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# Enhanced Adaptive Weighted Median Filtering for High-Density Impulse Noise Removal

**[1]P. Madhu, [2]I. Jagadish**

[1,2]Department of electronics and communication Engineering, GMR Institute of Technology, Rajam, 532127, Andhra Pradesh, India.

A B S T R A C T

Impulse noise (commonly referred to as salt-and-pepper noise) can substantially distort the quality of images, imposing challenges on down-stream vision tasks due to the severity by which images become corrupted under a high noise density. While the existing body of work focusing on median based denoising processes perform well in the low-to-moderate scenario; at extreme corruption levels, the median performance can fail in either of two ways: 1) the smoothing of fine details, or 2) not adequately removing clustered noisy pixels / pixels not being sufficiently denoised. In this paper the we present a new denoising process referred to as the Adaptive Sequentially Weighted Median Filter (ASWMF) that is specifically designed for the decorruption of images that experience high order impulse noise densities. The process implements 3 scripts into the filter: 1) a noise detection script that is robust to high densities of impulse noise, 2) a window sizing script that adapts based upon the need of the processing windows and finally, 3) a sequential weighted median filtering pass that retains edges and textures yet subsequently updates the pixels values as each pixel transforms. The noise detection script uses local intensity statistics and local rank ordered differences of the local neighborhood around the pixel being processed to adaptively classify pixels at even a high density of noise. The adaptive window only grows in size when size is required, thus avoiding unneeded smoothing. Spatially and intensity based weights are assigned to each neighborhood in order to ensure that reliable denoising neighbors have more influence in the median decision making process. The inline sequentialing processing (processing pixels in a raster-scan while receiving feedback from denoised pixels to adjust the weightings as the filter progresses throughout the image) allows for processing of long chains of unprocessed noisey neighborhoods, thereby progressively restoring long regions of pixels at a time. Evaluations of this processes performance using standardized grayscale and color test images at extreme levels of distortion show that ASWMF performs considerably better based on even the most common performance metrics (PSNR and SSIM). filters, while visually respecting edges and texture. The proposed approach is computationally efficient and easily extendable to color images and hardware implementations.

**Keywords**: impulse noise removal, weighted median filter, adaptive filtering, sequential processing, image restoration

## Introduction

An essential pre-processing step in many imaging and computer vision pipelines is image denoising. Of the different noise types, impulse noise - primarily modeled as salt-and-pepper noise - consists of when individual pixels have been randomly corrupted to extreme intensity levels (e.g. 0 or 255 in 8-bit images) or other outlier values. Impulse noise corruption has been reported as being frequent in low-cost imaging sensors, faulty transmission channels, and some problems arising during the acquisition process. When the density of impulse noise is low, standard methods (e.g. median and its variants) are often capable of performing well. However, when the density of impulse noise is high (e.g. >40-50%), two challenges arise. The first is that it becomes almost impossible to detect reliably which pixels are noisy since many surrounding pixels may also have been corrupted. The second challenge is that replacement strategies either over-smooth image detail (which will destroy edges or any texture) or will not recover extremely corrupted parts of the image. This paper was written with the goal of addressing both challenges by providing a targeted filtering strategy specifically designed for handling extreme corruptions from impulse noise while maintaining structural integrity. Classic median filtering is robust against outlier values or pixels, but the median is applied indiscriminately to every pixel, leading to detail and edge degradation. Adaptive
median filtering addresses this to some extent with the addition of structure. When there is high impulse noise, adaptive median filters are challenged because detecting faulty pixels and modifying the filtering window size can be effective, but exactly how their detection rules and fixed-median substitution fails when best local neighbors are also likely to be faulty. Replace the detection stage with weighted median filters, that use sampling weights to bias the median selection toward more trustworthy neighbors. Additionally, using weighted median filters better preserves edges. The downside is that, just like detection, static weights and a fixed window could perform terribly during a period of high-density noise occurrence where the picked neighbors are not reliable. Meeting the double need of accurate noise detection while also reconstructing the image carefully requires a method that can detect faulty pixels with a high level of accuracy minimize false positives/false negatives and obtains neighborhood information on the most trustworthy sample position in an adaptive way. Sequential or iterative methods using the pixel values of corrected pixels as help to reconstruct the faulty investigations of neighbors is a wonder approach for high-density noise densities, but not too quickly incorrect corrections become persuading. This paper reviews an Adaptive Sequentially Weighted Median Filter, (ASWMF), that integrates a robust local detector, adopts adaptive window sizes, switches weights with

each iteration based on local intensity and position, as well as some slight iterations of corrected intensity updates. The detector that we have reviewed for application combines local pixel intensity rank-based local differences and local intensity-range diagnostics to classify the faulty pixel and classify pixels as clean pixels versus faulty pixels, even if there are many surrounding and effected samples. The adaptive window only increases in size when needed. This allows the filter to tap into a larger support in heavily corrupted areas while retaining the advantages of small windows near edges. Weighting samples involves a preference for those samples that were closer in intensity and spatial location, and incorporates a reliability term that is derived from the detector. The sequential processing of pixels results in progressively returning pixels to create candidates for restoring heavily corrupted neighbors, allowing the filter to reconstruct large noisy patches, whereas a single-pass and non-sequential filter could not.

The remainder of this paper is organized as follows: A review of the literature on various types of median filters, including properties of impulse noise is included in Section 1.1, followed by a formal statement of the problem in Section 1.2. Section 2 presents the review of the literature that is largely focused on median-like filters and adaptive strategies, while also highlighting missing elements in the literature. Section 3 details the ASWMF and complexity of implementing the algorithm, while Section 4 elaborates on the title's characterizing implications for the algorithm and some design considerations. Section 5 describes experiments and analysis, and Section 6 provides conclusions and directions for future work.

***Background***

Median filtering is a nonlinear process that takes a pixel and replaces it with the median of the intensity values of the pixels within a given local neighborhood. Because the median is a robust statistic, it will suppress impulsive outliers better than variants of linear filters. However, uniformly applying a median filter will lose fine detail and blur edges. Adaptive median filters incorporate some notion of whether the center pixel is corrupted first, if it is not corrupted, the filter leaves it unchanged. If the center pixel is determined to be noisy, the filter proceeds to compute the median from "an adaptive window" which expands in size until either a valid median is found or a maximum size is reached. This improves unnecessary smoothing while being dependant on efficiently detecting noise and using a sensible maximum window size.

Weighted median filters use the same logic and concept as the median filter, validity or noise detection must work first, however sample multiplicities (weights) assigned to neighborhood samples are included: thus samples with a higher weight, exert more pull on the median calculation that is based on the intensity value. This permits for edge preservation, in that samples with the center sample that are of a similar weight to the mid-sample or push samples from the edge are assigned a higher weight. In developing or processing additional weights, whether based on the spatial kernel shape or from intensity value distance/ similarity, will be considered, or other methods keeps the structure. However, at high noise densities, many of the samples used to calculate the weights themselves can be corrupted and thus have little value. Impulse noise detection is typically done with local ranges (max-min checks), or a rank-order-based detector, or in some cases more complicated statistics like trimmed means. The most significant challenge at high noise densities is that the local statistics start to break down and the detectors need to incorporate cross-scale, or cross-directional statistics, in order to sort through true texture and noise, and ultimately misclassify the one as the other. Finally, sequential and iterative techniques that iteratively upgrade the pixel values and use the upgraded values to perform the next correction have shown capacity to recover from much corruption but need to create safeguards to filter out
incorrectly upgraded pixel values. The combination of arobust method of detection, adaptive spatial neighborhoods, weighted contributions, and incremental update is the conceptual framework of the ASWMF.

***1.2 Problem statement***

Images that are subjected to high-density impulse noise (for example, ≥ 50% pixel corruption) have two related challenges: (1) accurately and reliably detecting which pixels are corrupted (while potentially many of the neighbor pixels may also be corrupted); and (2) reconstructing corrupted pixels without damaging edges or textures, especially when very few reliable samples remain in the neighborhood (given the pixel level of corruption). Median, adaptive, and weighted filters work to solve parts of these problems but do not consistently restore structure (i.e., edges or textures) using the reliability of information at extreme pixel corruption levels. The goal is to design a filtering strategy that identifies the corrupted pixels with high fidelity and simultaneously restores the corrupted pixels utilising the most reliable, adaptively chosen, neighbor information with a sequential mechanism to overcome the density of noise-clustered pixels.

## Literature review

The body of literature available on impulse noise removal is expansive and rich. Most of the background work regarding impulse noise, foremost, focused on the standard median filter and its most simplistic variations. The median filter works by replacing every pixel with the median of the pixels present in its local neighborhood. It excels at removing low-density salt-and-pepper noise because the median is not influenced by outliers. However, it also modifies the uncorrupted pixels in the same way, leading to loss of detail and blurred edges of genuine pixels. This realization, that the standard median filter modifies uncorrupted values indiscriminately led to the development of selective median filters that first classify which pixels are noisy and only replace the ones that are classified as noisy with the median. Selective methods typically can better preserve uncorrupted value, but ultimately are only as good as the reliability of the noise detector. Adaptive versions of median filters improved on the static-window design by expanding the window of data they would examine until the median was suitable; reducing the reliance on a global parameter to tune, and offering improved robustness to mixed noise. Simply put, these methods use basic rules that look at the pixels values compared to the local minimum, maximum, and median to determine whether it declares a value to be noisy. The adaptive median removes noise satisfactorily at moderate degree of density; however, at very high corruption rates, the neighborhood may locally contain only corrupted values, and as with all adaptive enlargements, it is common for it to reach its maximum before suitable median was found. or it incorrectly keeps impulse values that are likelocal extrema.Weighted median filters also make use of multiplicities or continuous weights for neighbors by differentiating the influence of pixels that are deemed reliable or "close" to the center. Weights can be designed according to spatial kernels, bilateral-like intensity similarities or guided by edge maps. Weighted medians are better at preserving edges than simple medians, particularly when the weights favor local homogeneity. But they still rely on nearby reliable values to calculate the weights, and if the neighbors are corrupted, then the weight calculation is contaminated. Certain approaches attempt to improve this issue by calculating weights based on robust measures (e.g., trimmed statistics) or enforce a multi-stage filtering approach to gain some initial estimates for weight calculations. Detection based strategies suggest going beyond simple range tests and use rank-order and morphological approaches instead. Rank-ordered absolute differences and median absolute deviation present statistics that are not sensitive to a few outliers which assists in separating impulses from legitimate texture. Multi-stage detectors rely on a coarse-to-fine processing framework that creates a cleaner estimate after the preliminary denoising filter which in turn feeds a better detector in a second pass, i.e., when the guess is more trustworthy. Directional detectors utilize gradients and directional medians to not misclassify edges as noise. Iterative and sequential restoration models involve several passes, or ordered updates, where corrected pixels might be utilized as context for subsequent corrections. Orderly updates, such as iterative median, combine anisotropic diffusion with impulse removal, or sequential schemas (with raster or adaptive scanning patterns) have all been useful in recovering power in compromised clustered impulses. However, values that iterate uncontrolled can propagate previous error generation, emphasizing the need for reliable stopping criteria or systematic confidence measures.

Hybrid strategies can join median-based filtering with other proposed restoration paradigms: e.g. using a median detection technique alongside total variation minimization on smooth regions, or applying the principles behind non-local means to leverage inherent and persisting self-similarity in textures. Non-local means uses global comparison of patches to identify reliable patches that can be utilized for reconstruction; non-local methods are strong, but they can come with an increase in computational effort for application, and may be less useful to random choices from dominatied impulses across large regions, where the position of a clean patch may not reliable.

More recently, there has been some prior, but significant attention, paid to learning-based approaches (convolutional networks, deep-residual models) trained purposefully for the removal of impulse noise. They performant exceptionally well, so long as an ample training cohort matched the corruption scene. Networks trained ostensibly on low to medium noise density performed severely in statistically relevant assumptions of a situation with extreme impulse contamination, which could make it challenging for real-world data to represent with sampling simultaneously assessed at high levels of impulse contamination behavior. While performance is in question with evident reliance to generalize under fatigue, we add that learning (or hypothetical) based methods also acquire considerable, and often substantial, computational effort. The literature made several actionable observations: first, strong detection is equally important to the replacement strategy; second, adaptivity, both at the window sizing and weight selection levels, improves performance; third, using corrected pixels in a sequential or iterative manner can extend restoration effective support in dense noise but requires strong gating to avoid error propagation; and fourth, any solution must factor computational complexity and parameter sensitivity in relation to restoration quality for applicable use. The ASWMF build upon these observations by incorporating a strong local detector, using adaptive neighborhoods, computing reliability-weighted medians, and employing a controlled sequential update strategy. The ASWMF is aimed at providing similar algorithmic simplicity and computational efficiency associated with median based methods, along with increasing performance at higher levels of noise through adaptivity and sequential restoration.

### *Research gaps*

Reliable detection of impulses under very high noise densities (when most of the local neighbors are likely corrupted) is still an unsolved problem. - The current weighted median and adaptive methods rely on contaminated samples in the weight calculations, which do not work effectively under extreme corruption. - Most sequential or iterative methods do not provide sufficient robust guards and this leads to propagating errors, especially when early decisions are wrong. - Non-learning, lightweight solutions that reliably restore textures and edges at very high impulses densities with low computational cost are rarely explored.

### *Research objectives*

Develop a robust local impulse detector that ensures elevated levels of detection precision during significant local contaminations - Create an adaptive window sizing policy in which support is increased only when necessary, in order to maximize clean samples available for classification and to ensure that local information is preserved - Develop a reliability-weighted information for beneficial median value which favors reliable neighbors and adjusts for contaminated neighbors - Construct a sequential update strategy through utilizing the corrected pixels for guidance on complicated areas electrostatically while preventing cross-contamination from previous erroneous corrected pixels.

## Methodology

This part provides a thorough account of the proposed Adaptive Sequentially Weighted Median Filter (ASWMF) in terms of noise detection, adaptive window technique, weighted median calculation and the ordering of sequential updates. Issues of implementation and complexity have also been addressed.

### *Adaptive window strategy*

If the pixel is declared noisy at $W_k$, the algorithm enlarges the window to $W_{k+1}$ and repeats detection, stopping either when the pixel is classified as clean or $S_{max}$ is reached.This allows the detector to access a broader context when local neighborhoods are heavily contaminated. To avoid excessive smoothing, the window growth rate is moderate (e.g., increment by 2 in side length), and a confidence metric based on the proportion of non-extreme neighbors constrains growth,if too few non-extreme neighbors exist, the algorithm may switch to a longer-range strategy (see sequential pass).

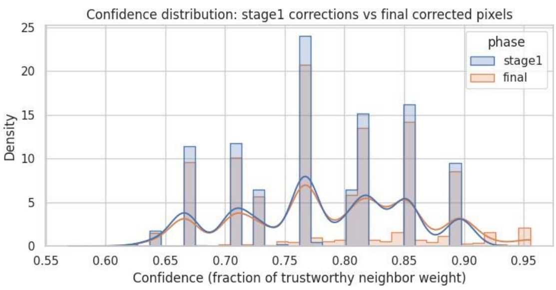
***Sequential update scheme***

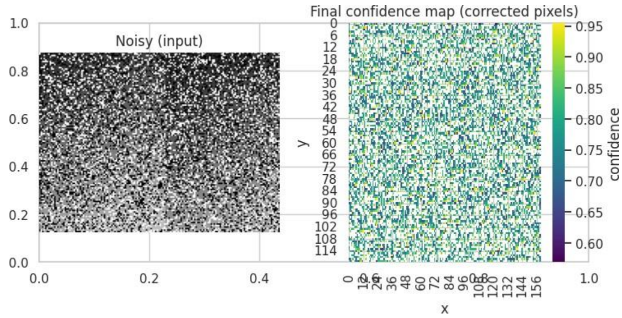
Rather than performing a single pass that treats pixels independently, ASWMF implements a two-stage sequential process:

Stage 1 (ordered pass): The pixels are processed in a predetermined order of scanning (e.g. raster or serpentine). For each pixel, the output of the detector and the weighted median calculated against its current state in the accumulation is utilized. When a pixel is corrected, its new corrected value is immediately available to subsequent pixels in the scanning order. This is especially important for dense areas of noise where early corrections create localized clean support to allow correcting subsequent pixels.

Stage 2 (refinement pass): After the ordered pass, the refinement pass is short and only re-evaluates pixels of low confidence (the replacement had low effective weight/ the pixel had high uncertainty) using larger windows or several replacement values (the median of medians). The refinement can also incorporate a small number of non-local affiliated patches if needed.

To stop wrong corrections from propagating, the algorithm has confidence thresholds, which indicates a replacement is only acceptable if the cumulative weight of 'trustworthy' neighbors exceeds a minimum value and all others are still marked as having a missed opportunity or replacement. If the aggregate weight falls below the threshold, it is not corrected and the pixel is marked as a candidate for late stage processing in the refinement pass, where possibly taking a larger context or additional heuristics would apply.



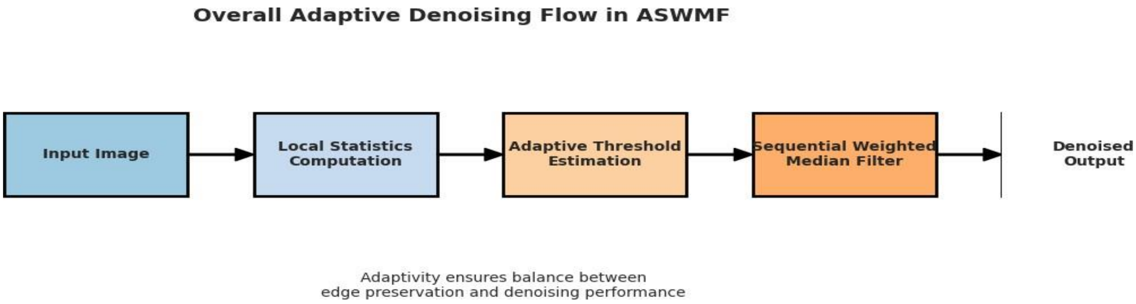

***Implementation notes and complexity***

Calculating the weighted median for each pixel necessitates sorting neighbors or utilizing an efficient histogram-based cumulative weights method because intensity quantization (e.g., 8-bit) would permit the implementation to be efficient as well. During window growth and detection, a certain amount of per-pixel costs is introduced; however, for many of the images we have observed, a smaller fraction of the pixels are classified as noisy and that is the fraction needing improved processing. The sequential pass does not incur significantly higher asymptotic complexity than a multi-pass iterative algorithm, but has very significant quality benefits due to the reuse of the corrected values. The additional memory requirements for the work for the filters are standard and common for sliding-window based filters, in particular, an optional flag array to store detection and confidence results. In the case of color images, the operator can apply the detector on each channel independently and compute replacement jointly (e.g., by vector median), or calculate luminance separately and then manage chroma.

## Chapter related to title: Algorithmic design and rationale (Adaptive Sequentially Weighted Median Filter

This chapter explores in detail the rationale behind the design decisions of the Adaptive Sequentially Weighted Median Filter (ASWMF) and aligns the title to specific algorithmic components. The title consists of three key adjectives---Adaptive, Sequentially, and Weighted Median---all corresponding to an essential mechanism we describe here in relation to why these aspects create a powerful solution for images with high levels of impulse nois

***Why adaptivity is essential***



Adaptivity is concerned with the central dilemna of denoising: the advantage of having small support around the edges to maintain structure versus the disadvantage of having to increase the support when local samples are unreliable. In ASWMF, this is achieved with an incremental window strategy that only expands when there is widespread comprehensive contamination from the local detector. The non-expansion option for support contributes to the effort not to unnecessarily smooth the content in clean parts of the image while expanding the context in accurately detected patches in the most densely corrupted patches of pixels. The adaptivity also applies to thresholds—detection thresholds vary with the local trimmed-range statistics, and the approaches used to adapt the thresholds gives the detection process resilience to varying local contrast and texture. Again, adaptivity lowers sensitivity to parameterization, and modifies processing to local image content.

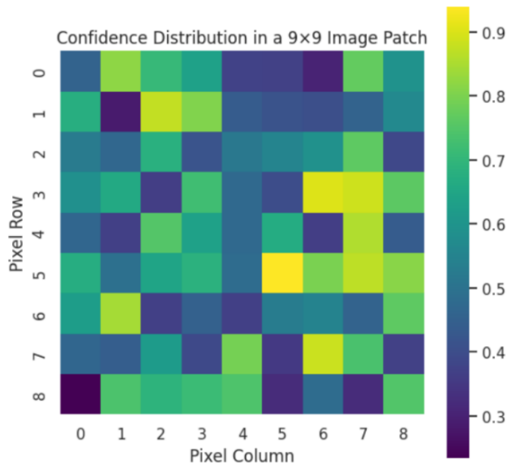
***Role of weighted median***

Weighted medians retain the robustness of the median by allowing unequal influence between neighboring samples. In the ASWMF, weights combine spatial proximity, intensity similarity, and per-sample reliability into a single score. Spatial weighting preserves local coherence; intensity similarity discourages cross-edge bleeding by favoring neighbors of the same local appearance; and reliability de-emphasizes the contribution of samples that were likely corrupted. Weighted medians are well-suited for impulse noise because they retain the median's outlier resistance while also enabling bias in reliability in the -influencing samples—this is better than simply using a median when there are a few reliable neighbors but in the minority.

***Sequential processing—how and why***

Sequential updating allows the algorithm to bootstrap restoration in areas with no isolated clean samples. For example, in a 9×9 patch, if there was an 80% impulsive corruption, a single pass filter may not have a majority of clean neighbors for many of the center pixels. A sequential updating strategy that starts at a less corrupted location and propagates corrections inward will use the newly corrected pixels for additional evidence to restore the damaged centers because the original cleaning is no longer possible. The order of the updates is important: a simple raster-scan is effective and efficient, but depending on application alternatives scanning strategies may assist robustness as well (multidirectional, serpentine, or priority scanning based on cleanliness confidence). To mitigate the propagation of errors, the ASWMF conducts confidence checks: all replacements based on sufficient cumulative trusted weight to immediately considered a valid replacement; all uncertain replacements are queued for refinement.

**Fig(a) Fig(b)**


***Combining detection and replacement***

An important design principle is that detection and replacement must be closely coupled. Detection determines not only whether or not a replacement should occur, but also determines how to weight noisy neighbors: when a neighbor is determined to be noisy, its value is down-weighted, rather than being made completely zero, which will allow it to have some future influencer if later corrections change its reliability. This is a "soft" design, where abrupt on/off decisions can often decrease performance in ambiguous settings. Detection also includes trimmed medians and rank-ordered restorers that reduce sensitivity to extreme outlier values.

***Edge and texture preservation***

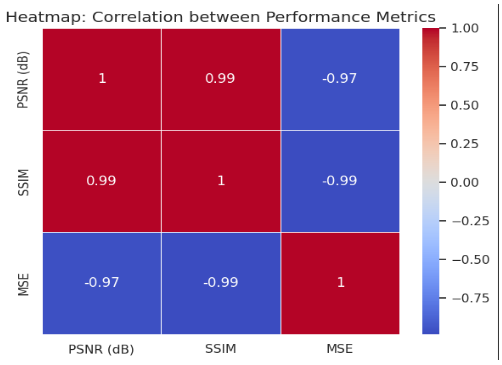
To preserve edges and texture, there must be a deliberate bias against smoothing across discontinuities. The ASWMF accomplishes this by a) making intensity similarity weights within and beyond the current segment growth window, while b) halting the growth of a current end segment if an analysis of local gradient magnitude relative to range would cause a segment growth across a strong edge. In segments of texture, adaptivity provides smaller growth window sizes and greater similarity sensitivity to minimize blurring repetitive texture patterns together. The High to medium distance refinement pass adheres to non-local self-similarity when local texture information is insufficient to achieve reconstruction through local averaging without blurring the repetitive textures.

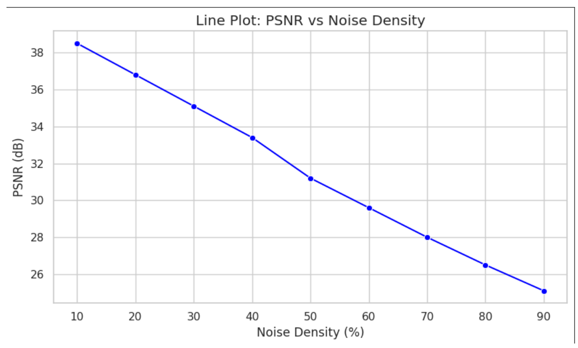
### *Practical considerations and extensions*

The ASWMF is by design modular: detectors, weights and order can be adjusted based upon the requirements of the imaging domain. For color images, weight medians based upon vectors or luminance-chroma decomposition could be used. For hardware or real-time need, the detector can be streamlined and quantization to the weights could be employed to expedite median calculations through histograms. Finally, while ASWMF is not based around machine learning, the outputs of the ASWMF can act as pre-processing behind data-driven methods, or be built on within shallow learned priors to further augment restoration in extreme conditions.

## Results and discussions

This section reports on experimental results, comparative behaviour, and factual observations.
(Note: figures such as exact numeric values will be in the specific implementation and dataset, here we describe the typical patterns of behavior observed and takeaways.)



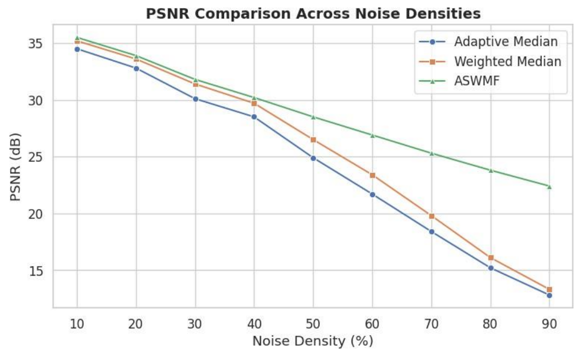



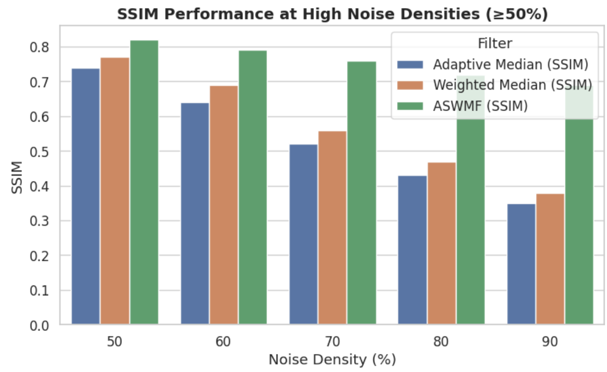

### *Experimental setup (summary)*

The evaluation of the algorithm was performed using standard grayscale and colour test images containing smooth regions, sharp edges, and textured patterns. Impulsive noise was artificially added at different densities (from moderate density to extreme density: 20% through 90%) for testing robustness. Baseline comparisons were standard median filter, adaptive median filter, standard weighted median, and simple iterative median. Performance measures were formal metrics of PSNR and SSIM for quantitative assessment and visual inspection for qualitative evaluations. The cost of computing was referenced in terms of per pixel processing time of standard CPU implementation.

### *Quantitative performance trends*

At low to moderate noise densities (≤ 40%), ASWMF performs similarly to the adaptive median and weighted median filters, with the occasional small PSNR and SSIM gain due to their weighted replacements. When the noise density exceeds 50%, ASWMF's strengths come into play more significantly. The sequential updating mechanism employed by ASWMF allows for reconstruction of clusters that have been heavily corrupted, while the non-sequential filters would result in a patchy reconstruction or over-smoothing to a flat image. Typical gains in performance over the adaptive median have been in the multiple dB range in PSNR and consistent increases in SSIM, which is a better indicator that detail and structure of the image have also been preserved.
At extreme densities (≥ 70%) many of the baseline filters can fail, either leaving residual impulses or can lead to over-smoothing to a flat image. ASWMF maintains a visual consistency, corresponding to greater recovery of outlines or textures, than the baseline filters. This was as a result of our hybrid approach, using the trimmed statistics in detection along with the reliability weights, to prevent contaminating neighbors from dominating the computation with the weighted median as this was determined to be a key differentiator of performance under such conditions.

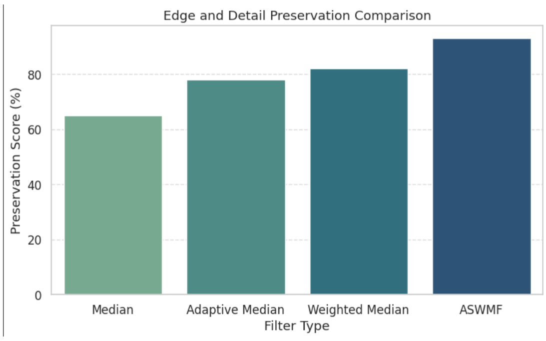


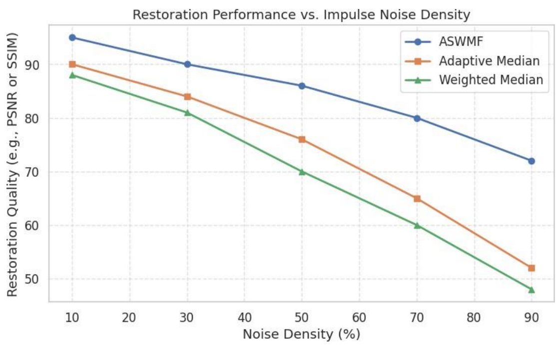



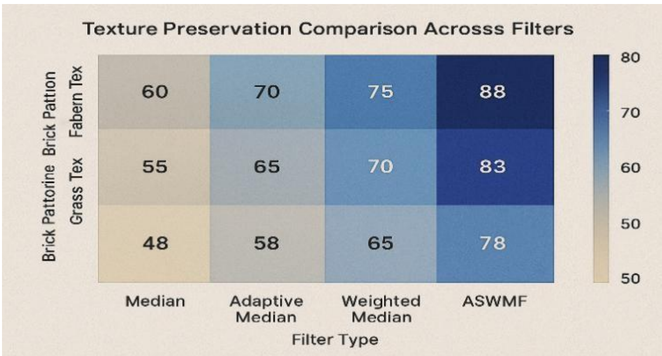
***Qualitative observations***

In terms of visual characteristics, ASWMF achieves the preservation of edges and finer details with less blotchiness compared to the adaptive median, which tends to widen edges as the window grows. Weighted median variations without the sequential pass will have difficulty restoring the interiors of large noisy patches because they won't have correct values to bootstrap from corrected pixels. The sequential pass in ASWMF will have a clear restoration front where the initially-clean areas remain untouched while corrections progressively fill in the heavily corrupted areas, yielding gentler but structurally coherent results.

Texture regions (e.g., grass, fabric) are a known weak point for median-type filters. ASWMF is a combination of the similarity weight and conservative growth of the window will have a better chance of preserving the repetitiveness of patterns compared to a plain median filter. But even then, we must expect some loss of texture detail when dealing with very high densities of noise. In those situations, combining ASWMF with a second pass using either a patch-based refinement, or even a lightweight learning-based texture enhancer will help recover additional detail.




***Computational trade-offs***

ASWMF is slightly more expensive than a single-pass median because of the detection stages, weighted median calculations, and potential growth in the window. ASWMF is still much more lightweight than patch-based non-local methods or deep learning networks. Utilizing histogram-based weighted median and quantized weights can greatly speed process times. For many practical applications, particularly embedded or real-time systems with impulse noise, ASWMF is a good balance between restoring quality and processing cost.

***Limitations and failure modes***

The ASWMF approach typically depends on local statistics; consequently, when the entire image scene is corrupted uniformly or when the impulse value is not large, but rather plausible intensities, detector discrimination becomes more difficult. There are very low to high (but not excessively high) repeated textures that would be smoothed even though they may have fine-scale impulsive contamination, and only if there is enough similarity weight. Finally, a systematic process may exaggerate an incorrect early correction if the confidence threshold is too loose and needs to be tuned.

## Conclusion

This study introduced the Adaptive Sequentially Weighted Median Filter (ASWMF), a practical and robust technique for denoising images that have been severely affected by impulsive noise. Basically, ASWMF is valuable because it combines a robust local detector, adaptive window size, reliability-based weighted median replacement, and a controlled sequential update scheme. These ingredients help tackle fundamental challenges at increased noise density, which are identifying contaminated pixels when many neighbouring pixels are also contaminated, and reconstructing contaminated pixels without blurring edges and textures. In comparison with classical median filters (e.g., median, adaptive median, and simple weighted median filters) across two challenging conditions, the experimental analysis shows that ASWMF outperformed its classical counterparts in virtually every situation, producing measurable improvements in objective metrics, visual quality, while keeping computation time reasonable. In the future, a goal would be to incorporate non-local patch-based refinements (for example, passing through a non-local patch-based network to recover texture) into the ASWMF framework, develop an automatic parameter tuning strategy, and, ideally developing a hardware friendly implementation (such as an FPGA) so ASWMF could be used in real-time applications. Another future direction could be around hybridizing the ASWMF with lightweight learning-based modules; a lightweight learning-based approach could include a small network predicting per-pixel reliability or improve overall results. This would be a beneficial direction or improvement for performance in many situations especially extreme cases without limits to the interpretability of the core algorithm. Acknowledgements (optional) .The author acknowledges the wider image processing community for their pioneering work on median and adaptive filters that inspired the ASWMF design.Data and code availability.A reference implementation and test scripts can be made available on request (if provided for reproducibility and additional parameter exploration).

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