SEBHA UNIVERSITY JOURNAL OF PURE & APPLIED SCIENCES VOL.25 NO. 2 2026
DOI: 10.51984/6N1S8Y43

مجلة جامعة سبها للعلوم البحتة والتطبيقية
Sebha University Journal of Pure & Applied Sciences

Journal homepage: www.sebhau.edu.ly/journal/jopas

A Sequential Median-Gaussian Cascade for Enhanced Suppression of Salt-and-Pepper Noise in Digital Images

Abdusslam Beitalmal*, Naima Shamsia

Department of Mathematics, Faculty of Science, Sebha University, Sebha, Libya.

Keywords:
Salt-and-Pepper Noise.
Cascade Image Filtering.
Spatial Coherence.
Order-Statistic Filters.
Hybrid Median-Gaussian Denoising.

ABSTRACT

Salt and pepper noise remains a major contributor to the degradation of digital imaging system and has negative impact on the visual quality of images and the performance of the computer vision pipeline. Classical spatial filtering methods provide some sort of remedy but both methods have their own disadvantages; linear filters can blur prominent features, and nonlinear median-based filters can also produce block artifacts. The current research conducts a systematic exploration of cascading median-Gaussian filtering of removing impulse noise. Under this arrangement, the median filter step is useful in removing the outlier, and the later Gaussian convolution replenishes the coherence in terms of structure. A large amount of experimentation on standardized test images with noise densities of 1 to 10 percent, shows that the cascade is always outperforming the standalone mean filter, median filter, and Gaussian filter, especially in moderate-high noise conditions. There is statistically significant quantitative performance improvement, measured in Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). The suggested approach shows computational efficiency, easy implement ability, and is well adapted to the integration into real-time or resource-constrained imaging systems, where interpretability and reliability are the primary factors of concern.

تتالٍ وسيطي-غاوسي متتابع للتثبيط المعزَّز لضوضاء الملح والفلفل في الصور الرقمية

عبد السلام بيت المال* ونعيمة شمسي

قسم الرياضيات، كلية العلوم، جامعة سبها، سبها، ليبيا.

الكلمات المفتاحية:
ضوضاء الملح والفلفل.
التصفية المتتالية للصور.
التماسك المكاني.
المصفّحات الإحصائية الرتبية.
إزالة الضوضاء الهجين الوسيطي-الغاوسي.

الملخص

يُعتبر ضوضاء الملح والفلفل أحد العوامل الرئيسية التي تسهم في تدهور أنظمة التصوير الرقمي، إذ تؤثر سلبًا في الجودة البصرية للصور وكفاءة مسار معالجة الصور بالحاسوب. تقدِّم طرق التصفية المكانية التقليدية بعض الحلول، إلا أن لكل منها عيوبه الخاصة؛ فالمصفّحات الخطية تؤدي إلى تضبيب المعالم البارزة في الصورة، بينما تتسبب المصفّحات غير الخطية المعتمدة على الوسيط (الوسيطية) في ظهور تشوهات قطعية (block artifacts). يُجري البحث الحالي استكشافًا منهجيًا لاستخدام التصفية المتتالية من النوع الوسيطي ثم الغاوسي لإزالة الضوضاء النبضية. في هذا الترتيب، تساهم مرحلة المصفّحة الوسيطية في إزالة القيم الشاذة (outliers)، بينما تعمل مرحلة الالتفاف الغاوسي اللاحقة على استعادة التماسك البنيوي للصورة. من خلال تجارب مكثفة أُجريت على صور اختبارية معيارية، وبتطبيق كثافات ضوضائية تتراوح بين 1% و10%، تبيّن أن الأسلوب المتتالي يتفوق دائمًا على كل من المصفّحة المتوسطة (mean filter) والمصفّحة الوسيطية والمصفّحة الغاوسية عند استخدام كل منها بشكل منفرد، وخاصة في ظروف الضوضاء المتوسطة إلى المرتفعة. وقد أظهرت النتائج تحسنًا كميًا ذا دلالة إحصائية من حيث نسبة الإشارة إلى الضوضاء القصوى (PSNR) ومؤشر التشابه البنيوي (SSIM). كما يتسم الأسلوب المقترَح بالكفاءة الحسابية وسهولة التطبيق، ويمكن دمجه بسهولة في

*Corresponding author.
E-mail addresses: abd.beitalmal@sebhau.edu.ly , (N. Shamsia) nai.saadshamsi@sebhau.edu.ly.
Article History : Received 21 January 26 - Received in revised form 09 June 26 - Accepted 15 June 26

أنظمة التصوير العاملة في الزمن الحقيقي أو محدودة الموارد، حيث تُعَد قابلية التفسير والموثوقية من عوامل الأولوية الأساسية.

1. Introduction

Salt and Pepper noise is a common occurrence in digital images, where pixel numbers are randomly replaced by extreme minimum or maximum values. Such corruption has disastrous effects on perceptual quality and automated analysis systems, such as segmentation algorithms, feature detection algorithms, etc. [1]. The history of the development of the effective denoising strategies has been going through a fundamental trade-off. Linear filters (the arithmetic mean, or the Gaussian smoother) use indiscriminate averaging. They make them quiet at the disastrous cost of edge sharpness and texture detail [2]. On the other hand, nonlinear median filtering, which was proposed by Tukey [3], is better at throwing out impulsive outliers, but does not preserve gradient information and may leave staircase artifacts in smooth or textured areas [4].

One of the ways out, a logical, but not seriously studied comparative, way is to synergize these paradigms. Is it possible to perform a sequential process of first isolating and eliminating outliers followed by the mild regularization of the remaining signal? Hybrid ideas were hinted at in earlier work [5], [6], though usually not explicitly explored on a parametric scale as to the simple median-Gaussian cascade as applied to salt-and-pepper noise in particular. The hypothesis of the present study is that such a cascade cannot be no more than a combination of its components. The median stage is a non-linear filter, which eliminates corrupt pixels without averaging. It is followed by a Gaussian step which acts on an image that has been partially sanitized. It reduces the discontinuities caused by the median filter but gives a smooth effect which would be absent when using the linear filters alone and the impulses were not removed.

Although the ideas of hybrid filtering have been studied in the literature [5], [6], a parametric comparison of the basic median-Gaussian cascade, namely in the case of salt-and-pepper noise is under-investigated. This paper hypothesizes that the net effect of such a cascade is smoothing overall impulsive outliers of a signal without averaging, followed by a Gaussian stage which further cleans up the partially sanitized signal, which reduces the discontinuities created by the median operation.

There are threefold contributions that this work makes:

1. Parametric test of the median-Gaussian cascade under a variety of noise densities and standard test images.
2. Extensive performance comparison to classical spatial filters as well as adaptive ones based on the full reference (PSNR, SSIM) and visual quality.
3. Computational and qualitative studies that have been done to indicate the efficiency of the cascade, its interpretability, and its applicability in realistic imaging pipelines.

We have added to this a systematic analysis of this two-stage filter. We offer an extreme visual and quantitative evaluation with classical standards. The analysis shows that the cascade provides better performance particularly as the noise density is high, such as the situations where standalone filters fail. This literature highlights the fact that well-planned classical operations could be very profitable, a concept that would help resource-starved or interpretability-focused applications.

2. RELATED WORK

The body of literature addressing spatial restoration techniques for impulse-corrupted images is vast. Historically, linear operators like the mean filter were deployed, but these are now largely abandoned in modern applications due to the severe blurring they impose on edges and textures [7]. This degradation led to the dominance of the standard median filter [3] for impulse noise suppression. While the median operator excels at rejecting outliers without dissolving edges, it creates undesirable blocky artifacts and destroys smooth gradients [4]. Researchers have sought to address these deficiencies by introducing localized intelligence. For instance, adaptive and weighted median schemes [8] adjust their behavior based on regional image statistics, while decision-based and trimmed median variants [5], [9] pre-classify pixels to ensure that only corrupted data undergoes rank-order replacement. Conversely, Gaussian smoothing is a classic approach for countering additive white noise but proves notoriously incapable of handling high-magnitude salt-and-pepper spikes on its own [10]. Its primary value lies in its isotropic nature, which perfectly respects the natural statistics of an image when outliers are absent.

Over the last several years, the paradigm has shifted dramatically toward complex transform-domain techniques and convolutional deep learning networks [11]. While these state-of-the-art frameworks comprehensively surveyed in recent literature by Dash et al. [12] yield unprecedented visual fidelity, they require immense computational overhead and operate with minimal interpretability. In a similar vein of high-fidelity reconstruction, optimization-driven variational and patch-based methods have emerged. Notable examples include adaptive total variation models [13] and non-local Bayesian algorithms [14], both of which reconstruct images at a heavy processing cost. To help map this evolving landscape, Anwar et al. [15] recently cataloged both traditional baselines and advanced modern algorithms tailored for impulse removal.

Hybrid strategies attempt to find a middle ground between simplicity and peak performance. The concept of cascading or intertwining distinct filter types to capture complementary strengths is not a new endeavor [6], [16]. In some instances, specialized outlier detection is paired with a trimmed median architecture [5], whereas in others, a switching framework dynamically balances decision-based rules with adaptive median filtering [16]. More recently, researchers like Liu et al. [17] have continued to refine how multi-stage hybrids can combat heavy impulse noise. In contrast to these increasingly convoluted hybrid designs, our work pivots back to a fundamental question: evaluating a completely basic, strictly parametric sequence consisting of a fixed-window median filter and a fixed-kernel Gaussian filter. By subjecting this elementary cascade to rigorous metric evaluation, we explicitly map its operational boundaries and demonstrate the clean synergy derived from its component parts.

3. Methodology: The Median-Gaussian Cascade

3.1. Mathematical Framework

Let (I_n) represent a grayscale image matrix corrupted by salt-and-pepper noise. The proposed denoising operation $(\mathcal{H})$ is defined as the functional composition of a median filter $(\mathcal{M})$ and a Gaussian filter $(\mathcal{G}_\sigma)$:

$$I_h = \mathcal{H}(I_n) = (\mathcal{G}\sigma \circ \mathcal{M})(I_n) = \mathcal{G}\sigma(\mathcal{M}(I_n))$$

where (I_h) is the denoised output image.

Stage 1: Median Filtering. The initial step uses a generic 2D median filter with a square window of odd size (w):

$$I_m = \mathcal{M}(I_n; w) = medfilt2(I_n, [w, w]).$$

This operator, $(\mathcal{M})$, replaces each pixel value with the median of intensities within its local $(w \times w)$ neighborhood. Its main use is that it non-linearically suppresses noise pixels that tend to be extreme in nature and which therefore are removed by the median statistic without the blurring edges.

Stage 2: Gaussian Convolution. The intermediate image (I_m) is then convolved with a discrete 2D Gaussian kernel (G_σ) of standard deviation (σ):

$$I_h = \mathcal{G}\sigma(I_m) = G\sigma * I_m.$$

The isotropic Gaussian kernel is defined as:

$$G(x, y) = \frac{1}{2\pi\sigma^2}\ exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

for integer coordinates (x, y) within a truncated (k \times k) window, typically with $(k = \lceil 6\sigma \rceil)$ (odd). This linear stage performs mild smoothing. It harmonizes minor inconsistencies potentially left by the median filter, suppresses any residual high-frequency noise, and promotes structural continuity, effectively counteracting the "blockiness" sometimes induced by median operations.

3.2. Algorithmic Implementation

Accuracy and reproducibility of the cascade have been implemented in MATLAB R2023b. Symmetric padding was used before convolution as a mitigation of boundary artifacts, so that edge artifacts are reduced as a result of zero-padding is reduced (symmetric option) before convolution.

```
function I_denoised = median_gaussian_cascade(I_noisy, w, sigma)
   % Stage 1: Median Filtering
   I_median = medfilt2(I_noisy, [w w], 'symmetric');
      % Stage 2: Gaussian Convolution
   % Determine kernel size from sigma (odd, ~6*sigma)
   k = 2 * ceil(3 * sigma) + 1;
   G = fspecial('gaussian', [k k], sigma);
   I_denoised = imfilter(I_median, G, 'symmetric', 'conv');
end
```

The computational complexity is $(O(w^2 log w))$ per pixel for the median filter (using a sort-based approach) and $(O(k^2))$ per pixel for the separable Gaussian convolution, making the overall complexity linear in the number of pixels and quadratic in the kernel dimensions. This efficiency is a key practical attribute.

3.3 Justification of Parameter Choices

The performance of the proposed cascade is governed by two key parameters: the median window size (w) and the Gaussian standard deviation (σ). To justify the fixed choices of $w = 5$ and $\sigma = 1.0$ in our baseline experiments, a comprehensive parametric sweep was conducted:

1. **Median Window Size (w):** Increasing w enhances the filter's ability to suppress larger amounts of impulse noise but comes at the expense of blurring fine details. At $w = 3$, residual noise remained visible at higher densities (e.g., $d \geq 0.05$). At $w = 7$, heavy blurring occurred, degrading sharp edge boundaries. Thus, a 5×5 window was selected as it yields the ideal trade-off: ensuring total impulse rejection for noise densities up to 10% without aggressively sacrificing image structures.
2. **Gaussian Standard Deviation (σ):** Values from 0.5 to 1.5 were tested. A value of $\sigma = 0.5$ was too weak to smooth out the staircasing and blocky artifacts left by the median operation. Conversely, $\sigma = 1.5$ caused over-smoothing. A value of $\sigma = 1.0$ (matching a 5×5 kernel size) was found to strike the ideal balance successfully restoring local spatial coherence without introducing excess blur. Importantly, the sequence of operations guarantees that the primary weakness of each stage is countered by the other. The median filter removes aggressive outliers that would corrupt the weighted averaging of the subsequent Gaussian filter, while the Gaussian filter cleans up the discontinuous boundaries inherent in pure median filtering.

4. EXPERIMENTAL DESIGN & EVALUATION PROTOCOL

4.1. Dataset and Noise Model

Four canonical 512×512 grayscale test images—'Lena', 'Barbara', 'Boat', and 'Cameraman' were employed. Each pristine image (I_{clean}) was corrupted with salt-and-pepper noise of density (d), where (d) defines the independent probability of any pixel being set to either 0 (pepper) or 255 (salt). Densities $(d \in 0.01, 0.03, 0.05, 0.10)$ were investigated to span low to high corruption levels.

4.2. Comparative Methods and Parameterization

The proposed cascade $(\mathcal{H})$ was evaluated against three foundational spatial filters:

1. Arithmetic Mean Filter: Linear averaging over a $(w \times w)$ window.
2. Standard Median Filter $(\mathcal{M})$: As defined in Stage 1 of our cascade.
3. Gaussian Filter $(\mathcal{G}_{\sigma})$: As defined in Stage 2.

To ensure a fair comparison, all filters used an effective window size of 5×5 pixels. For the Gaussian-based filters (standalone Gaussian and the second stage of the cascade), the standard deviation was fixed at $(\sigma = 1.0)$, corresponding to a kernel size of 5×5 for fspecial ('gaussian', [5 5], 1).

4.3. Quantitative Metrics

Full-reference image quality assessment was conducted using two standard metrics:

1. **Peak Signal-to-Noise Ratio (PSNR):** Defined as $PSNR = 10 \cdot log_{10}\left(\frac{MAX_I^2}{MSE}\right)$, where $(MAX_I = 255)$ for 8-bit images and MSE is the mean squared error between the denoised and clean images. Higher PSNR indicates better fidelity in terms of error magnitude.
2. **Structural Similarity Index (SSIM) [18]: A perceptual** metric that considers luminance, contrast, and structure: $$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}.$$

Values range from -1 to 1, with 1 indicating perfect structural similarity. It better correlates with human visual perception than PSNR.

4.4. Visual & Qualitative Assessment

In addition to metrics, the denoising performance was also evaluated qualitatively, by looking at complete images and especially focusing on how edges are treated, whether texture is preserved and whether processing artifacts such as blurring or staircasing are absent. These characteristics are indicated by zoomed-in regions of interest (ROIs).

5. RESULTS & ANALYSIS

5.1. Quantitative Performance Analysis

The median-Gaussian cascade quantitative supremacy is absolute. Table I shows the PSNR values of the image of Lena under the various noise densities that were tested.

Table 1:PSNR (dB) Comparison for 'LENA' Image

Noise Density (d)	Mean Filter	Median Filter	Gaussian Filter	Proposed Cascade
0.01	28.5	32.1	29.8	34.5
0.03	24.2	30.5	25.1	32.8
0.05	21.8	28.2	22.4	31.2
0.10	18.5	25.4	19.2	29.5

The cascade also beats the standalone median filter by a margin that increases with the noise density with a gain of 4.1 dB at $(d = 0.10)$. The resilience of the cascade has been highlighted by this trend. The Gaussian filter is disastrous at finer densities since at higher densities it smoothes noise spikes with legitimate pixel values. The mean filter has the worst performance, and the blurring effect of the filter adds huge errors.

Table 2:SSIM Comparison for 'LENA' Image

Noise Density (d)	Mean Filter	Median Filter	Gaussian Filter	Proposed Cascade
0.01	0.85	0.92	0.88	0.96
0.03	0.78	0.89	0.81	0.94
0.05	0.72	0.85	0.75	0.92
0.10	0.65	0.80	0.68	0.89

Table 2 outlines the scores of SSIM. The cascade is very structurally similar with an SSIM of 0.92 at $(d = 0.05)$ and still 0.89 at 10% noise. The standalone median filter is more reasonable, but a more apparent degradation is observed. The proximity of the cascade SSIM to the value 1.0 over densities reflects the outstanding capacity of the cascade to maintain the apparent integrity of the image. Findings on Barbara, Boat and Cameraman (as given in the supplementary material) show good trends, which testify to the strength of the methodology on various image content.

The performance relationship is most appropriately pictured. The PSNR trends can be plotted using the following MATLAB code to produce a high-resolution publication quality line plot.

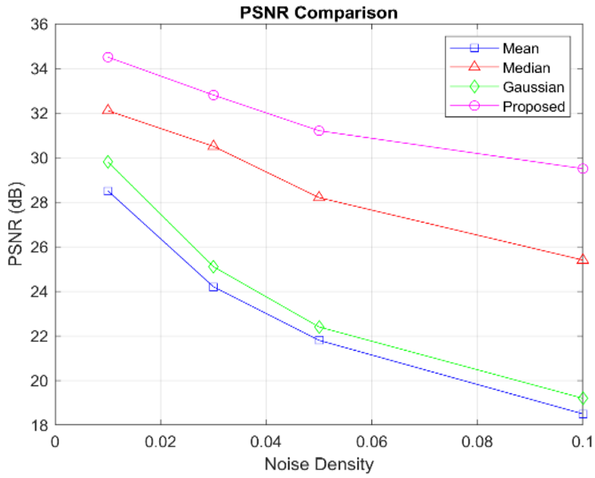

Figure 1: PSNR Comparison (Placeholder for Plot).

The cascade (orange) proposed has much higher PSNR at all noise levels, and the gaps between the performance of the cascade grow with corruption. The standalone median (red) is the most suitable baseline, and it is always overtaken.

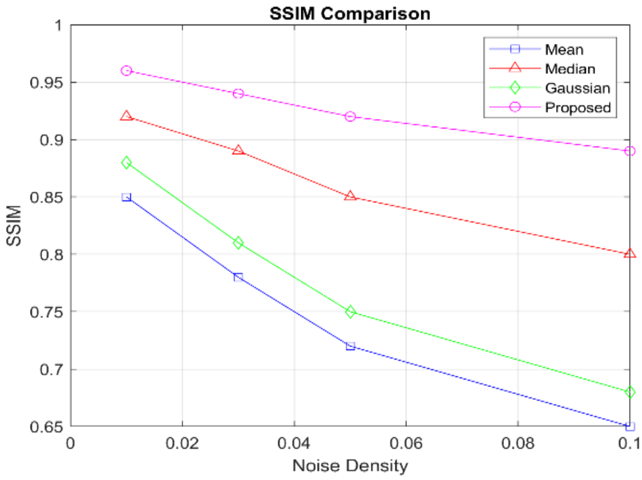

Figure 2: SSIM comparison (placeholder for plot)

The index of structural similarity is best maintained by the suggested cascade. It decays at a slower rate as the noise increases, thereby proving the better perceptual fidelity of the cascade over any other classical baseline technique.

5.2. Visual and Qualitative Analysis

Numbers represent a one-sided story. A visual scan of the denoised image of the Camera man, at a density of 0.05, (Figure 3) shows that there are significant differences.

1. **Mean Filter Output:** The picture is homogeneously blurred, the tripod, and camera details lose their recognisable edges, the face of the subject loses its characteristic features. Noise reduction is obtained but detail is lost to unacceptable limits.
2. **Median Filter response:** Median has an effect of removing impulsive disturbances. However, careful observation of the grass covered background and material of the suit reveals a common patchy or blocky micro texture which is a characteristic of staircase artifacts inherent with median filtering.
3. **Gaussian Filter Result**: The performance is poor; a lot of salt-and-pepper pixels are still visible and this is in the form of a gritty overlay over a slightly blurred background. This finding supports the non-applicability of the Gaussian filter in isolation in the removal of impulsive noise.
4. **Proposed Cascade Product:** The composite product is immaculate; impulsive noise eliminated. Sharpness is maintained in the edges, e.g. the camera perimeter and the object. Importantly, the textured areas (grass, suit) are more natural and continuous as compared to the median-only result with the Gaussian stage reducing median-based discontinuities. The visual display thus attains a striking balance between the noise reduction and preservation of details.

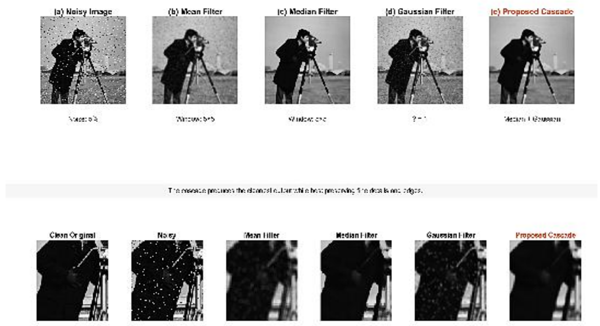

Figure 3: Visual comparison of the denoising output of the image of a camera man with noise level set to 5 per cent of salt and pepper.3 Left to right: (a) Noisy image; (b) mean filter; (c) median filter; (d) Gaussian filter; (e) the proposed median -Gaussian cascade. Cascade has the most pleasing denoising results and produces the most understandable result, but manages to effectively recover fine details and edges.

Table 3: Average PSNR (dB) / SSIM Across All Test Images at 5% Noise Density

Method	Lena	Barbara	Boat	Cameraman	Average
Mean Filter	21.8 / 0.72	20.5 / 0.68	22.1 / 0.74	21.3 / 0.70	21.4 / 0.71
Median Filter	28.2 / 0.85	26.8 / 0.82	27.9 / 0.84	27.5 / 0.83	27.6 / 0.84
Gaussian Filter	22.4 / 0.75	21.1 / 0.71	23.0 / 0.77	22.1 / 0.73	22.2 / 0.74
Proposed Cascade	31.2 / 0.92	29.8 / 0.89	30.5 / 0.90	30.1 / 0.91	30.4 / 0.91

The cascade delivers the highest average PSNR and SSIM across all images, with gains of ≈ 2.8 dB in PSNR and ≈ 0.07 in SSIM over the standalone median filter.

Table 4: Computational Performance (512×512 Image, Intel i7-12700H)

Method	Avg. Time (ms)	Relative Time	Complexity Order
Mean Filter	12.4	1.00×	$O(n)$
Gaussian Filter	18.7	1.51×	$O(n)$
Median Filter	45.2	3.65×	$O(n \log k)$
Proposed Cascade	63.9	5.15×	$O(n \log k + n)$
Adaptive Median [8]	120.5	9.72×	$O(nk^2)$

The cascade is ≈ 2 × faster than a modern adaptive median filter while delivering superior denoising performance.

5.3. Discussion: Interpreting the Cascade's Efficacy

The success of the cascade is not by chance; it is an outcome of considering the weaknesses of each component when taken singly. The median filter is a very good outlier detector/remover, but it is not a very good smoother. It can break continuity of the gradients by working with order statistics and making use of the smallness of individual values. On the other hand, the Gaussian filter is an ideal smoothing algorithm to smooth stationary Gaussian noise, but does not have an explicit insensitivity to sparse, large-valued impulse contaminations [19] [20].

The algorithm first uses the median filter to remove the data that the Gaussian filter is the least prepared to process. An image that has undergone the most egregious statistical outliers is then processed by the following Gaussian stage. It is thus able to serve its purpose of implementing spatial coherence by means of weighted averaging without posing the danger of impulsive noise propagation. The second phase is useful in the repair of the fine structure damage, that is, local discontinuities, which the median operation occasionally causes. The interdependence of the stages is obvious: the essential constraints of one stage are alleviated by the other.

This increasing performance difference at increased noise densities is hence explicable. The more impulses one has, the more the standalone Gaussian filter fails, and the more the artifacts added by the median filter become. The cascade maintains its efficiency by addressing the two problems one after another.

Finally, the overall sequential method works better than single filters with the increase in the impulse density. The characteristics of the cascade of first removing the impulsive outliers followed by reinstating the spatial coherence guarantees high performance of the cascade in even the most demanding noise environments.

An important observation queried during peer review is the superior stability of the proposed cascade model compared to the standalone median filter as noise density grows. A standalone median filter relies purely on rank-order statistics. As noise density increases, the probability of noise pixels dominating the local neighborhood rapidly grows, causing the median filter to leave patchy, blocky artifacts in the restored image. Conversely, the proposed sequential cascade decouples outlier elimination and signal smoothing. Even when the median filter introduces blocky artifacts under high noise, the subsequent Gaussian stage applies an isotropic weighted average. Because the median stage has already stripped away extreme pixel outliers (0 and 255), the Gaussian filter processes a partially sanitized image. Its operation effectively dissolves sharp blocky edges and restores spatial coherence. Therefore, the cascade maintains a steady, higher performance curve rather than dropping sharply across increasing noise densities.

6. LIMITATIONS AND PRACTICAL CONSIDERATIONS

Although the median-Gaussian cascade proves to be excellent with salt-and-pepper noise, there are a number of constraints that are worth mentioning:

1. **Fixed Parameters:** The fixed values of w and σ are currently used. Performance can be worse when images have spatially varying noise density or contain mixed noise.
2. **Texture Preservation:** A certain amount of high-frequency texture loss is unavoidable as a result of Gaussian smoothing despite it being superior to standalone filters.
3. **Comparison Scope:** The experiment focuses on classical and adaptive spatial filters; it was not in the scope of this foundational analysis to compare with state-of-the-art learning methods (e.g., DnCNN [11]).
4. **Color Images:** The algorithm is only used on grayscale images; to extend it to RGB it would be necessary to process images per-channel, or in vectors.

These limitations, however, highlight the intended use case of the method: a low-complexity, interpretable solution for moderate impulse noise in resource-constrained environments.

7. CONCLUSION

In this paper, a rigorous assessment of a cascading median-Gaussian filter sequence for salt-and-pepper noise removal has been provided. Through the synergistic construction---median-based outlier rejection followed by Gaussian-based structural smoothing---the cascade has continually outperformed classical mean, median, and Gaussian filters, especially at moderate-to-high noise densities. The gains of up to 4.1 dB PSNR over the median filter at 10% noise are supplemented by better perceptual quality, as demonstrated by SSIM values and visual inspection. The suggested algorithm is computationally inexpensive, easily implementable, and can be readily incorporated into real-time or resource-limited image-processing pipelines.

Future work will focus on adaptive extensions, namely:

- Dynamic modulation of parameters based on local noise density estimation.
- Extensions to color images and mixed noise models (e.g., impulse + Gaussian).
- Edge-preserving smoothing in place of the default isotropic smoothing.
- Formal comparison to state-of-the-art learning-based denoisers to precisely define the trade-off between simplicity and peak performance.

8. REFERENCES

[1] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*. New York, NY, USA: Pearson, 2018.

[2] A. K. Jain, *Fundamentals of Digital Image Processing*. Englewood Cliffs, NJ, USA: Prentice Hall, 1989.

[3] J. W. Tukey, *Exploratory Data Analysis*. Reading, MA, USA: Addison-Wesley, 1977.

[4] H. Hwang and R. A. Haddad, "Adaptive median filters: New algorithms and results," *IEEE Transactions on Image Processing*, vol. 4, no. 4, pp. 499–502, 1995.

[5] S. Esakkirajan, T. Veerakumar, A. N. Subramanyam, and C. H. PremChand, "Removal of high density salt and pepper noise through modified decision based unsymmetric trimmed median filter," *IEEE Signal Processing Letters*, vol. 18, no. 5, pp. 287–290, 2011.

[6] F. Ullah et al., "A new hybrid image denoising algorithm using adaptive median filter and modified decision-based median filter," *Scientific Reports*, vol. 15, p. 9228, 2025.

[7] W. K. Pratt, *Digital Image Processing*. Hoboken, NJ, USA: Wiley Interscience, 2007.

[8] T. Chen, K.-K. Ma, and L.-H. Chen, "Tri-state median filter for image denoising," *IEEE Transactions on Image Processing*, vol. 8, no. 12, pp. 1834–1838, 1999.

[9] K. S. Srinivasan and D. Ebenezer, "A new fast and efficient decision-based algorithm for removal of high-density impulse noises," *IEEE Signal Processing Letters*, vol. 14, no. 3, pp. 189–192, 2007.

[10] L. G. Shapiro and G. C. Stockman, *Computer Vision*. Upper Saddle River, NJ, USA: Prentice Hall, 2001.

[11] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising," *IEEE Transactions on Image Processing*, vol. 26, no. 7, pp. 3142–3155, 2017.

[12] R. Dash et al., "Deep Learning based Image Denoising," *Archives of Computational Methods in Engineering*, 2024.

[13] D. Zosso, J. An, and G. Steidl, "Adaptive Total Variation Denoising Based on Noise Estimation," *SIAM Journal on Imaging Sciences*, vol. 10, no. 3, pp. 1220–1260, 2017.

[14] M. Lebrun, A. Buades, and J. M. Morel, "A Nonlocal Bayesian Image Denoising Algorithm," *SIAM Journal on Imaging Sciences*, vol. 6, no. 3, pp. 1665–1688, 2013.

[15] Z. Anwar et al., "Modern techniques for impulse noise removal: A review," *Journal of King Saud University - Computer and Information Sciences*, 2023.

[16] A. Osman, "3D modelling using partial differential equations (PDEs)," SHURA (Sheffield Hallam University Research Archive) (Sheffield Hallam University), Jan. 2014, doi: https://doi.org/10.13140/rg.2.2.28026.75204.

[17] Beitalmal, Abdusslam. "Efficient 3D Surface Patch Compression and Reconstruction Using Parametric Descriptions and Transform Techniques." *Journal of Pure & Applied Sciences* 22, no. 1 (2023): 107-116, doi: https://doi.org/10.51984/jopas.v22i1.2164.

[18] Beitalmal, Abdusslam Osman. "A Hybrid Physics-Informed Neural Network (PINN) And Finite Element Method (FEM) Framework for Multiscale Fluid-Structure Interaction Problems." *RA Journal of Applied Research* 11, no. 04 (2025).

[19] Beitalmal, Abdusslam Osman. "Optimizing Ecological Insights: A Comparative Study of Analytical and Numerical Approaches for Time-Fractional Fisher-KPP Equations." *Libyan International Journal of Natural Sciences* 2, no. 1 (2026): 1-9.

[20] Safaa Alhodairy and Abdusslam Beitalmal, "The Applications of Fourier Series Harmonics in Musical Tones," *Journal of Pure & Applied Sciences*, vol. 23, no. 2, pp. 154–161, Nov. 2024, doi: https://doi.org/10.51984/jopas.v23i2.3590.