlight important features [29].

There are various methods for two-dimensional image sharpening, and one common approach is to use convolution filters, such as the Laplacian or Sobel filters. These filters emphasize changes in intensity, effectively enhancing the edges within an image [29].

Table 4: Image Sharpening Techniques Overview [30]

Technique	Description
Laplacian Filter	The Laplacian filter is often used for edge detection and sharpening. Applying the Laplacian filter to an image highlights regions where the intensity changes rapidly, indicating the presence of edges.
Sobel Filter	The Sobel filter is another popular choice for edge detection and is especially effective for detecting vertical and horizontal edges. It uses convolution with two 3x3 kernels, one for detecting changes in the vertical direction and the other for changes in the horizontal direction.
Unsharp Masking	Unsharp masking is a common technique where a blurred version of the image is subtracted from the original, enhancing fine details and edges.
High-pass Filtering	High-pass filters can also be used to emphasize the high-frequency components of an image, which often correspond to edges.

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VII. RELATED WORKS

Table (5) compiles a comprehensive summary of diverse studies focused on image enhancement and processing methods. Each entry in the table corresponds to a research article, presenting valuable insights into problem statements, objectives, methodologies, outcomes, and the pros and cons of proposed solutions. The studies encompass various image processing applications, including license plate identification, facial feature segmentation, contrast improvement, noise reduction, and fruit defect detection. The methods employed range from traditional techniques like Gaussian filters and histogram equalization to more advanced approaches such as wavelet denoising and machine learning-based classification. The outcomes highlight improved image quality, enhanced feature recognition, and increased accuracy in tasks like defect detection, while acknowledging potential drawbacks like computational complexity.

Table 5: Related works Analysis

Researcher	Problem Statement	Objectives	Methods	Results	Strength points	Limitation
(Gupta & Goyal, 2019) [31]	Dependency on weighting coefficient in Weighted Median Filter.	Preserve image details, highly dependent on the weighting coefficient.	Weighted Median Filter	Preservation of image details, dependency on weighting coefficient.	Preservation of image details, difficulty in finding suitable weighting coefficient.	High computation time in practical settings.
(Vasanth et al., 2015) [32]	Effectiveness of Adaptive Median Filter at low noise density and its drawbacks at high noise levels.	Performs well at low noise density, removal of image features at high noise levels.	Adaptive Median Filter	Effective performance at low noise levels, easy implementation.	Easy implementation, effective at low noise density.	Removes image features at high noise levels.
(Beniwal& Singh, 2013) [33]	Development of a hybrid technique combining median and Wiener filters for noise reduction.	Implement a hybrid technique for noise reduction using median and Wiener filters.	Median and Wiener Filters	Reduction of impulse, Gaussian, and blurredness noise.	Effective noise reduction, dependence on blurring angle and length.	Dependence on blurring angle, length, and impulse noise percentage.
(Zhang et al., 2012) [34]	Presentation of a hybrid algorithm utilizing Gauss filter, top-hat, and bot-hat transforms for image enhancement.	Utilize Gauss filter in frequency domain and top-hat, bot-hat transforms in spatial domain.	Hybrid Algorithm for Image Enhancement	Enhancement of image details in frequency domain, smoothing contours in spatial domain.	Improved image details and contour smoothing through hybrid processing.	Specificity to Gauss filter, top-hat, and bot-hat transforms.
(Khan et al., 2019) [35]	Evaluating Pan-sharpening Algorithms for Image Synthesis	To explore and assess various pan-sharpening techniques for the synthesis of multispectral and panchromatic images	Methodologies categorized into CS-based, MRA, VO, and Hybrid. Employed 21 case studies featuring images from diverse satellite sources.	MRA-based approaches excelled in spectral quality, while Hybrid methods demonstrated superior spatial quality. CS-based methods showcased efficiency with the fastest run-time.	Thorough evaluation based on 4 Spectral and 3 Spatial quality metrics.	Neural network-based methods were omitted due to computational demands for operational mapping. MRA and VO methods exhibited comparatively lengthier processing times.
(AKSOY & SALMAN, 2020)	Advancing Image Processing	To address the limitations of	Introduced a novel Mean-	The MMG hybrid algorithm	Enhanced image smoothing and	The applicability of MMG may be

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[36]	through Hybrid Filtering Techniques	traditional mean, median, and Gaussian filtering in certain image processing scenarios.	Median-Gaussian (MMG) hybrid filtering approach, combining the strengths of mean, median, and Gaussian techniques.	outperformed individual mean, median, and Gaussian filters in smoothing images and accurately delineating boundary lines.	boundary detection capabilities.	context-dependent and requires further validation across diverse datasets and scenarios.
(Zhang et al., 2023) [37]	Advancing Infrared Image Enhancement for Enhanced Quality	Addressing the growing demand for improved infrared image quality in military and civilian applications.	Proposed an innovative infrared image enhancement method utilizing high-low pass hybrid filtering.	Detail enhancement and background suppression achieved through Butterworth high-pass and Gaussian low-pass filters, respectively. Optimized combination yields an enhanced infrared image.	Enriched details and enhanced contrast in the resulting infrared image.	The method's effectiveness may be context-dependent, and further validation is needed across diverse scenarios and applications.
(Pham, 2022) [38]	Advancing Grayscale Image Sharpening with Anisotropic Averaging	Addressing the specificity and limitations of conventional sharpening filters for different image types.	Introduced a novel method integrating anisotropic averaging with Laplacian kernels for grayscale image sharpening.	Utilized kriging computation from geostatistics to determine optimal interpolation weights in the spatial domain. Convolved kriging and Laplacian kernels for image sharpening.	Demonstrated advantages over traditional sharpening filters in terms of sharpness and natural visualization balance. Does not require input statistical parameters.	Enhanced balance of sharpness and natural visualization.
(Deng et al., 2021) [39]	Advancing Image Processing with a Unified Smoothing and Sharpening Filter	Addressing the fundamental operations of smoothing and sharpening in image processing and their relationship through unsharp masking.	Developing a novel filter with tunable parameters for performing both smoothing and sharpening operations. Utilizing (1) a new Laplacian-based filter formulation unifying smoothing and sharpening, (2) a patch interpolation model akin to the guided filter for edge-awareness, and (3) the	Detailed studies on two versions of the proposed filter (self-guidance and external guidance). Conducting experiments for applications such as adaptive smoothing and sharpening based on texture, depth, and blurriness information. Applications include enhancing human face images, creating shallow	Thorough evaluation based on 4 Spectral and 3 Spatial quality metrics.	The effectiveness of the proposed filter may depend on specific image characteristics, and further validation is needed across diverse scenarios and image types.

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			generalized Gamma distribution for parameter estimation.	depth of field effects, focus-based enhancement, and seam carving.		
(Liang et al., 2021) [40]	Enhancing Real-time Image Recognition in Foggy Conditions	Addressing challenges in real-time performance, clarity, and reliability of image recognition within IoT monitoring systems under foggy weather conditions.	Proposing a fast defogging image recognition algorithm based on bilateral hybrid filtering. Establishing a mathematical model for bilateral hybrid filtering, utilizing the dark channel for filtering and demising. Introducing a bilateral hybrid filtering method combining guided filtering and median filtering to enhance robustness and transmittance of defogging images. Reducing computation complexity and image execution time for efficient defogging image recognition.	Experimental results demonstrate promising defogging effects and high-speed image recognition, achieving a recognition rate of 98.8% post-defogging.	Enhanced image smoothing and boundary detection capabilities.	The proposed algorithm's performance may be influenced by specific foggy conditions, and further validation across diverse scenarios and environments is recommended.
(Wangno & Pichai, 2020) [41]	The degradation of image quality due to haze and fog	To improve image quality by removing haze using a hybrid algorithm	Hybrid algorithm combining dark channel prior (DCP) and guided filter	Improved mean structural similarity (MSSIM) and peak signal-to-noise ratio (PSNR), effective haze removal	Effective in hazing scenarios, addresses background areas and low contrast	Performance may vary in certain environmental conditions, potential sensitivity to specific image characteristics

VIII. CONCLUSIONS

With an emphasis on noise reduction, this study offers a thorough investigation of image processing methods. External artefacts on film, such scratches and cracks, provide processing issues that need for manual intervention, highlighting the shortcomings of quantitative analysis when it comes to non-uniform flaws. The complex trade-offs involved in image processing make the search for a universal filtering algorithm challenging. Basic techniques for removing noise, such as spatial filtering and Gaussian filters, are covered, with special attention to the careful balancing act between noise reduction and fine detail preservation. The investigation delves into diverse forms of noise, including multiplicative and additive noise, elucidating their influence on the integrity of images.

The categorization of de-noising methods, in particular spatial filters and transform domain approaches, offers academics and practitioners a more nuanced comprehension of their properties, benefits, and drawbacks. This categorization is an invaluable resource for choosing appropriate de-noising techniques for particular noise situations.

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This study discusses contrast enhancement, noise reduction, and picture editing through a review of various research findings. It encompasses a wide range of topics, from the shortcomings of current filters to the use of deep learning in picture editing applications. These observations underline opportunities for innovation and advancement while also advancing our grasp of the current situation.

Building on the findings, future image processing research should look at developing deep learning integration in a variety of image processing applications, investigating new methods for reducing noise, and tackling particular difficulties in picture manipulation jobs. The study opens up interesting directions for future research and development by pointing out possible areas for improvement in forecast accuracy and execution speed.

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