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Research paper

Performance Comparison of Five Spatial Filtering Algorithms for Salt-and-Pepper Noise Removal

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A R T I C L E I N F O

Keywords:
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Median filter
Order-statistic filter

A B S T R A C T

This work presents a rigorous quantitative evaluation of five core spatial filters for the mitigation of salt-and-pepper impulse noise, namely mean, median, maximum, minimum and order-statistic filters (with k=7), using MATLAB simulation. Three well-established standard greyscale benchmark images form the test dataset, with Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM) and Signal-to-Noise Ratio (SNR) adopted as quantitative performance metrics. The bulk of published research focuses on refining single filter architectures, yet few studies offer holistic cross-algorithm testing within identical experimental constraints. To resolve this identified research gap, this paper quantifies operational use-cases for each classic spatial filter and develops measurable selection benchmarks for industrial image processing workflows, with direct relevance to clinical medical imaging, continuous surveillance capture and embedded vision hardware. Empirical testing confirms that the median filter achieves optimal noise reduction at a noise density of 0.1, recording average scores of 30.30 dB PSNR, 0.989 SSIM and 0.97 SNR. The denoising performance of the k=7 order-statistic filter falls midway between the median filter and the two extremum variants. Maximum and minimum filters produce negative SNR outputs, confirming their unsuitability for mixed dual-polarity salt-and-pepper noise. Adjusting the integer parameter k allows the order-statistic filter to adapt to differing noise polarities; peak performance of 26.58 dB PSNR occurs at k=5, with rapid degradation observed as k diverges from the median index.

1. Introduction

Salt-and-pepper impulse noise routinely corrupts digital imagery across capture, transmission and storage stages. This artefact appears as randomly scattered solid black or white pixels with extreme greyscale values, which erode visual integrity and disrupt subsequent computer vision pipelines such as semantic segmentation, object recognition and feature extraction. Spatial filtering methods remain the dominant denoising approach due to their minimal computational load and ability to run in real time on embedded hardware platforms[1].

The five core algorithms investigated in this work cover linear and nonlinear filtering paradigms: the mean filter generates smoothed outputs via neighborhood averaging; it performs well for Gaussian noise yet blurs object edges when confronted with impulse noise[2]. The median filter substitutes the central pixel with the median gray value of its surrounding window, eliminating isolated impulse noise artifacts while retaining sharp edge information[3]. The maximum and minimum filters output the highest and lowest grayscale values within the local window correspondingly, and only work reliably for single-polarity noise interference[4]. The order-

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statistic filter generalizes the above four filtering schemes, adjusting noise adaptability by extracting the k-th entry from sorted neighborhood pixel sequences[5]. In this paper, k=7 (leaning toward high gray values) is selected to demonstrate performance degradation caused by offsetting from the median sorting position.

Published work largely focuses on refining standalone filter architectures [6-7], and systematic side-by-side evaluation of all five baseline filters remains scarce. Recent academic work has produced numerous enhanced variants built upon classic spatial filtering frameworks. Reference [8] introduces a regeneration filter tailored for mosaic image salt-and-pepper interference that boosts fine-detail preservation atop order-statistic filtering, though no benchmark comparison against basic maximum and minimum filters is provided. Reference [9] develops a hardware-efficient approximate median filter architecture to cut sorting overhead, yet validation is limited solely to median filtering without cross-testing multiple spatial filter types. Reference [10] delivers a broad overview of impulse noise reduction spanning spatial, fuzzy and deep learning methodologies, yet fails to quantify operational performance thresholds for the five baseline filters across consistent noise density increments. Reference [11] builds a Transformer-driven denoising network for remote-sensing salt-and-pepper noise, which outperforms conventional filters under heavy noise loads; nevertheless, classic spatial filters retain unrivalled low-latency performance for embedded hardware operating under mild noise conditions. Reference [12] utilises weighted nuclear norm regularisation for impulse noise suppression, though the scheme carries vastly higher computational complexity than mean and median filtering. Reference [13] devises a two-stage directional mean filter capable of strong noise reduction at the expense of extended processing latency. The majority of contemporary studies centre on modified filter variants, and comprehensive cross-filter testing of the five fundamental methods within a fixed 3×3 window and graded noise densities is seldom documented. This gap leaves industry practitioners without defined criteria for selecting baseline denoising modules. This paper carries out comparative testing across four assessment dimensions within a fixed 3×3 window setup: subjective visual quality, three quantitative metrics (PSNR, SSIM, SNR) and computational latency. Complete MATLAB simulation scripts and tailored industrial filter selection guidance are provided alongside the analysis.

The main contributions of this research paper are listed as below:

· A full cross-filter performance benchmark for mean, median, maximum, minimum and k=7 order-statistic filters is constructed using three standard test images, tested within a consistent 3×3 window and three graded noise densities (0.05, 0.1, 0.2);
· The failure mechanism of maximum and minimum filters under mixed dual-polarity salt-and-pepper noise is quantified using negative SNR outputs, with clear operational limits defined for single-polarity noise environments;
· The sensitivity of order-statistic filter noise reduction to parameter k is systematically examined, and the scale of PSNR degradation induced by deviation from the median sorting index is numerically quantified;
· Actionable matching guidance balancing low-latency computation and noise reduction accuracy is supplied for embedded hardware, clinical medical imaging hardware and continuous surveillance vision systems.

2. Algorithm Principles

2.1 Mean Filter

Notation convention:

(f(i,j): Original grayscale value of pixel at coordinate (i,j);
g(i,j): Output grayscale value after filtering;
S: 3×3 sliding filtering neighborhood containing total N=9 pixels;
$f_1, f_2, \dots, f_9$: Gray values of neighborhood pixels sorted in ascending order, f_1 minimum, f_9 maximum;
k: Sorting serial number selected as output for order-statistic filter, 1≤k≤9.

The arithmetic mean of pixel grayscale values within the neighborhood replaces the central pixel[2].

$$g(i,j) = (1/N)\sum_{(x,y)\in S} f(x,y) \tag{1}$$

Formula (1) calculates arithmetic average of all 9 neighborhood pixels, N=9 denotes total pixel quantity within 3×3 window, (x,y)∈S represents all coordinate points belonging to filtering neighborhood S.

Impulse noise pixels carry extreme gray values that are incorporated into the averaging computation, dispersing noise energy across the window and creating blurry gray patches, which severely degrades overall noise suppression performance.

2.2 Median Filter

Based on the unified notation convention defined in Section 2.1, the median of the sorted neighborhood values replaces the central pixel[3-7].

$$g(i,j) = Med_{(x,y)\in S} f(x,y) = f_{(N+1)/2} \tag{2}$$

Formula (2) takes the median term of the sorted pixel sequence within neighborhood S. N=9, so the median position is (9+1)/2=5, corresponding to the sorted gray value f_5; $Med_{(\cdot)}$ denotes the median extraction operation over all pixels in set S.

Salt-and-pepper noise corresponds to extreme gray values that occupy the two terminals of the sorted pixel sequence. Extracting the median term inherently excludes these impulse artifacts, enabling effective noise elimination with well-preserved edge textures.

2.3 Max Filter

Consistent with the notation convention in Section 2.1, the maximum value within the neighborhood is taken as output[4].

$$g(i,j) = Max_{(x,y)\in S} f(x,y) = f_N \tag{3}$$

Formula (3) selects the maximum gray pixel from the entire 3×3 window S. N=9, f_9 is the largest gray value after ascending sorting; $Max_{(\cdot)}$ represents the maximum value extraction operation for pixel set S.

This filter eliminates dark pepper noise yet amplifies bright salt noise, leading to overall over-brightening of the output frame. It cannot be deployed for dual-polarity mixed impulse noise.

2.4 Min Filter

Refer to the unified variable definition listed in Section 2.1. The minimum value within the neighborhood is taken as output[5].

$$g(i,j) = Min_{(x,y)\in S} f(x,y) = f_1 \tag{4}$$

Formula (4) extracts the minimum gray value from neighborhood S. f_1 stands for the first element after ascending sorting of all window pixels; $Min_{(\cdot)}$ denotes the minimum value operation over pixel set S.

The minimum filter suppresses bright salt noise while magnifying dark pepper noise, resulting in global image darkening. It is also incompatible with mixed dual-polarity salt-and-pepper noise.

2.5 Order-Statistic Filter

All symbols follow the definition rules presented in Section 2.1. After sorting, the k-th value is selected as output[1-6].

$$g(i,j) = Sort_k f(x,y) | (x,y) \in S = f_k \tag{5}$$

Formula (5) extracts the k-th sorted gray element from pixel set S. $Sort_k\{\cdot\}$ is the operation to pick the k-th item after ascending sorting; adjustable integer $k \in [1,9]$ controls the filtering tendency. When k=1, the formula is equivalent to Min filter; k=5 corresponds to Median filter; k=9 equals Max filter. When k=1, the filter reduces to the minimum filter; $k = (N+1)/2$ reproduces median filtering behavior; k=N replicates maximum filtering output. This paper adopts k=7, which biases filtering toward high gray values, to quantify performance loss induced by deviation from the median sorting index.

3. Experimental Design

3.1 Experimental Environment

Software: Windows 10 64-bit, MATLAB R2021b, Image Processing Toolbox.

Hardware: Intel Core i7-11800H processor, 32 GB DDR4 RAM.

3.2 Test Images

Three standard 256×256 greyscale benchmark images are adopted for testing: barbara.jpg, cameraman.jpg and Lena.jpg. The original Lena asset is supplied in colour and converted to single-channel greyscale prior to testing. The dataset incorporates distinct visual categories, including human portraits, outdoor scenery and intricate fine textures.

3.3 Experimental Flowchart

The overall experimental process is shown in **Figure 1.**

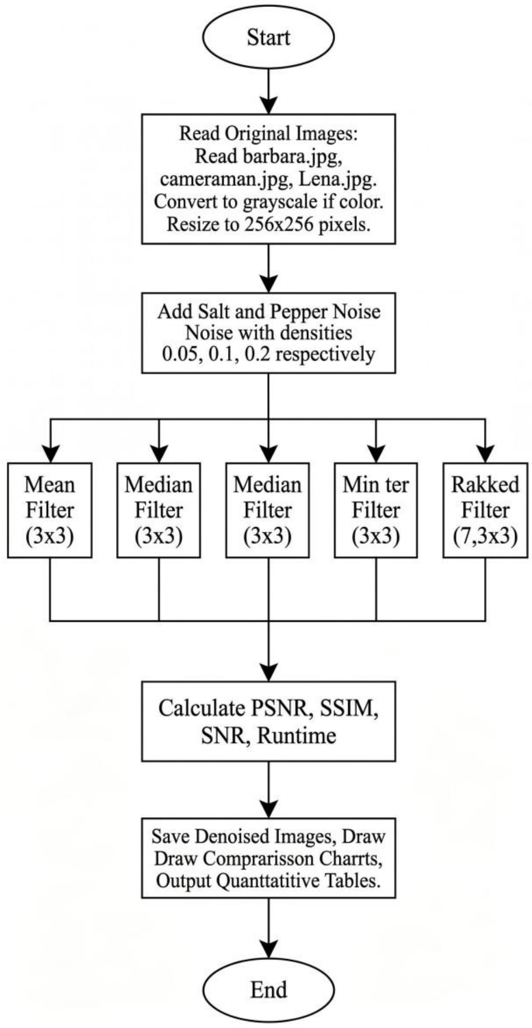


Fig.1 Experimental flowchart

3.4 Evaluation Metrics

1. PSNR (Peak Signal-to-Noise Ratio, dB): Measures pixel-level error between the denoised image and the original image; higher is better.

2. SSIM (Structural Similarity Index): Ranges from 0 to 1; values closer to 1 indicate better structural preservation.

3. SNR (Signal-to-Noise Ratio):

$$SNR = 1 - ({\sigma_d}^2/{\sigma_n}^2) \tag{6}$$

A SNR value close to 1 signifies robust noise reduction performance, while values close to zero demonstrate only negligible interference removal. Negative SNR readings reveal that residual noise variance exceeds the variance of unfiltered noisy input, meaning the filter amplifies noise artefacts instead of mitigating them.

4. Experimental Results and Analysis

4.1 Visual Comparison at 10% Noise Density

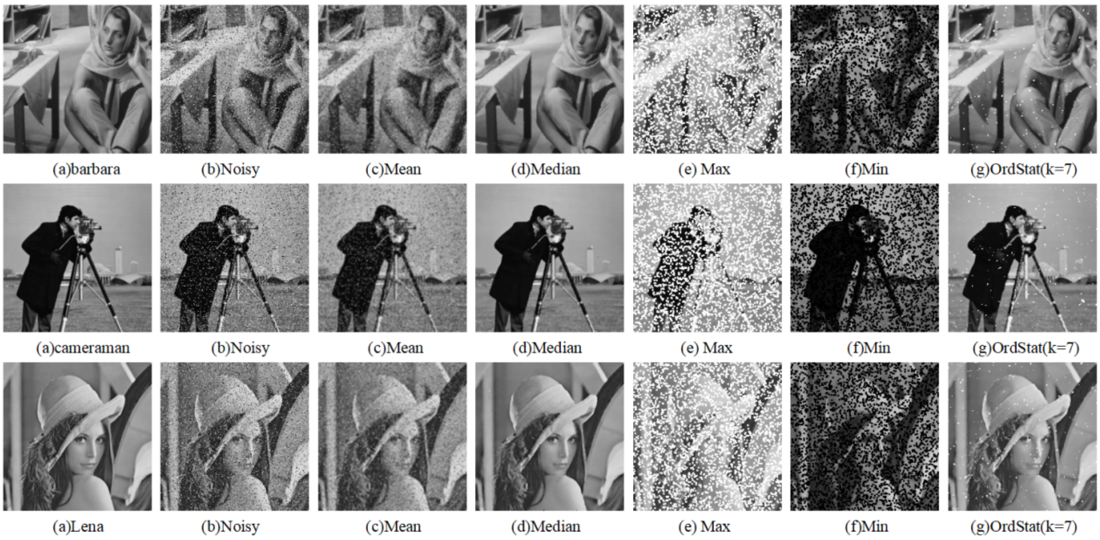


Fig.2 Comparison of denoising results of various algorithms under salt-and-pepper noise with a 3×3 neighborhood (10% Noise Density)

Table.1 Performance comparison of various algorithms at noise density 0.1 (cameraman)

Algorithm	**PSNR(dB)**	**SSIM**	**SNR**	**Time(ms)**
Mean filter	22.59	0.9483	0.82	1.85
Median filter	29.13	0.9894	0.96	6.46
Max filter	8.68	0.4019	-1.68	6.04
Min filter	9.77	0.4501	-1.14	5.80
OrdStat (k=7)	21.26	0.9412	0.79	6.34

Figure 2 and Table 1 collectively demonstrate that the median filter delivers superior performance on every evaluation metric at a noise density of 0.1. It records a PSNR of 29.13 dB, roughly 6.5 dB above the mean filter, alongside an SSIM of 0.9894 which reflects near-perfect retention of image structures, and an SNR of 0.96 corresponding to 96% noise elimination. Visual inspection confirms that median filtering almost fully erases noise artefacts, retaining crisp facial outlines and fine grass texture details.

The mean filter yields a PSNR of 22.59 dB and an SNR of 0.82. Nevertheless, substantial residual noise remains visible in processed frames, where isolated noise pixels spread out to form indistinct grey patches and blur the whole scene. This observation reveals that although mean filtering offers mild smoothing effects, it cannot fundamentally eradicate impulse noise; it only distributes noise energy to adjacent pixel regions [2], which constitutes an intrinsic drawback of linear filtering when tackling impulse interference.

Maximum and minimum filters produce drastically substandard results, with PSNR values of just 8.68 dB and 9.77 dB respectively, SSIM scores hovering around 0.40, and crucially, negative SNR readings of −1.68 and −1.14. These negative SNR metrics act as a vital caution for industrial practitioners: the variance of residual noise after filtering exceeds that of the original unprocessed noisy image. The underlying cause is clear: the maximum filter solely eliminates dark pepper noise yet retains and amplifies bright salt noise, brightening the whole frame, while the minimum filter operates in the reverse manner. In mixed dual-polarity noise environments, these single-polarity filters cannot deliver valid denoising and will instead deteriorate visual quality. We can therefore draw an unambiguous conclusion: maximum and minimum filters are entirely inappropriate for mixed salt-and-pepper noise removal, and are only viable for niche applications where noise polarity can be fully confirmed (for instance, sensor faults generating solely bright or dead dark pixels).

The k=7 order-statistic filter attains a PSNR of 21.26 dB with an SNR of 0.79. Its overall denoising capacity sits between the median and mean filters, yet far exceeds that of maximum and minimum variants. This outcome suggests that the filter delivers targeted suppression of dark noise when k=7, yet its general noise reduction power weakens substantially due to its deviation from the median sorting index under mixed noise conditions.

4.2 Comprehensive Comparison Across Three Images at Different Noise Densities

Table.2 Performance comparison of five algorithms on three images under different noise densities (PSNR/SSIM/SNR)

Image	Density	Metric	Mean	Median	Max	Min	OrdStat(k=7)
barbara	0.05	PSNR	26.14	33.35	11.22	12.57	25.42
		SSIM	0.9694	0.9944	0.5225	0.5873	0.9727
		SNR	0.84	0.97	-2.49	-1.55	0.86
	0.10	PSNR	23.42	31.86	8.94	10.01	22.56
		SSIM	0.9410	0.9922	0.3701	0.3813	0.9439
		SNR	0.85	0.98	-1.49	-0.94	0.85
	0.20	PSNR	20.45	28.24	6.82	8.05	16.71
		SSIM	0.8783	0.9820	0.2382	0.1878	0.8025
		SNR	0.85	0.97	-0.43	-0.13	0.69
cameraman	0.05	PSNR	25.01	30.06	11.14	12.12	23.64
		SSIM	0.9713	0.9915	0.5811	0.6341	0.9660
		SNR	0.79	0.93	-2.75	-2.04	0.75
	0.10	PSNR	22.59	29.13	8.68	9.77	21.26
		SSIM	0.9483	0.9894	0.4019	0.4501	0.9412
		SNR	0.82	0.96	-1.68	-1.14	0.79
	0.20	PSNR	19.79	26.45	6.72	7.65	16.46
		SSIM	0.8960	0.9805	0.2662	0.2221	0.8363
		SNR	0.83	0.96	-0.54	-0.31	0.68
Lena	0.05	PSNR	25.36	30.62	11.81	12.12	24.58
		SSIM	0.9562	0.9876	0.5056	0.5287	0.9574
		SNR	0.80	0.94	-2.17	-1.99	0.80
	0.10	PSNR	23.27	29.90	9.40	9.81	22.46
		SSIM	0.9275	0.9854	0.3422	0.3574	0.9297
		SNR	0.83	0.96	-1.35	-1.16	0.83
	0.20	PSNR	20.44	26.98	7.29	7.74	17.04
		SSIM	0.8555	0.9715	0.2056	0.1799	0.7797
		SNR	0.84	0.96	-0.31	-0.21	0.71

Table:2.1 Average PSNR (mean ± standard deviation) across three images is summarized below:

Noise density	Mean	Median	Max	Min	OrdStat(k=7)
0.05	25.51±0.58	31.34±1.76	11.39±0.37	12.27±0.26	24.55±0.89
0.10	23.09±0.44	30.30±1.41	9.00±0.36	9.86±0.13	22.10±0.72
0.20	20.23±0.38	27.22±0.92	6.94±0.31	7.81±0.21	16.74±0.29

From the multi-density, multi-image data in **Table 2**, the following regularities can be observed:

First, the performance superiority and robustness of the Median filter are outstanding. Across three noise densities, the average PSNR of the Median filter on three images reaches 31.34 dB (density 0.05), 30.30 dB (density 0.1), and 27.22 dB (density 0.2), averaging approximately 6-7 dB higher than the Mean filter. SSIM consistently remains above 0.97 (reaching 0.9944 for barbara at density 0.05), and SNR is always ≥0.93, indicating that noise suppression exceeds 93% in all cases. Notably, when noise density increases from 0.05 to 0.2, the Median filter's PSNR decreases from 31.34 dB to 27.22 dB (a 13% decline), while the Mean filter drops from 25.51 dB to 20.23 dB (a 21% decline). This demonstrates that the Median filter not only excels in absolute performance but also exhibits gentler performance degradation under increasing noise intensity, offering stronger engineering robustness. The Median filter's superior performance fundamentally arises because salt-and-pepper noise manifests as grayscale extremes within a 3×3 neighborhood; after sorting, these extremes are inevitably positioned at both ends, allowing the median to naturally avoid them–a characteristic determined by the algorithm's principle [Error! Unknown switch argument.].

Second, the Max and Min filters completely fail in mixed-noise scenarios. **Table 2** clearly shows that across all nine test scenarios (three images × three noise densities), SNR values for both algorithms are universally negative, ranging from -2.75 to -0.13. The standard deviation of PSNR across the three images is merely 0.26-0.37 dB (at density 0.05), indicating that this failure is not accidental but represents a universal conclusion. Negative SNR means their output images are worse in quality than the input images-a counterproductive operation in engineering terms. Therefore, in practical image processing systems, if the noise type is unknown or confirmed as mixed-polarity salt-and-pepper noise, these two filtering algorithms should be avoided.

Third, the performance of the Order-Statistic filter (k=7) accelerates in degradation as noise density increases. At low density (0.05), the average PSNR of the Order-Statistic filter is 24.55 dB, differing from the Mean filter's 25.51 dB by only about 1 dB; but when density increases to 0.2, the Order-Statistic filter drops to 16.74 dB while the Mean filter stands at 20.23 dB, a gap widening to approximately 3.5 dB. This trend indicates that once k deviates from the median position, the Order-Statistic filter can maintain some denoising capability in low-noise environments but significantly deteriorates in high-noise environments. This has clear practical guidance: if the Order-Statistic filter must be used in higher-density noise scenarios, k should be kept as close to the median position (k=5) as possible, avoiding values that deviate significantly.

4.3 Effect of Different k Values in Order-Statistic Filtering

Under 0.2 noise density, the denoising effects of different k values on cameraman are shown in **Figure 3**, with quantitative metrics in **Table 3.**

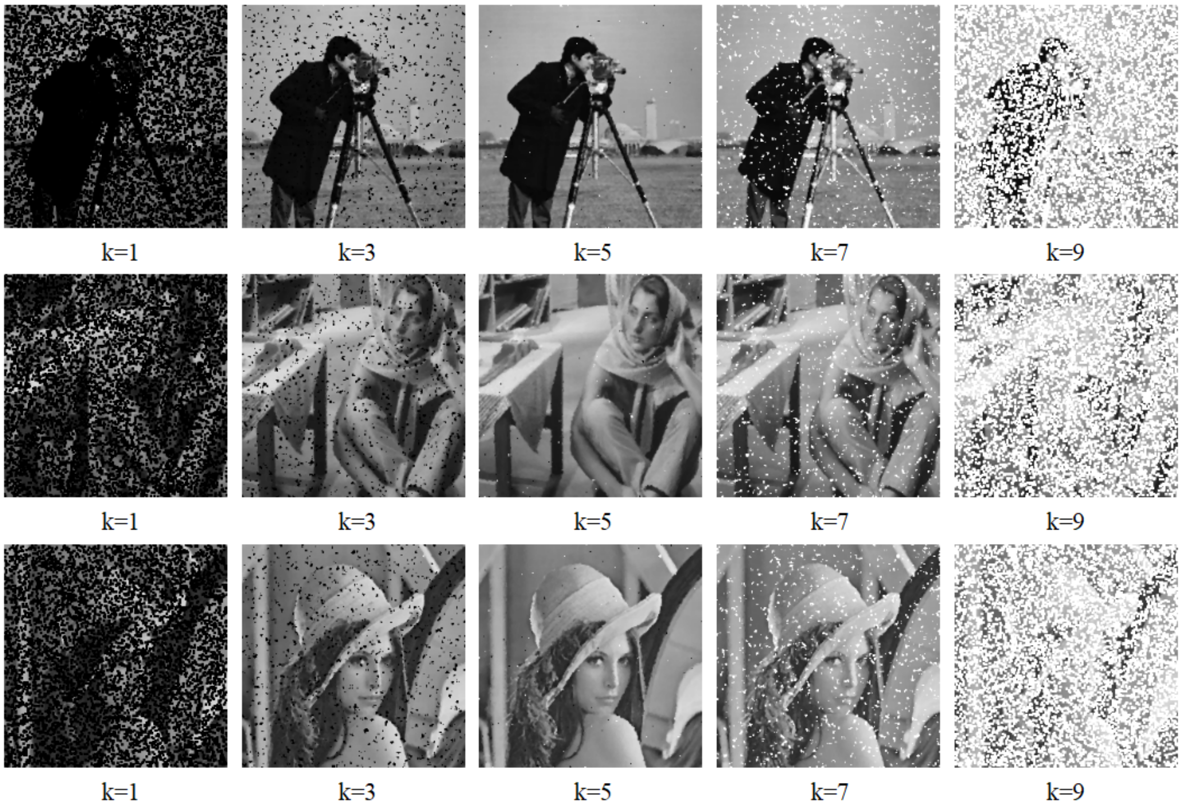


Fig.3 Processing effect of different k values in order-statistic filtering on salt-and-pepper noise (density 0.2)

Table.3 *Performance comparison of different k values in order-statistic filtering (cameraman, density 0.2)*

k	PSNR(dB)	SSIM	SNR	Visual effect
1	7.66	0.2204	-0.33	Dark, only bright noise removed
3	17.13	0.8589	0.72	Somewhat dark, residual dark noise
5	26.58	0.9811	0.96	Balanced,both noises effectively removed
7	16.64	0.8423	0.69	Somewhat bright, residual bright noise
9	6.77	0.2772	-0.55	Bright, only dark noise removed

The data in **Table 3** vividly demonstrate the decisive influence of parameter k on order-statistic filter noise suppression capacity: At k=5 (the median sorting index, equivalent to standalone median filtering), the filter achieves peak performance with a PSNR of 26.58 dB, SNR of 0.96, and SSIM of 0.9811, delivering well-balanced outputs with nearly complete noise elimination. At k=3, the PSNR plummets to 17.13 dB, a reduction of almost 10 dB; at k=7, the PSNR falls further to 16.64 dB. At boundary values k=1 and k=9, SNR metrics turn negative (-0.33 and -0.55), signifying total loss of effective noise suppression capability.

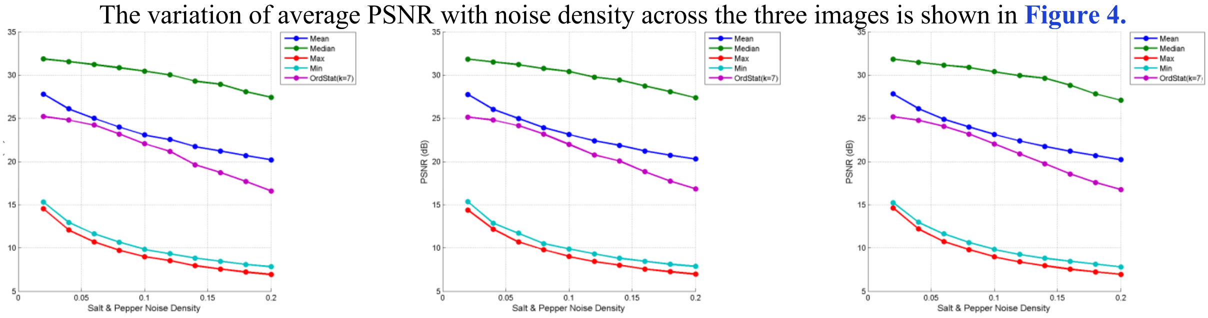
Variations in PSNR output driven by changes to parameter k stem directly from the sorting logic inherent to order-statistic filtering within a fixed 9-pixel 3×3 window. Salt noise pixels carry a peak greyscale value of 255, whilst pepper noise registers at the minimum intensity 0; these two extreme intensities occupy the outermost positions within the sorted local pixel sequence. Setting k to the median index of 5 allows the filter to avoid both classes of impulse noise in a single pass, preserving intact valid image signal information and producing the maximum achievable PSNR score. If k drifts upward to 7 or 9, the filter output leans toward high gray levels and cannot eliminate residual bright salt noise; if k drifts downward to 1 or 3, dark pepper noise artifacts remain unfiltered. The wider the offset between k and the optimal median index 5, the more residual mixed noise persists in reconstructed images, triggering continuous degradation of PSNR and SSIM. At extreme k=1 and k=9, the filter only suppresses single-polarity noise while amplifying the opposite noise type, leading to residual noise variance larger than the original noisy input and negative SNR readings.

This dataset reveals a highly practical regularity: the order-statistic filter’s noise suppression performance exhibits extreme sensitivity to parameter k, with a far higher degree of sensitivity than general engineering intuition suggests. Every two-index offset from the optimal k=5 triggers approximately 10 dB of PSNR attenuation, which constitutes unacceptable performance degradation for real-world image processing deployment.

An important engineering guideline can therefore be summarized: when using the Order-Statistic filter for mixed-polarity salt-and-pepper noise, unless prior information has clearly identified noise polarity bias (e.g., sensor calibration confirming that over 90% of noise points from certain equipment are bright noise), k should be strictly set to (N+1)/2 (i.e., the median position). Only when polarity bias is definitively established should k be appropriately adjusted in the corresponding direction: k<5 when the primary goal is bright noise removal, k>5 when dark noise removal is prioritized. Even with such targeted adjustment, however, the gap between k and 5 should not be excessive, as this would severely compromise suppression capability for the opposite polarity.

4.4 Overall PSNR Trends

The variation of average PSNR with noise density across the three images is shown in **Figure 4.**



(a)barbara (b)cameraman (c)lena

Fig.4 PSNR comparison of five filters under different noise densities

From the PSNR curves in **Figure 4**, the performance hierarchy and degradation trends of each algorithm can be intuitively grasped. The Median filter's curve remains at the highest position across all noise densities with the gentlest downward slope. The Order-Statistic filter (k=7) curve is relatively close to the Mean filter in the low-density region, but the two gradually diverge from density 0.06 onward, with the Order-Statistic filter's PSNR clearly lower than the Mean filter in the high-density region. The Max and Min filter curves nearly overlap, persistently occupying the lowest position on the graph, with PSNR never exceeding 12 dB across the entire noise density range.

The engineering application value of this line graph lies in its ability to help system designers quickly assess expected performance of each algorithm under specific noise conditions. For example, if an image acquisition system typically operates at noise densities not exceeding 0.05, the performance gap between the Mean filter and Order-Statistic filter (k=7) is small, allowing selection of the faster Mean filter[2]; however, if noise density may reach 0.1 or above, the Median filter's advantage becomes very pronounced and should be the preferred choice. Simultaneously, all algorithms in the figure have processing times in the millisecond range (1.85-6.46 ms), which is fully adequate for conventional real-time processing requirements, so denoising accuracy should be prioritized over processing speed when selecting algorithms.

5. Conclusion

This work presents systematic comparative testing to analyse salt-and-pepper noise reduction across five spatial filtering variants: mean, median, maximum, minimum and k=7 order-statistic filters. Testing is completed using three standard greyscale images under three distinct noise densities, with core findings outlined below.

Experimental results show that the Median filter achieves the best performance in all test conditions. When the noise densities are 0.05, 0.1 and 0.2, its average PSNR reaches 31.34 dB, 30.30 dB and 27.22 dB respectively. Its SNR is always no less than 0.93 and SSIM maintains above 0.97, which enables the filter to retain image edges and fine details effectively. In all mixed noise test cases, the Max and Min filters produce negative SNR values ranging from -2.75 to -0.13, which indicates that they cannot be applied to mixed-polarity salt-and-pepper noise removal. The denoising performance of the Order-Statistic filter with k=7 sits between the Median filter and Mean filter. The filter's performance will degrade sharply once k deviates from the median position: when k=5, the PSNR is 26.58 dB and SNR is 0.96; when k=3, the PSNR declines to 17.13 dB; when k=7, the PSNR drops to 16.64 dB; when k is set to 1 or 9, the SNR becomes negative.

Combined with the above research conclusions, several practical suggestions for engineering algorithm selection are put forward as follows.

First, the Median filter is the optimal option for common scenes with mixed-polarity salt-and-pepper noise, including monitoring video and medical imaging. It possesses outstanding denoising precision, structural retention ability and generalization performance, so it can be adopted as the default denoising module at the front end of image processing systems.

Second, the Max and Min filters are only applicable when the noise polarity is fully confirmed. Experimental data proves that these two algorithms fail to suppress mixed noise and even worsen image quality. They can only be adopted when the sensor feature is clear (i.e., the sensor generates purely white or black noise points) or the detection result verifies single-polarity noise.

Third, the order parameter k of the Order-Statistic filter needs to be set prudently. Experiments verify that every two positions of deviation from the optimal k value will lead to about 10 dB reduction in PSNR. It is suggested to build a noise polarity detection module to dynamically adjust k within the interval [3,7] according to detection outcomes instead of adopting a fixed k value.

Fourth, the Mean filter can be adopted as a substitute for scenarios demanding high real-time performance and low noise density (density ≤0.05). Its runtime is roughly 1.85 ms, less than one-third of that of the Median filter, while the PSNR difference between the two filters is about 5–6 dB, which makes the Mean filter fit embedded and mobile devices.

This research systematically compares five classic spatial filtering algorithms horizontally, clearly defines their performance ranking and applicable scope under salt-and-pepper noise interference, and intuitively reflects the invalid characteristics of Max and Min filters via the SNR index. The quantitative conclusions and matching selection suggestions offered in this paper can provide direct guidance for image processing engineers to select suitable denoising algorithms in practical engineering, avoiding image quality degradation and unnecessary development cycle waste caused by inappropriate algorithm selection.

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Conflicts of Interest: The authors declare no conflict of interest.

Ethical Statement:

All greyscale test imagery utilised within this study are standard open-access benchmark assets sourced from the USC SIPI image repository. This dataset has undergone extensive validation across thousands of peer-reviewed imaging publications for algorithm benchmarking purposes. The resource contains no identifiable personal portraits or sensitive private data. No human participant trials or original portrait photography were conducted throughout this research, so written informed consent from subjects is not required.

AI Use Statement:

Generative AI tools were only deployed for minor grammatical refinement and sentence rephrasing during manuscript revision. All experimental framework design, MATLAB simulation scripts, raw measured data, quantitative calculations, analytical logic and core academic conclusions are independently designed, computed and manually cross-checked by the full author group. Every author has reviewed the complete manuscript text, tables, figures and cited references, and accepts full accountability for the accuracy and completeness of all presented content. No generative AI models were used to generate experimental datasets or core academic arguments within this paper.

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