

Eliminating Impulse Noise From Images By The Combination Of a Fuzzy Inference System and SWM-I Method

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Abstract

Impulse noise presents significant challenges in image processing, often resulting in degraded visual quality and the loss of crucial information. Common methods for detecting and removing noise include various approaches from the Switching Median filter (SWM) family. However, one method, SWM-I, is limited in its ability to identify all noisy pixels. This paper presents an effective approach for detecting and removing impulse noise by integrating a Fuzzy Inference System (FIS) with the SWM-I method. The proposed method is called FSWM. The SWM-I method is employed to effectively restore the corrupted pixels while preserving image details and edges. Subsequently, the FIS enhances the detection process by evaluating \sqrt{x} and $\circ x \circ$ windows that improve classification accuracy. Experimental results demonstrate that the proposed method significantly outperforms traditional noise reduction techniques, achieving superior performance metrics in terms of Signal to Noise Ratio (SNR), Root Mean Square Error (ERMS), and visual quality. This framework not only facilitates robust impulse noise mitigation but also provides a foundation for future research into advanced noise reduction methodologies.

Keywords: Fuzzy inference system, Impulse noise, SWM method.

Introduction

Impulse noise refers to the random replacement of image pixels with values that differ from their original ones [1]. This randomness means that impulse noise does not adhere to any specific patterns or rules, making it one of the most challenging types of noise to deal with in image processing. Other types of noise, such as Gaussian, Rayleigh, and others, follow specific probability density functions and therefore exhibit more predictable behavior, making them relatively easier to manage. One of the most well-known methods for combating this noise is the traditional median filter, which became popular in the 1970s [2]. The main drawback of the median filter is that it processes non-contaminated pixels as well, thus eliminating image details. To preserve details, the Topological Median Filter (TMF) was proposed [3]. However, there was still another issue: processing was still carried out on non-contaminated pixels, which resulted in a decrease in image quality. Therefore, identifying noise before filtering became necessary. To achieve this goal, methods named SWM-I and SWM-II were proposed based on the similarity of a pixel with its neighbors. If a noisy pixel had similar values to its neighbors, these methods encountered difficulties. After that, the Modified SWM (MSWM) method was introduced, which has somewhat addressed this problem, but the processed images still did not have satisfactory quality. In this paper, the SWM-I is combined with the fuzzy inference system to remove impulse noise efficiently. In [4] the authors examined and compared noise reduction methods based on median filtering and advanced nonlinear techniques for images contaminated with impulse noise. It also focuses on the use of deep learning to reduce this type of noise and the limitations present in various approaches. In [5], the method for removing impulse noise is such that, in the first stage, it identifies contaminated pixels using a cellular automaton-based algorithm, and in the second stage, it recovers these pixels using cosine similarity. This method is resilient at various noise levels and preserves important image details well. The performance of various filtering techniques for removing or reducing impulse noise from images is analyzed in [6]. Impulse noise randomly alters pixel values and can affect image quality and the ability to detect issues. The article also examines performance metrics such as MSE, SNR, and PSNR in evaluating these techniques. A method for removing impulse noise in medical images that include nested filtering and morphological operations is introduced in [7]. This method provides high-quality recovery using the median filter and Laplacian vector. In [8], three stages are used to remove impulse noise: the first stage is the detection of noisy pixels, the second stage is noise removal using an adaptive median filter, and the third stage is the identification of images using a neural network for recognizing cleaned images. This method effectively restores damaged pixels.

Background Knowledge

A. Impulse noise

Impulse noise is a frequent problem that affects images by randomly changing some pixel values, which often shows up as unwanted black or white spots. This type of noise can seriously lower the quality of an image, making it difficult to perform accurate image analysis. Because of this, it's crucial to use a reliable noise removal technique that can effectively reduce the noise while still preserving the original structure of the image.

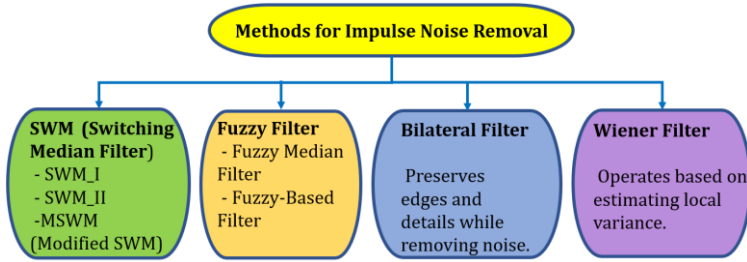


Figure (1) some methods for removing impulse noise

B. SWM-I, SWM-II, and MSWM Methods

The SWM-I, SWM-II, MSWM, and methods, a modified form of median filtering, are utilized for noise reduction in this proposed approach [9]. SWM-I enhances traditional median filtering by assigning weights to neighboring pixels based on their similarity to the center pixel. This allows for more efficient noise removal in the presence of impulse noise by considering the contextual relationships between pixels. The self-weighting mechanism also adapts to varying levels of noise, making the method more robust in handling different types of impulse noise.

If we consider the values $\{x_{i-L}, x_{j-L}, \dots, x_{i,j}, \dots, x_{i+L}, x_{j+L}\}$ as all available samples in a window of size $(2L+1) \times (2L+1)$ centered at the current pixel $x_{i,j}$ the output of SWM is defined as follows:

$$y_{i,j} = \begin{cases} x_{med} & \Delta x \geq T_r \\ x_{i,j} & \Delta x < T_t \end{cases} \quad (1)$$

In equation (1), $\Delta x = |x_{i,j} - x_{med}|$ and x_{med} is the median of the specified window, where the current pixel $x_{i,j}$ is repeated w times. If $w=1$, meaning the current pixel is considered only once in the median calculation, the method is called SWM-I. If the current pixel is considered multiple times in the median calculation, the method is called SWM-II. T_r

is a threshold, and y_{ij} is the value that will replace the current pixel. The condition $\Delta x \geq T_r$ indicates that the current pixel significantly differs from its neighbors and is considered noise, thus replaced by the median value. Conversely, $\Delta x < T_r$ means that the current pixel is quite similar to its neighbors, indicating that this pixel is not contaminated by noise and will not be replaced by the median value. As expected, if the impulse noise values are similar to neighboring pixels, this algorithm cannot detect it unless the threshold T_r is reduced, which would result in losing more details. To address the issues in these methods, another method called MSWM is proposed. This method is essentially a modification of the two previous methods. In this approach, when the condition $\Delta x < T_r$ occurs in SWM-I and SWM-II (which means non-detection in the presence of noise), another test is conducted to find potential noise. The method works by sorting all pixels in the window in ascending order: $x^{(1)} \leq x^{(2)} \leq \dots \leq x^{(L+1) \times (L+1)}$ where the values $1, 2, \dots$ that appear above the sorted variables refer to the rank of each pixel in the desired ascending series, where its value can be obtained using the function $R(x)$. Therefore, in the case of $\Delta x < T_r$, the following test is performed:

$$y_{i,j} = \begin{cases} x_{med} & \Delta R \geq T_m \\ x_{i,j} & \Delta R < T_m \end{cases} \quad (2)$$

In equation (2), $\Delta R = |R(x_{i,j}) - R(x_{med})|$ and T_m is a new threshold. The condition $\Delta R \geq T_m$ indicates that the difference in rank between the current pixel and the median in the ascending series is significant, and this pixel can be recognized as noise and replaced by the median value. The condition $\Delta R < T_m$ suggests that the current pixel is close to the median and is less likely to be noise, so its value is retained. Selection of parameters L , w , T_r , and T_m depends on the noise density and the characteristics of each image. Generally, the lower the noise density, the smaller the selected window size will be. To determine the size of w , experiments have been conducted on various images in this reference, and based on the results, it has been stated that the value of w for uniform images with low details, such as the Lena image, should be 1 (meaning that in calculating the median for each pixel, the current pixel is repeated only once, as in the normal case). However, for images with high details, such as the Baboon image, w is 3.

C. Fuzzy inference system

A Fuzzy Inference System (FIS) is a computational framework that mimics human reasoning by utilizing fuzzy logic to handle uncertainty and imprecision in data [10]. Unlike traditional binary logic that categorizes inputs into strict true or false values, FIS employs fuzzy sets, allowing for degrees of truth that reflect real-world conditions more accurately. The system operates through a series of rules that describe how input variables relate to output results, often expressed in natural language terms. This capability makes FIS particularly effective in complex decision-making processes, such as image processing or control systems, where it can adaptively process various inputs to produce reliable outcomes while accommodating ambiguity and variability.

Proposed method

In this paper, a new method is proposed for removing impulse noise from digital images by combining an FIS with the SWM-I method. This hybrid approach aims to leverage the strengths of both techniques: the robustness of fuzzy logic in handling uncertainty and the accuracy of the SWM-I method in identifying noisy pixels. The proposed method is executed in two main stages:

Stage 1: Impulse Noise Identification Using SWM-I

The first stage is employed to accurately identify potential impulse noise pixels using the SWM-I method. A local window around each pixel is analyzed, and each pixel is classified as either noisy or noise-free based on predefined criteria. Specifically, the median value of the pixels within the window is calculated and compared to the value of the central pixel. If the difference exceeds a certain threshold, the central pixel is flagged as a potential candidate for impulse noise. This stage provides a binary mask indicating the locations of suspected noisy pixels. This mask is crucial for the subsequent fuzzy filtering stage.

Stage 2: Adaptive Fuzzy Filtering

The second stage is utilized to adaptively filter the identified noisy pixels using a FIS. Information provided by the noise mask from Stage 1 is leveraged during this stage. For each pixel identified as non-noisy by the SWM-I method, the optimal filtering strategy is determined by the FIS based on the characteristics of its neighborhood. Instead of applying a fixed filter, several input variables are considered by the FIS, such as:

- The gray level value of the pixel in a $\sqrt{x} \times \sqrt{x}$ median filter.
- The gray level value of the pixel in a $\phi \times \phi$ median filter.

These input variables are fuzzified using membership functions, which represent them as linguistic variables (e.g., "low," "medium," "high"). A set of fuzzy rules, designed based on expert knowledge and experimentation, is used to map these input fuzzy sets to output fuzzy sets that represent the appropriate filtering action. The type and strength of the filter to be applied are determined by the output of the FIS. Finally, the fuzzy output is converted into a crisp value through the defuzzification process, which is then used to modify the noisy pixel. This adaptive filtering approach allows the noise removal process to be tailored to the local characteristics of the image, preserving image details while

effectively suppressing impulse noise. Figures (۲) and (۳) indicate the flowchart and the fuzzy inference system of the proposed method.

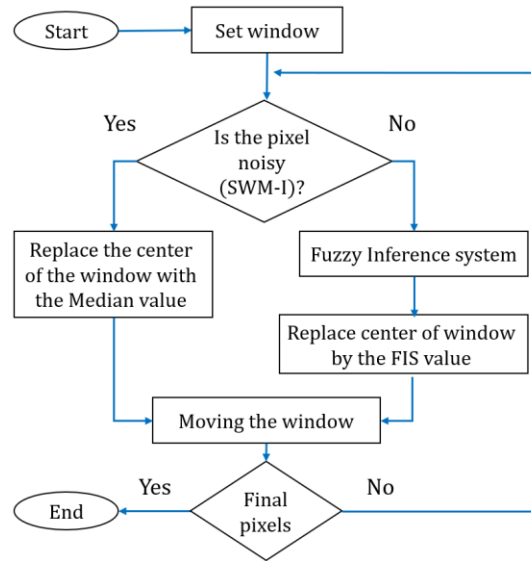


Figure (۲) flowchart of the proposed method

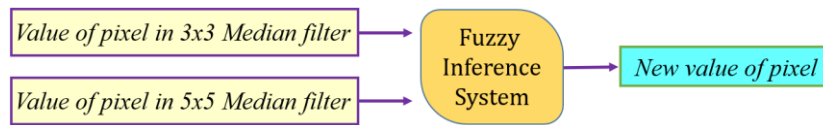


Figure (۳) the proposed fuzzy inference system

Experimental results

To evaluate the effectiveness of the proposed method for impulse noise removal, several experiments were conducted using synthetic noise images as well as real-world images. The performance of the FIS was compared against traditional noise removal methods, including median filtering. We utilized a combination of standard benchmark images affected by impulse noise. Impulse noise was introduced to the images at varying noise densities (e.g., ۳۰%, ۷۰%).

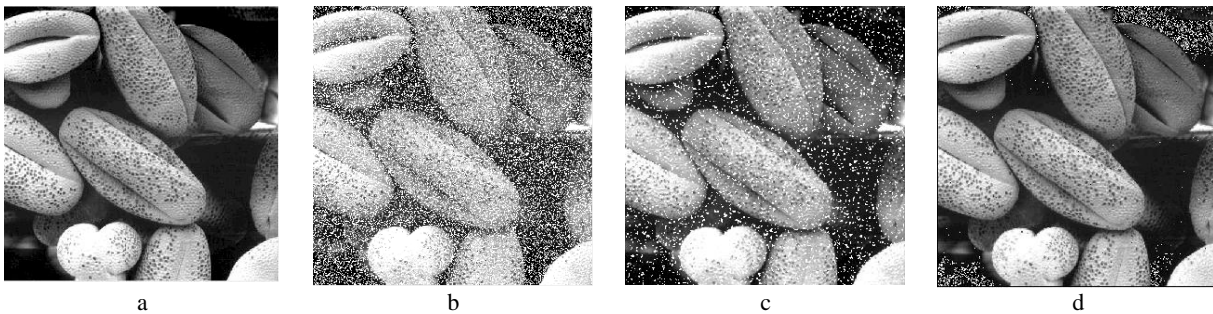


Figure (۴) a. Original image, b. Noisy with probability ۰.۳, c. Median filter (۳x۳), d. FSWM

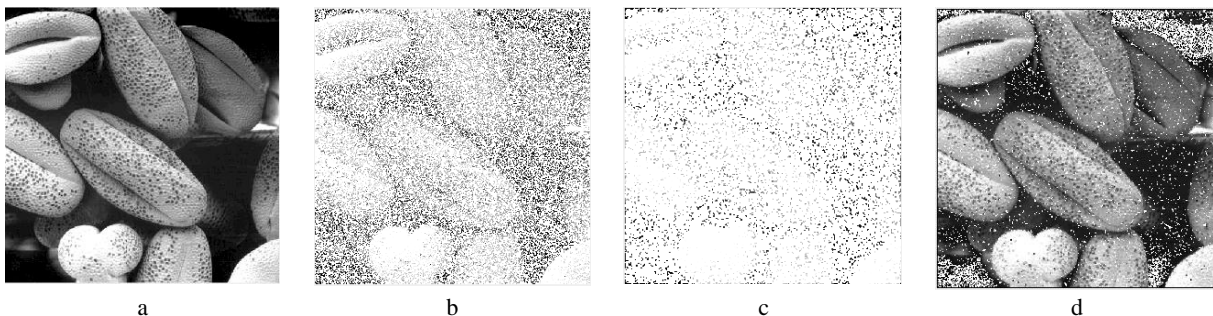


Figure (۵) a. Original image, b. Noisy with probability ۰.۷, c. Median filter (۳x۳), d. FSWM

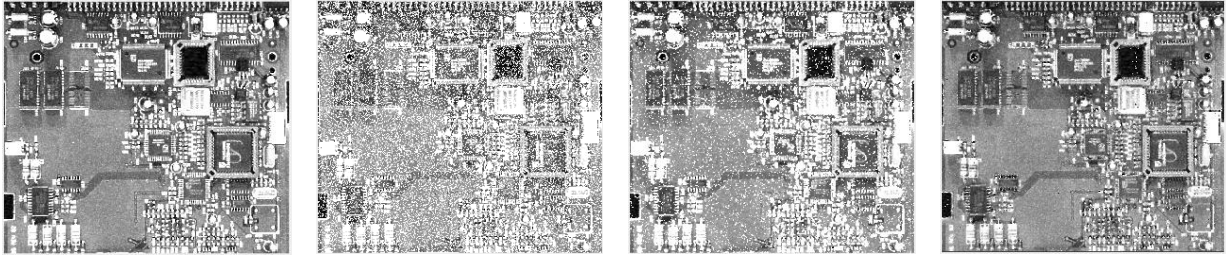


Figure (٦) a. Original image, b. Noisy with probability ٠,٣, c. Median filter (٣x٣), d. FSWM



Figure (٧) a. Original image, b. Noisy with probability ٠,٧, c. Median filter (٣x٣), d. FSWM

Performance was assessed using SNR and the ERMS as key metrics for image quality [١١]. SNR is a measure used to quantify the level of a desired signal relative to the level of background noise. It is typically expressed in decibels (dB). SNR indicates the quality of a signal; a higher SNR means that the signal is clearer and the noise is less prominent. ERMS is a metric used to quantify the magnitude of noise in a signal or image. It is particularly useful in the context of noise reduction techniques, as it provides a measure of the residual noise present after processing an image. ERMS is derived from the Root Mean Square (RMS) calculation of the noise values and indicates how much noise is still affecting the quality of the desired signal after applying noise reduction methods.

Table ١- the result of the methods by SNR and ERMS metrics

	Corrupted by ٣٠٪ noise		Corrupted by ٧٠٪ noise	
	Median filter	FSWM	Median filter	FSWM
SNR	١,٠٢١٤	١,٠٢٧٧	١,٠٠٨١	١,٠٠٩٦
ERMS	٢٠,٠٤	١٤,٧١	٩٠,٢١	٣١,٤٦

SNR and ERMS criteria are shown in the equations (٣) and (٤), respectively.

$$SNR = \frac{\sum_{i=1}^{l_1} \sum_{j=1}^{l_2} r_{i,j}^2}{\sum_{i=1}^{l_1} \sum_{j=1}^{l_2} (x_{i,j} - r_{i,j})^2} \quad (٣)$$

$$ERMS = \sqrt{\frac{1}{l_1 l_2} \sum_{i=1}^{l_1} \sum_{j=1}^{l_2} (x_{i,j} - r_{i,j})^2} \quad (٤)$$

Where l_1 and l_2 are the size of the picture. $x_{i,j}$ is the pixel in i -th row and j -th column of the original picture and $r_{i,j}$ is the pixel in i -th row and j -th column of the final picture.

High SNR and low ERMS values are excellent indicators of the effectiveness of the proposed noise reduction method. The SNR values achieved by the proposed method were significantly higher than those of traditional filtering techniques, indicating that the desired signal (the clean image) was effectively distinguished from the background noise. This suggests that the image quality was preserved well during the denoising process. Alongside high SNR, the method also achieved low ERMS values. This metric confirms that the residual noise after processing is minimal. A lower ERMS indicates that the noise removal was effective, resulting in a cleaner, clearer image without significant distortion or loss of detail.

Conclusion

This paper tackles the ongoing challenge of impulse noise in image processing by introducing FSWM, a novel noise reduction technique that effectively combines the Switching Median filter variant SWM-I with a Fuzzy Inference

System (FIS). By utilizing the SWM-I filter's capacity to restore corrupted pixels while safeguarding essential image details and edges. Experimental results show marked improvements in SNR, ERMS, and visual quality, demonstrating that our proposed method outperforms existing techniques. The robust capabilities of FSWM in mitigating impulse noise highlight its potential for practical applications across various image processing fields. Additionally, this research provides a strong basis for future investigations into advanced noise reduction techniques, particularly those that merge intelligent systems like FIS with established filtering methods. By advancing noise reduction technologies, we can further enhance the clarity and reliability of digital images, maximizing their utility for analysis and interpretation.

References

- [1] K. Kaynardag, C. Yang, and S. Salamone, "An impulsive noise filter for rail vibration measurements using a laser Doppler vibrometer on a moving platform," *Mechanical Systems and Signal Processing*, vol. 223, p. 111918, 2020/01/15/ 2020, doi: <https://doi.org/10.1016/j.ymssp.2020.111918>.
- [2] T. Jarske and O. Vainio, "A review of median filter systems for analog signal processing," *Analog Integrated Circuits and Signal Processing*, vol. 2, no. 2, pp. 127-135, 1993/03/01 1993, doi: 10.1007/BF01239371.
- [3] H. G. Senel, R. A. Peters, and B. Dawant, "Topological median filters," *IEEE Transactions on Image processing*, vol. 11, no. 2, pp. 89-104, 2002.
- [4] A. P. Sen, T. Pradhan, N. K. Rout, and A. Kumar, "Comparison of algorithms for the removal of impulsive noise from an image," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 3, p. 100110, 2023/03/01/ 2023, doi: <https://doi.org/10.1016/j.prime.2023.100110>.
- [5] M. M. Piroozmandan, F. Farokhi, K. Kangarloo, and M. Jahanshahi, "Removing the impulse noise from images based on fuzzy cellular automata by using a two-phase innovative method," *Optik*, vol. 255, p. 168713, 2022/04/01/ 2022, doi: <https://doi.org/10.1016/j.jjleo.2022.168713>.
- [6] A. Maity and R. Chatterjee, "Impulsive noise in images: a brief review," *Computer Vision Graphics and Image Processing*, vol. 4, no. 6-15, p. 1, 2018.
- [7] T. M. Alanazi, K. Berriri, M. Albekairi, A. Ben Atitallah, A. Sahbani, and K. Kaaniche, "New Real-Time High-Density Impulsive Noise Removal Method Applied to Medical Images," *Diagnostics*, vol. 13, no. 10, doi: 10.3390/diagnostics13101709.
- [8] A. Ozaev, P. Lyakhov, V. Baboshina, and D. Kalita, "Neural Network System for Recognizing Images Affected by Random-Valued Impulse Noise," *Applied Sciences*, vol. 13, no. 3, doi: 10.3390/app13030580.
- [9] C.-C. Kang and W.-J. Wang, "Modified switching median filter with one more noise detector for impulse noise removal," *AEU-International Journal of Electronics and Communications*, vol. 63, no. 11, pp. 998-1004, 2009.
- [10] M. Z. Naufal, M. P. Hadi, F. A. Ghifari, R. A. Alhakim, S. M. Pallawagau, and A. D. Kalifia, "Sistem Penilaian Kinerja Siswa Menggunakan Fuzzy Inference System (FIS)," *Scientica: Jurnal Ilmiah Sains dan Teknologi*, vol. 3, no. 3, pp. 406-410-406-410, 2020.
- [11] S. Kakiyara, M. AbdelSalam, K. Zhuang, and A. A. Fawzi, "Epiretinal Membrane Is Associated with Diabetic Retinopathy Severity and Cumulative Anti-VEGF Injections," *Ophthalmology Science*, p. 100733, 2020.