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Rank Order Weighted Mean Switching Filter for Salt and Pepper Noise Removal with Edge Preservation

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Abstract

Salt and pepper impulse noise remains one of the most disruptive forms of image corruption from acquisition, transmission, and low-quality sensor pipelines, with classical filters continuing to trade off noise suppression against edge and texture fidelity. This paper presents the Rank Order Weighted Mean Switching Filter (ROWM-SMF), a two-stage restoration scheme that first detects candidate impulse pixels using a rank-order median-based detector, then restores only the identified noisy pixels through a locally adaptive weighted mean combining a similarity weight with a rank-order salt-and-pepper penalty term, leaving uncorrupted pixels untouched. The filter is evaluated on the 24-image Kodak Lossless True Colour Image Suite corrupted with salt-and-pepper noise at six total noise densities (10%–60%) derived from nine salt-and-pepper density combinations, yielding 214 grayscale test cases. Performance is assessed using PSNR, SSIM, and FSIM, and compared against a standard 5×5 Median Filter and the recent OPERA-Net method. Averaged over all test cases, ROWM-SMF achieved a mean PSNR of 23.68 dB, SSIM of 0.790, and FSIM of 0.656, versus 21.81 dB, 0.617, and 0.420 for the Median Filter, gains of 1.87 dB, 0.173, and 0.236, respectively. Comparisons at noise densities of 10%, 20%, and 30% further show that ROWM-SMF consistently outperformed OPERA-Net in both PSNR and SSIM. These results confirm ROWM-SMF's effectiveness over both classical and recent methods. Despite added computational cost in the current implementation, the framework offers an effective, lightweight, training-free solution for high-fidelity salt-and-pepper image denoising.

Keywords: Salt and pepper noise; impulse noise removal; switching median filter; rank order statistics; weighted mean filter; edge preservation; image quality assessment; PSNR; SSIM; FSIM; Kodak dataset.

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1. Introduction

Digital images acquired through low-cost sensors, noisy or bandwidth-limited transmission channels, or faulty memory and analogue-to-digital conversion are often corrupted by impulse noise, with salt-and-pepper (S&P) noise being the most common form. S&P noise randomly replaces pixels with extreme intensity values (0 or 255 in 8-bit images) while leaving other pixels unchanged, significantly degrading image quality and adversely affecting edge detection, segmentation, feature extraction, and compression.

S&P noise removal methods are broadly classified into non-switching and switching filters. Non-switching filters, such as the standard median filter, process every pixel uniformly (Hwang & Haddad, 1995). Although simple and robust, such filters can blur edges, remove fine details, and produce streaking artefacts, particularly when large filtering windows or high noise densities are involved (Bovik, 1987; Nodes & Gallagher, 1982). Order-statistics filtering has therefore been extensively applied to image restoration, with Pitas and Venetsanopoulos providing a comprehensive treatment of order-statistics filters and their applications (Pitas & Venetsanopoulos, 1992). Several improvements to conventional median filtering have subsequently been proposed. Hwang and Haddad introduced the Adaptive Median Filter (AMF), which enlarges the filtering window in heavily corrupted regions (Hwang & Haddad, 1995), while Ko and Lee proposed the Centre Weighted Median Filter (CWMF), which assigns greater importance to the centre pixel to improve detail preservation (Ko & Lee, 1991).

A major development in impulse-noise removal was the introduction of switching or decision-based filters. Unlike non-switching filters, these methods first identify potentially corrupted pixels and restore only those pixels, leaving uncorrupted pixels unchanged (Esakkirajan et al., 2011; Hwang & Haddad, 1995). This detect-and-restore strategy reduces unnecessary modification of clean image regions and has therefore become particularly important for high-density impulse noise. Several approaches have explored different mechanisms for improving this detection process. The Progressive Switching Median Filter (PSMF), for example, iteratively detects and restores noisy pixels to reduce streaking (Zhou Wang & Zhang, 1999). Other approaches use centre-weighted median statistics and local extrema for adaptive impulse detection (T. Chen & Hong Ren Wu, 2001; S. Zhang & Karim, 2002). The Decision Based Algorithm (DBA) demonstrated effective restoration under high salt-and-pepper noise densities (Srinivasan & Ebenezer, 2007), while the Modified Decision Based Unsymmetric Trimmed Median Filter (MDBUTMF) became a widely adopted decision-based approach for impulse-noise restoration (Esakkirajan *et al.*, 2011).

The effectiveness of a switching filter, however, depends not only on how accurately corrupted pixels are detected but also on how their replacement values are estimated. This has led to different restoration strategies, particularly rank-order and weighted-mean approaches. Rank-order methods typically replace detected noisy pixels with a local or trimmed median (Esakkirajan et al., 2011; Hwang & Haddad, 1995), whereas weighted-mean approaches estimate the replacement value from neighbouring pixels according to their local characteristics (Erkan, Thanh, et al., 2020; P. Zhang & Li, 2014). Boundary Discriminative Noise Detection (BDND), for instance, improves impulse detection through boundary discrimination within a local window and has demonstrated strong performance under different impulse-noise densities (Pei-Eng Ng & Kai-Kuang Ma, 2006). Subsequent

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studies have further investigated improved decision-based and adaptive filtering strategies (Aiswarya *et al.*, 2010; Chen & Lien, 2008; Jayaraj & Ebenezer, 2010; Ze-Feng *et al.*, 2007; Zhou *et al.*, 2012).

Weighted restoration has also received considerable attention because neighbouring pixels do not necessarily provide equally reliable information. The Noise Adaptive Fuzzy Switching Median Filter incorporates fuzzy reasoning into the restoration process (Toh & Isa, 2010), while the Adaptive Weighted Mean Filter (AWMF) uses an adaptively enlarged window and locally weighted averaging to restore detected noisy pixels (P. Zhang & Li, 2014). Further developments include the Improved Adaptive Weighted Mean Filter (Erkan, Thanh, *et al.*, 2020), the Adaptive Frequency Median Filter (Erkan, Enginoğlu, et al., 2020), and other adaptive weighted approaches (Enginoğlu *et al*., 2019; Erkan & Gökrem, 2018; Thanh *et al*., 2020). These approaches demonstrate that assigning different levels of importance to neighbouring pixels can improve restoration quality compared with treating all available pixels equally.

Despite these developments, important limitations remain. Rank-order switching filters generally rely on binary and often fixed decision rules for classifying pixels as noisy or clean. Such rules may misclassify genuine fine-scale structures, such as thin lines and isolated bright or dark details, while also failing to reliably identify impulse pixels that do not occur exactly at the extreme intensity values. Weighted-mean approaches address some of these limitations, but potentially corrupted pixels within the restoration window may still receive nonzero weights and influence the estimated replacement value. This can result in residual noise or blurred edges. The problem becomes more challenging at high noise densities, where a fixed neighbourhood may contain too few reliable pixels to support accurate restoration. Adaptive window-growing strategies can alleviate this problem but may increase computational cost.

Other image-denoising approaches have attempted to improve structural preservation through similarity-based and learning-based techniques. Bilateral Filtering, Non-Local Means, and BM3D, for example, exploit spatial or neighbourhood similarity to preserve image structures (Tomasi & Manduchi, 1998; Buades *et al.*, 2005; Dabov et al., 2007). However, these methods were primarily developed for other noise models. Deep learning approaches such as DnCNN have achieved strong denoising performance but generally require substantial training data and computational resources (Zhang et al., 2017). More recent studies have explored hybrid and adaptive approaches, including adaptive median filtering (Aslam et al., 2023), metaheuristic optimisation of MDBUTMF (Mohan & Paulchamy, 2024), adaptive median filtering for interference fringe restoration (Guan *et al.*, 2024), Type-2 fuzzy detection with regression-based restoration (Kumar *et al.*, 2024a, 2024b), and iterative weighted mean filtering combined with deep learning (Yahaya *et al.*, 2026). Although these approaches demonstrate continued progress in impulse-noise removal, they also highlight the need for lightweight, training-free methods that can combine reliable noise detection with effective local restoration.

These observations motivate the development of a method that addresses both stages of the restoration process: reliable identification of corrupted pixels and reliable estimation of their replacement values. To address this need, this paper proposes the Rank Order Weighted Mean Switching Filter (ROWM-SMF), a lightweight and training-free method

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for salt-and-pepper noise removal. ROWM-SMF combines rank-order impulse detection with a locally adaptive weighted-mean restoration strategy. The restoration weight incorporates two complementary components: a similarity term that assigns greater importance to neighbouring pixels whose intensities are close to the local median, inspired by similarity-based filtering approaches (Buades et al., 2005; Tomasi & Manduchi, 1998), and a salt-and-pepper penalty that suppresses neighbouring pixels close to the extreme intensity values of 0 and 255, which are likely to be corrupted. Only pixels identified as noisy are restored, while uncorrupted pixels retain their original values.

The proposed approach differs from existing representative methods in how detection and restoration are combined. Adaptive weighted-mean filters such as AWMF generally assign weights to pixels according to local statistics without explicitly separating the detection and restoration processes, allowing potentially corrupted pixels to remain part of the weighted estimation (P. Zhang & Li, 2014). In contrast, ROWM-SMF first identifies corrupted pixels and then performs weighted restoration only for those pixels. Similarly, MDBUTMF removes extreme values from the restoration window and uses the remaining values for replacement (Esakkirajan *et al.*, 2011), whereas ROWM-SMF further differentiates the remaining neighbouring pixels according to their similarity to the local median and their likelihood of being additional salt-and-pepper noise. BDND provides strong noise detection through boundary discrimination but typically uses median-based restoration after identifying noisy pixels (Pei-Eng Ng & Kai-Kuang Ma, 2006). ROWM-SMF instead combines the detection process with a similarity- and rank-based weighted restoration mechanism.

Therefore, ROWM-SMF integrates switching-based detection with a two-term similarity- and salt-and-pepper-penalty-weighted restoration strategy, rather than treating detection and estimation as a simple detect-then-uniformly-average process. This design is intended to improve impulse suppression while preserving local image structures without requiring model training.

Impulse noise removal is a fundamental preprocessing step in applications such as medical imaging, remote sensing, industrial inspection, consumer photography, and astronomical spectrometer imaging (Guan *et al.*, 2024). Improving S&P noise suppression while preserving structural and perceptual quality, measured using PSNR, SSIM, and FSIM, can enhance the reliability of downstream tasks including edge detection, segmentation, feature extraction, and image compression. Computational efficiency is also important when selecting an image-restoration method for practical deployment.

The main contributions of this work are threefold. First, it introduces ROWM-SMF, which combines rank-order noise detection with a restoration strategy based on similarity weighting and a salt-and-pepper penalty. Second, it provides a mathematical formulation and algorithmic description to facilitate implementation and reproducibility. Third, it presents a comprehensive evaluation using the 24-image Kodak dataset with impulse-noise densities ranging from 10% to 60%, comparing PSNR, SSIM, and FSIM performance against a standard 5×5 median filter while also analysing the associated computational cost.

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2. Materials and Methods

This section describes the materials, experimental setup, and methodology used to develop and evaluate the proposed ROWM-SMF method. It presents the dataset, compared methods, evaluation metrics, and implementation details, followed by the experimental workflow and the formulation of the proposed filtering approach.

2.1. Dataset

Experiments were conducted on the 24-image Kodak Lossless True Colour Image Suite (Franzen, 1999), converted to 8-bit grayscale. Each image was corrupted with salt and pepper noise at nine (salt, pepper) density combinations, denoted by the suffix S{s}_P{p}_T{t}, where s and p are the salt and pepper percentages and $t = s + p$. The combinations cover six total noise densities, $T \in \{10, 20, 30, 40, 50, 60\}\%$, yielding 214 noisy/clean grayscale image pairs.

2.2. Compared Methods

The proposed ROWM-SMF ($h = 20$, $\sigma = 30$, window = 5×5, $\tau = 50$) was compared with the standard 5×5 Median Filter (Nodes & Gallagher, 1982) and OPERA-Net (Sharma *et al.*, 2025), while the noisy image was included as a lower-bound reference.

2.3. Evaluation Metrics

Performance was assessed using three full reference metrics against the corresponding clean Kodak image: PSNR, SSIM (Wang *et al.*, 2004), and FSIM (Lin Zhang *et al.*, 2011). Filtering time (ms) was also recorded to evaluate computational cost.

2.4. Implementation

The algorithms were implemented in Python using NumPy, OpenCV, SciPy, and scikit-image. The ROWM-SMF restoration stage (Algorithm 1, lines 7–17) was executed pixel by pixel over detected noisy pixels without vectorisation or parallelisation, a design choice that increases runtime and is discussed as a limitation in Section 4.

2.5. Experiment Workflow

The workflow follows a systematic restoration and evaluation process as shown in Figure 1. First, clean Kodak images are artificially corrupted with different levels of salt and pepper noise to establish a controlled testing environment.

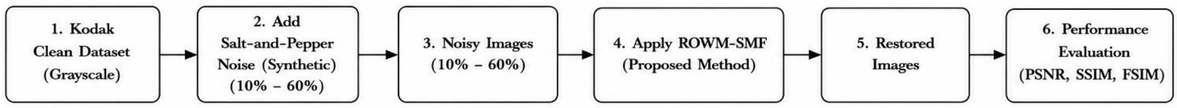

Figure 1. Experimental Evaluation Workflow

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2.6. Proposed ROWM-SMF Method

The noisy images generated from Figure 1 are subsequently processed using the proposed ROWM-SMF algorithm of Figure 2, producing restored images that are compared with their corresponding ground truth images. The use of multiple objective image quality metrics ensures a comprehensive assessment of the proposed method under varying impulse noise conditions.

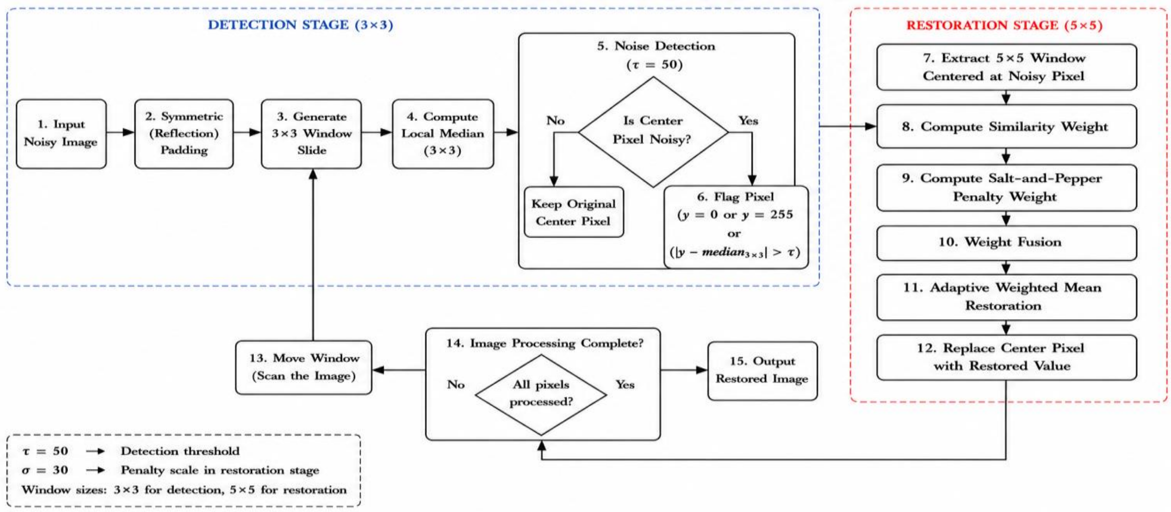

Figure 2. ROWM-SMF Algorithm Flow

ROWM-SMF of Figure 2 follows a two-stage switching filter architecture: (1) impulse detection, which flags candidate corrupted pixels using rank-order statistics, and (2) selective restoration, which replaces only the flagged pixels using a locally adaptive weighted mean. Figure 2 summarises the pipeline; a full mathematical formulation follows in Section IV and the corresponding pseudocode in Section 2.8.

2.6.1. Detection Stage

For each noisy image channel, a 3×3 median image is computed. A pixel is identified as a candidate impulse if its intensity is 0 or 255, or if its absolute deviation from the local 3×3 median exceeds a fixed threshold (τ = 50). The first condition detects classical salt and pepper noise, while the second uses the local median as a robust reference to identify rank order outliers that may not lie at the intensity extremes.

2.6.2. Restoration Stage

Only detected impulse pixels are restored. For each flagged pixel, a 5×5 neighbourhood is examined, and two weights are computed for every neighbouring pixel: a similarity weight, which favours intensities close to the local median, and a salt and pepper penalty, which suppresses neighbours with intensities near 0 or 255. Their product defines the restoration weight. The centre pixel is excluded, and the corrupted pixel is replaced by the weighted neighbourhood mean. If all weights are zero or negligible, such as within large corrupted regions, the local median is used instead, ensuring a valid output.

This approach combines two common restoration strategies: rank order replacement, which is robust but may oversmooth, and weighted mean replacement, which preserves smoothness but relies on reliable neighbouring pixels. By integrating local similarity with explicit penalisation of likely corrupted neighbours, ROWM-SMF maintains robust impulse detection while producing smoother restorations with reduced quantisation effects compared to standard median replacement.

2.7. Mathematical Formulation

Let y denote the noisy grayscale or a single channel in a coloured image of size H×W, with pixel intensities in [0, 255]. Let $m_3(y)$ denote the 3×3 median-filtered image (reflect boundary padding). The detection mask M is defined pixel-wise as

$$M(r,c) = 1 \text{ if } y(r,c) \in \{0, 255\} \text{ or } |y(r,c) - m_3(y)(r,c)| > \tau, \quad M(r,c) = 0 \text{ otherwise} \quad (1)$$

with $\tau = 50$. Pixels with $M(r,c) = 0$ are copied unchanged to the output; only pixels with $M(r,c) = 1$ are restored.

For a flagged pixel at location $p = (r,c)$, let P_p denote its w×w local window ($w = 5$) extracted from the reflect-padded image, and let $m_p = \text{median}(P_p)$ be the local window median. For every location i inside the window, the similarity weight is

$$w_s(i) = \exp(-(P_p(i) - m_p)^2 / (h^2 + \varepsilon)) \quad (2)$$

With bandwidth $h = 20$ and $\varepsilon = 10^{-6}$ for numerical stability. This term is largest when the neighbour's intensity is close to the local median and decays for neighbours that deviate strongly from it, in the manner of a bilateral range kernel (Tomasi & Manduchi, 1998).
The rank-order salt-and-pepper penalty is defined from each pixel's distance to the nearer of the two extreme intensity values,

$$d(i) = \min(P_p(i), 255 - P_p(i)), \quad w_p(i) = 1 - \exp(-d(i)^2 / (\sigma^2 + \varepsilon)) \quad (3)$$

With $\sigma = 30$. This term approaches zero when the neighbouring pixel itself lies close to 0 or 255, which is a likely additional impulse corruption and approaches one for pixels well inside the mid-range of intensities, so that likely corrupted neighbours are excluded from the restoration average regardless of how close they happen to sit to the local median.

The combined restoration weight is the elementwise product $\omega(i) = w_s(i)\cdot w_p(i)$, with the centre weight forced to zero, $\omega(\text{centre}) = 0$, so a flagged pixel never contributes to its own replacement value. The restored intensity is the weighted mean

$$\hat{y}(p) = \Sigma_i\, \omega(i)\cdot P_p(i) \,/\, \Sigma_i\, \omega(i) \quad \text{if } \Sigma_i\, \omega(i) > 10^{-6}, \quad (4)$$

$\hat{y}(p) = m_p$ otherwise and the final output is clipped to the valid range and quantised, $\hat{y}(p) \leftarrow \text{round}(\text{clip}(\hat{y}(p), 0, 255))$. Unflagged pixels retain their original value, $\hat{y}(p) = y(p)$ for $M(p) = 0$, which is the defining switching property of the filter.

2.8. Algorithm

Algorithm 1 summarises the ROWM-SMF procedure exactly as implemented, operating independently on each channel of the input image.

Algorithm 1: ROWM-SMF(y, h, σ, w)
Input: noisy image y, bandwidth h, penalty scale σ, window size w ($\tau = 50$ fixed)
Output: restored image $\hat{y}$
1: pad ← ⌊w/2⌋

```
2:  for each channel c of y do
3:     m₃ ← median_filter(y_c, size = 3)
4:     M ← (y_c = 0) OR (y_c = 255) OR (|y_c − m₃| > τ)
5:     if M has no true entries: continue
6:     y_pad ← reflect_pad(y_c, pad)
7:     for each (r, col) with M(r, col) = 1 do
8:        P ← window of size w×w centered at (r+pad, col+pad) in y_pad
9:        m_p ← median(P)
10:       w_s ← exp(−(P − m_p)² / (h² + ε))
11:       d  ← min(P, 255 − P)
12:       w_p ← 1 − exp(−d² / (σ² + ε))
13:       ω  ← w_s · w_p ; ω(center) ← 0
14:       if Σω > ε:  val ← Σ(ω·P) / Σω
15:       else:       val ← m_p
16:       ŷ_c(r, col) ← val
17:    end for
18: end for
19: ŷ ← round(clip(ŷ, 0, 255))
20: return ŷ
```

The detection step in lines 3–4 is applied once per channel using a vectorised 3×3 median filter, so its cost scales with image size but not with noise density. The restoration step in lines 7–17 is applied only to flagged pixels, so its cost scales with the number of flagged pixels and therefore with the noise density T, which is the dominant factor behind the runtime trends reported in Section 3.

3. Results and Discussions

This section evaluates the proposed ROWM-SMF on the Kodak24 dataset across multiple salt and pepper noise levels using PSNR, SSIM, and FSIM. Results are compared with the Median Filter (Nodes & Gallagher, 1982) and OPERA-Net (Sharma et al., 2025), whose performance values were obtained from the published literature.

3.1. Quantitative Performance Evaluation

Table 1 summarises the average PSNR, SSIM, and FSIM values for the noisy images, the 5×5 Median Filter (Nodes & Gallagher, 1982), and the proposed ROWM-SMF across all Kodak images at the six total noise densities, together with the overall average for the 214 test cases.

Table 1. Quality metrics averaged over the 24-image Kodak set, by overall noise density

T (%)	PSNR Noisy	PSNR Median	PSNR proposed	SSIM Noisy	SSIM Median	SSIM Proposed	FSIM Noisy	FSIM Median	FSIM Proposed
10	15.20	**25.41**	**28.94**	0.214	**0.737**	**0.949**	0.634	0.419	0.843
20	12.22	**25.12**	**27.90**	0.115	**0.730**	**0.925**	0.476	0.420	0.781
30	10.80	**24.09**	**26.32**	0.083	**0.708**	**0.888**	0.400	0.416	0.709
40	9.28	21.27	22.86	0.056	0.609	0.781	0.323	0.409	0.626
50	8.27	19.92	21.18	0.039	0.555	0.711	0.285	0.428	0.579
60	7.47	17.97	18.91	0.028	0.441	0.578	0.253	0.441	0.531
Aveg.	**10.01**	**21.81**	**23.68**	**0.077**	**0.617**	**0.790**	**0.367**	**0.420**	**0.656**

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Across all test cases, ROWM-SMF increased the mean PSNR from 21.81 dB (Median Filter) to 23.68 dB (+1.87 dB) and by 13.66 dB over the noisy input. It also improved mean SSIM from 0.617 to 0.790 (+0.173) and FSIM from 0.420 to 0.656 (+0.236). The larger FSIM improvement reflects the filter's ability to suppress impulse-corrupted neighbours, preserving edges and structural details.

ROWM-SMF consistently outperformed the Median Filter at all noise densities, with the largest gains at low noise levels. At T = 10%, it achieved +3.54 dB PSNR, +0.424 FSIM, and 0.949 SSIM, indicating near-complete structural recovery. As noise increased, the performance gap narrowed; at T = 60%, the gains reduced to 0.94 dB PSNR and 0.090 FSIM because fewer reliable neighbouring pixels were available, causing the filter to rely more often on its median fallback and behave more similarly to the Median Filter.

Although the noisy images exhibited very low SSIM (0.214) and FSIM (0.634) even at T = 10%, demonstrating the sensitivity of structural metrics to impulse noise, both filters substantially restored image quality, with ROWM-SMF consistently providing greater recovery than the Median Filter.

3.2 Comparison with Existing Methods

In addition to the quantitative evaluation presented in Table 1, the proposed ROWM-SMF was further compared with representative image denoising methods reported in the literature. This comparison aims to position the proposed filter relative to both traditional and recent approaches using the Kodak24 benchmark.

Table 2. Quantitative Comparison of the Proposed ROWM-SMF with Existing Methods on the Kodak24 Dataset under Salt and Pepper Noise

Reference	Method	Dataset	Noise Type	Metrics	10%	20%	30%
(Nodes & Gallagher, 1982)	Median Filter	Kodak24	Salt and Pepper	PSNR	25.41	25.12	24.09
				SSIM	0.737	0.730	0.708
(Sharma et al., 2025)	OPERA-Net	Kodak24	Salt and Pepper	PSNR	19.96	17.29	15.83
				SSIM	0.33	0.22	0.17
Proposed	ROWM-SMF	Kodak24	Salt and Pepper	PSNR	28.94	27.90	26.32
				SSIM	0.949	0.925	0.888

Table 2 compares the proposed ROWM-SMF with the Median Filter (Nodes & Gallagher, 1982) and OPERA-Net (Sharma et al., 2025) on the Kodak24 dataset at 10%, 20%, and 30% salt and pepper noise. ROWM-SMF consistently achieved the best performance across all metrics. At 10% noise, it reached 28.94 dB PSNR and 0.949 SSIM, outperforming the Median Filter (25.41 dB, 0.737) and OPERA-Net (19.96 dB, 0.330). Similar trends were observed at 20% and 30% noise, where ROWM-SMF maintained PSNR > 26 dB and SSIM > 0.88, demonstrating that its switching strategy with similarity and rank order penalty weighting effectively removes impulse noise while preserving image structure.

3.3. Computational Cost

Table 3 reports the mean per-image filtering time for the median filter and ROWM-SMF at each noise density.

Table 3. Mean per-image runtime by noise density

Reference	Method	Dataset	Noise Type	Metrics	10%	20%	30%
(Nodes & Gallagher, 1982)	Median Filter	Kodak24	Salt and Pepper	PSNR	25.41	25.12	24.09
				SSIM	0.737	0.730	0.708
(Sharma et al., 2025)	OPERA-Net	Kodak24	Salt and Pepper	PSNR	19.96	17.29	15.83
				SSIM	0.33	0.22	0.17
Proposed	ROWM-SMF	Kodak24	Salt and Pepper	PSNR	28.94	27.90	26.32
				SSIM	0.949	0.925	0.888

The 5×5 median filter runs in a near-constant ≈157 ms per image regardless of noise density, since it is applied uniformly to every pixel via a vectorised routine. ROWM-SMF, in contrast, restores only flagged pixels but does so with an unvectorized, per pixel Python loop (Algorithm 1, lines 7–17), so its runtime scales approximately linearly with the number of flagged pixels and therefore with T, rising from 2.45 s per image at T = 10% to 13.61 s per image at T = 60%, an average slowdown of roughly 55× relative to the median filter across all densities. This is the principal limitation of the present implementation: the accuracy gains reported above are obtained at a runtime cost that would need to be addressed, for example through vectorised window extraction or a compiled/JIT implementation, before the filter would be suitable for real-time use.

3.4 Qualitative Observations

Because unflagged pixels are copied unchanged, ROWM-SMF does not introduce the global smoothing associated with uniform filters; at low to moderate densities, this switching behavior is consistent with the correspondingly higher SSIM and FSIM scores observed in Table I, since large uncorrupted regions of each image are left substantially untouched rather than being subjected to unnecessary median replacement, an effect the median filter cannot reproduce since it filters every pixel regardless of whether that pixel was corrupted.

4. Conclusion

This paper presented the Rank Order Weighted Mean Switching Filter (ROWM-SMF), a lightweight, training-free method for salt-and-pepper noise removal. The proposed method combines rank-order noise detection with locally adaptive weighted-mean restoration, using similarity and salt-and-pepper penalties to prioritise reliable neighbouring pixels. Experiments on the Kodak24 dataset demonstrated consistent improvements over standard median filtering and competitive performance with recent learning-based methods, without requiring training data.

Despite these promising results, the study has some limitations. The evaluation was conducted on a single 24-image Kodak benchmark using grayscale images corrupted with combined salt-and-pepper noise; therefore, further validation on larger datasets, colour images, and random-valued impulse noise is required. In addition, the pixel-wise restoration implementation was not vectorised, meaning that the measured runtime reflects both the algorithmic complexity and the current implementation. Furthermore, the filter parameters h, σ, window size, and τ were fixed rather than adaptively optimised for different noise levels.

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Future work will therefore focus on improving computational efficiency through JIT compilation and vectorisation, extending the method to colour images and random-valued impulse noise, and developing adaptive parameter selection mechanisms to improve robustness across varying noise conditions.

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