Review Article

*International Journal of Advanced Technology and Engineering Exploration, Vol 5(43)*
*ISSN (Print): 2394-5443 ISSN (Online): 2394-7454*
*http://dx.doi.org/10.19101/IJATEE.2018.543008*

# A survey on impulse noise removal techniques in image processing

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## Abstract
***In image processing, an essential and most challenging process is removing the noise from the color images. Images are often corrupted by impulse noise during image acquisition and transmission. Therefore, impulse noise reduction is the most crucial aspect during image transmission. Over the past decades, several approaches have been proposed for removing the impulse noise from the images in such a way that the most significant information of the images is preserved. Hence, the original image quality can be restored efficiently. This paper presents a detailed survey of impulse noise removal techniques. Initially, different techniques are analysed and its limitations are addressed. Moreover, performance of all techniques was compared to identify their effectiveness for further improvement on impulse noise removal techniques. Finally, some future contributions are also provided to improve the impulse noise removal techniques significantly.***

## Keywords
***Image processing, Impulse noise, Noise removal, Image restoration.***

## 1.Introduction
Any unwanted pixels in the original images are known as noises. Noise is mostly classified into blur noise and impulse noise. Images are often corrupted by different noises during its acquisition or transmission [1]. The most well-known noise is the fat tailed distribution or impulse noise or spike noise. Impulse noise occurs as a result of malfunction of detector pixels in a digital camera or from missing memory components in imaging hardware. There are two types of impulse noise such as salt-and-pepper noise and random valued noise [2]. The salt-and-pepper noise matches an extreme dynamic range of a pixel value. In this case, noisy pixels can be quite easily detected by an Adaptive Median Filter (AMF). An image containing salt-and-pepper noise can have dark pixels i.e., pepper in bright regions and bright pixels i.e., salt in dark regions. Random-Valued Impulse Noise (RVIN) occurs within the dynamic range of an image pixel and it cannot be easily detected by AMF.

Number Nowadays, impulse noise removal is an active research area in image processing. A better noise filter is required for satisfying two criteria such as noise suppression and useful information preserving in the image with low computational complexity [3].

There is a tradeoff between preservation and noise removal. It is more effective in terms of removing impulse noise and preserving the edges and fine information of digital images. Therefore, the primary step before processing the image is the restoration of the image by removing noises in the images. The main objective of noise removal technique is suppressing the noise. The filter can be applied successfully for reducing heavy noise.

For preserving the information, the noise is eliminated gradually. Such noise removal techniques are applied depending upon the camera sensors and the environmental interferences. When noise is non-additive, linear filtering techniques are not effective in removing the impulse noise. This has led to the utilization of non-linear filter techniques [4]. Over the past decades, different techniques were applied for noise removal process. However, still several challenges and issues are observed in removing the impulse noise from the color images.

Hence, the main objective of this article is studying the detailed information on different impulse noise removal techniques and their drawbacks to further improve the noise removal process. Then, based on the observed limitations, further improvements on impulse noise removal techniques are suggested.

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## 2.Survey on impulse noise removal techniques

A novel and unique principle of adaptive dual threshold median filter [5] was proposed for detecting a random valued impulse noise. In this method, the thresholds were computed by averaging process and a brilliant quality of recovered image was provided by using simple Median (MED) filter which removes noise from the image. A weighted couple sparse representation model [6] was proposed for removing impulse noise. In this approach, the complicated relationships between the reconstructed and the noisy images were exploited for making the coding coefficients more suitable in order to recover the noise-free image. Additionally, the image pixels were classified into clear, slightly corrupted and heavily corrupted. Then, various data fidelity regularizations were applied to various pixels for further improving the denoising performance. Here, the dictionary was directly trained on the noisy raw data through addressing a weighted rank-one minimization problem.

A low-rank prior in small oriented noise-free image patches was introduced for removing impulse noise [7]. A low-rank matrix approximation was significant for preserving the texture information in the optimally oriented path by considering an oriented patch as a matrix. According to this prior, a single-patch method was proposed within a generalized joint low-rank and sparse matrix recovery method for simultaneously detecting and removing nonpointwise random-valued impulse noise. A weighting matrix was integrated for encoding an initial estimate of the spatial noise distributions. An accelerated proximal gradient method was adopted for estimating the optimal noise-free image patches.

A novel denoising scheme was proposed [8] in which all noisy pixels were mutually restored through non-uniform sampling and supervised piecewise autoregressive modelling based super-resolution. In this framework, the noisy pixels were equally estimated in groups by solving a well-designed optimization issue in which image structure feature was assumed as a significant limitation. Another objective was that piecewise autoregressive model was not only adopted but also designed therefore all noise-free pixels can be utilized for supervising the model training and optimization issue solving for achieving higher accuracy.

A blind compressed sensing (BCS) technique was proposed [9] to eliminate sparse impulse noise from hyper-spectral images and also deal with the spatial redundancy and spectral correlation of such images by using individual dictionaries. Initially, the issues of denoising hyper-spectral images while they were corrupted by impulse noise were investigated. To overcome such issues, BCS was proposed such that it empirically learns the spatial and spectral sparsifying dictionaries during image denoising.

Localised rank-ordered differences vector filter [10] was proposed for suppression of high-density impulse noise in color images. This method was proposed based on an impulsive noise detector for greyscale images that has been adapted in a localized fashion using geometric information for processing color images. According to this statistic, a filtering between the identity and a non-linear vector filter was proposed. By using this method, each pixel was checked for whether it was noisy or not based on the fixed window mask size for all ratio noise intensities. A finite number of sub-windows were defined which are utilized for removing impulsive noise while preserving fine information. Once a corrupted pixel was detected, a non-linear filtering was performed.

A two stage quaternion switching vector filter [11] was proposed for removing impulse noise in the color images. Initially, an effective color distance measure method was proposed by using quaternion representation. Then, the directional samples along with four directions were utilized by this filter according to the new color distance measure for classifying the image pixels into possible noisy and noise-free pixels. For possible noisy pixels, the idea of peer group was modified and extended to the directional samples for further detecting whether they were corrupted by impulse noise or not. Finally, a weighted vector median filter was performed only on the pixels that were identified as noisy.

A combination of adaptive vector median filter (VMF) and weighted mean filter was proposed [12] to remove high-density impulse noise from color images. In this approach, the noisy and non-noisy pixels were classified according to the non-causal linear prediction error. The adaptive VMF was processed over the noisy pixel where the window size was adapted based on the availability of high-quality pixels. On the other hand, a non-noisy pixel was substituted with the weighted mean of high-quality pixels of the processing window. A new edge preserving contextual model based image restoration technique [13] was proposed for images affected by impulse noise. This method consists of two processes such as identification of noisy pixels and restoration of the original image. Initially, an absolute directional difference of the neighborhood pixels was followed for identifying the pixels those were affected by impulse noise. Also, an edge preserving contextual model was proposed for restoring the identified noisy pixels. Here, the parameters of the contextual window were obtained by using a Gaussian kernel. This approach was depending on the context model of the noise-free pixels in the selected window.

A fast non-locally centralized sparse representation (FNCSR) algorithm [14] was proposed for image denoising. In this algorithm, a dictionary for each image was obtained by using dictionary learning approach such as k-means and principal component analysis (PCA). After that, Peak Signal-to-Noise Ratio (PSNR) index was applied for assessing the image quality of the reconstructed images based on such dictionaries. Moreover, quality-aware features and support vector machine (SVM) were employed for constructing a fast noise level estimator (NLE) to estimate the noise level from a single noisy image. According to the estimate noise level, the parameters such as search window and search step were selected automatically.

Sparse and low-rank decomposition of Hankel structured matrix [15] was proposed for impulse noise removal. This approach was proposed based on the annihilating filter-based low-rank Hankel matrix (ALOHA). Thus, it was known as robust ALOHA according to the observation that an image corrupted with the impulse noise can be modeled as sparse components whereas underlying image can be modeled using a low-rank Hankel structured matrix. The sparse and low-rank matrix decomposition problem was solved by alternating direction technique of multiplier approach including initial factorized matrices coming from a low-rank matrix-fitting algorithm. This algorithm was applied in a patch-by-patch fashion for adapting the local image statistics that have different spectral distributions.

This section illustrates an overview of merits and demerits of different impulse noise removal techniques whose functional scenarios are discussed in above section. Through the literature survey on impulse noise removal techniques, the following limitations are observed.

- When number of uncorrupted pixels was zero, the size of filtering window was considered as inadequate by using improved boundary discriminative noise detection (BDND) algorithm.
- In some cases, noise-free pixels were detected as corrupted pixels and the quality of performance was image dependent.
- Computational complexity and time edge preserving method must be maintained at lower level for preserving the edge information and removing the noise at high density levels.
- Weighted couple sparse representation model requires additional non-local self-similarity priors to preserve more information of image and texture which improves the output image quality.
- The original patches were over-smoothened by low-rank prior in small oriented noise-free image patches and only low level information in the images was considered.
- The computation complexity of non-uniform sampling and autoregressive modelling, two stage quaternion switching vector filter and CAVMFWMF was high.
- Reconstruction error of BCS method was high. As well, noisy pixels were considered for preserving the original images using LRODF method.
- Computational feasibility of FNCSR algorithm was limited.
- Moreover, sparse and low-rank decomposition of Hankel structured matrix requires an automatic optimal patch size selection method for filtering process.

From the following *Table 1*, the most challenging issues in impulse noise removal techniques are observed and an ideal solution is identified to overcome those issues in image processing.

## 3.Discussions

**Table 1** Comparison of different impulse noise removal techniques (Considering lena image)

| Ref. No | Methods | Merits | Demerits | Performance metrics |
|---|---|---|---|---|
| [5] | Adaptive dual threshold median filter | Better PSNR. | Quality of performance was image dependent. | (Noise Density=10%) PSNR=41.02dB |
| [6] | Weighted couple sparse representation model | Better performance in noise reduction. | Requires an integration of non-local self-similarity priors for preserving more image and texture information to obtain the higher quality outputs. | (Noise Density=30%): PSNR=34.26dB, Structural Similarity Index Metric (SSIM)=0.9442 |

| Ref. No | Methods | Merits | Demerits | Performance metrics |
|---|---|---|---|---|
| [7] | Low-rank prior in small oriented noise-free image patches for nonpointwise impulse noise removal | Better performance in noise removal. | Inevitably over-smooth the original patches and it does not consider any high level information in the images. | (Mixed sizes from 1×1 to 3×3): PSNR=30.58dB |
| [8] | Non-uniform sampling and autoregressive modelling based super-resolution for high quality impulse noise removal | High restoration accuracy and efficiently removing the detected impulse noises when image edges and information were preserved. | Computational complexity was very high. | (Noise Density=70%): PSNR=32.08dB, SSIM=0.9744 CPU time=4.3sec |
| [9] | BCS technique based impulse denoising | It can be used for reconstructing hyperspectral images from compressive measurements in the presence of impulse noise. | Reconstruction error was high. | WDC mall image (Noise Density=10%): PSNR=55.24dB |
| [10] | LRODF based high-quality impulse noise removal | Robust to noise, easy to implement. | A group of noisy pixels were assumed as information to preserve during removal of impulse noise. | (Noise Density=10%): PSNR=38.77dB Normalized Color Difference (NCD)=0.46×$10^2$, Color Multiscale SSIM (CMSSIM)=0.999 |
| [11] | Two stage quaternion switching vector filter for impulse noise removal | It can detect noisy pixels on gradient edges. | Computational complexity was high. | (Noise Density=10%): PSNR=34.16dB, Mean Absolute Error (MAE)=1.61, NCD=0.0143, Feature Similarity Index Metric (FSIM)=0.9919 |
| [12] | CAVMFWMF for high-density impulse noise removal | Better performance for both low and high-density of impulse noise. | Computational complexity during detection process was high. | (Noise Density=10%): PSNR=42.27dB, SSIM=0.883, FSIM=0.9983, CMSSIM=0.9988 |
| [13] | Edge preserving contextual model | Better denoising ability. | Computational time was high. | (Noise Density=40%) PSNR=34.91, Mean SSIM=0.93, Non-Shifted Edge Ratio (NSER)=0.61, Correlation Factor (CF)=0.996, Computational time=275.09seconds |
| [14] | FNCSR algorithm | High computational efficiency. | Computational feasibility was limited. | (Noise level=5) Running time=35.92seconds, PSNR=38.55dB, SSIM=0.9433 |
| [15] | Sparse and low-rank decomposition of Hankel structured matrix for impulse noise removal | High robust to noise. | It requires an automatic selection of optimal patch size for filtering process. | (Noise Density=10%): PSNR=38.91dB |

## 4.Conclusion and future work

In this article, a detailed survey on impulse noise removal techniques in image processing was presented. It is obvious all researchers have tried in different techniques for removing the impulse noise from color images to achieve better results than the other filtering-based noise removal techniques. Based on the analysis, robust ALOHA has better performance than the other impulse noise removal techniques. This technique was derived based on the consideration that the spectrum of a noiseless image patch is sparse in Fourier domain. Moreover in the future contribution, this technique can be further improved by automatically selecting an optimal patch size and reducing the computational complexity. Additionally, it can be extended for image patches which are sparse in the other transform domains i.e., wavelet, frequency, etc.

## Acknowledgment
None.

## Conflicts of interest
The authors have no conflicts of interest to declare.

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