Journal of Information Hiding and Multimedia Signal Processing ©2010 ISSN 2073-4212
Ubiquitous International Volume **2**, Number **2**, April **2011**

Fuzzy Rule based Median Filter for Gray-scale Images

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Received May 2010; revised August 2010

Abstract. *The paper proposes a new algorithm for detection and filtering of impulse noise from gray-scale images. The detection scheme consists of two stages. In the first stage, it is tested whether the centre pixel in the window of the image is healthy or not by incorporating the condition of the rank-conditioned median filter. The cen- tre pixel may be an impulse if it lies outside the trimming range. The first stage is empowered by the second stage, in which the centre pixel is further clarified by the soft thresholding method of impulse detection by Arakawa's fuzzy-based median filter. The centre pixel is replaced by the median of the pixels in the window, if both stages conclude that the centre pixel is an impulse noise. It was shown experimen- tally that the proposed method outperforms the other methods under consideration visually and in term of PSNR values.*
Keywords: Median filter, Rank-conditioned median filter, Soft thresholding, Fuzzy logic, Trimming set.

1. **Introduction.** Digital images are often distorted by impulse noises during acquisition, transmission and storage, when they are taken by a camera with a faulty sensor, or transmitted over a noisy channel. Median filters, which are among the most popular nonlinear filters, are extensively applied to eliminate impulse noise due to its outstanding computational effi- ciency. Median filter belongs to the class of nonlinear filters that have been proven very useful for impulse noise suppression. filters of this class have been subject to growing interest since the discovery of the standard median (SM) filter by Tukey ~[1] who applied it to the smoothing of statistical data. Pratt [2] was the first to use median filters in image processing. However, median filters are accustomed in replacing pixels which are undisturbed by the noise, thereby causing artifacts including edge jitter and streaking. Modified median based filters, which retain a rank order structure have been enhanced to eliminate these deficiencies. One of the earliest contributions is the weighted median (WM) filter [3, 4], which gives more weight to some pixels within the window than others. It emphasizes or de-emphasizes specific input samples, because in most applications, not all samples are equally important. The special case of theWM filter is the centre-weighted median (CWM) filter [5], which gives more weight only to the central value of the window.

The median filter and its modifications are generally implemented to all pixels in an image. They tend to alter pixels undisturbed by noise. As a result, their effectiveness in noise suppression is often at the expense of blurred and distorted image features. A better way to circumvent this drawback is to incorporate some decision-making processes in the filtering framework. The simplest detection scheme [6] is based on the principle of outlier detection in statistical data. It thresholds the absolute value of the deviation of the centre pixel from the median of the pixels in the window. A simple but effective impulse-detection-based filter is the rank-conditioned median (RCM) filter [7, 8, 9], in which pixels in the filtering window are ranked according to their magnitudes and ranks are given according to their positions in the sorted order. The centre pixel is considered to be corrupted if it lies outside the trimming set [10], which is formed by excluding the extreme values from the sorted pixels. In the conventional conditional median filters, thresholds are set to separate the input signal and the median. Recently, impulse noises removal based on fuzzy inference logic have attracted investigation.

In 1996, Arakawa proposed fuzzy median (FM) filters in an attempt to apply ambiguous rules at image restoration [11]. FM filters are constructed as a weighted sum of the input signal and the output of the median filter, and the weighting coefficients concerning the state of the input signal sequence are set by deriving fuzzy rules. Then, the learning process is realized by training over a reference image to obtain the optimal weight. Yang and Toh proposed adaptive fuzzy multilevel median filter [12] for suppressing impulse noise while preserving edges. Russo proposed fuzzy-rule-based operators for smoothing, sharpening and edge detection [13, 14]. He employed heuristic knowledge to build the rules for each of the underlying operations. Taguchi proposed fuzzy weighted median (FWM) filter [15] that defines the output of a Boolean function to vary continuously from 0 to 1. References [16, 17] describe the application of fuzzy clustering to the removal of impulse noise.

In this paper, we propose a fuzzy based median filter that integrates Arakawa's fuzzy rules for soft-detection of impulse noise from gray-scale images [11] and rank-conditioned median filter [7, 8, 9] for checking whether the centre pixel is an impulse or not. Performance of integration of these two algorithms is much better in removal of impulse noise from gray-scale images than performance of either of the two applied individually.

The paper is organized as follows. Section 2 gives a brief on Arakawa's fuzzy based median filter. Section 3 is devoted to the proposed technique. Section 4 is on computational cost of the proposed filter. Section 5 is on the experimental results, followed by Section 6 for conclusions.

2. **Arakawa's Fuzzy Median Filter.** Arakawa's fuzzy based median filter is constructed as a weighted sum of the input signal and the output of the median filter, and the weighting coefficients concerning the state of the input signal sequence are set by deriving fuzzy rules. Then, the learning process is realized by training over a reference image to obtain the optimal weight. Moreover, considering the combination of the fuzzy rules during the inference process, each mem- bership function is proposed by approximating with a step-like function, and setting the height of each step so that the mean square error of the filter output can be the minimum for training signal data. However, the computation time is a compromise. Furthermore, if the inference process adopts another smooth nonlinear membership function, such as a Gaussian type or sigmoid functions, in approximating the membership function, the performance is frugal. Because the form of the membership function is limited to be close to these functions, and the filter is expressed as a nonlinear form of the parameters to be controlled, the performance of their training can be worse, or a local minimum can exist in some cases. According to Arakawa's proposition, median filters based on fuzzy rules can be expressed as follows:

$$y = m + \mu[w]\{x - m\} \tag{1}$$

where $\mu[w]$ denotes the membership value representing whether an impulse noise is considered not to be located at the centre pixel x at the centre of the sliding window of size $n \times n$ and m is the median value of all pixels in the window. The result of $\mu[w]$ is determined by the state of the input signals in the filter window. That is,$\mu[w] = 0$ indicates that an impulse noise is located at the centre pixel. Hence, the output of the filter is set to equal the median value of the input signals. Conversely, $\mu[w] = 1$ indicates that an impulse noise is considered not to be located at the centre pixel. In this case, the output of the filter is set to equal the original input x. Furthermore, $\mu[w]$ also takes a continuous value from 0 to 1 to cope with the uncertain case of whether an impulse noise exists.

Accordingly, because the membership value $\mu[w]$ can be set by the local characteristics of the input signals, the amplitudes of most noises can be used to indicate the degree of $\mu[w]$. Hence, the following rules are adopted:
Rule 1: IF u is small and v is small, THEN $\mu[w]$ is large,
Rule 2: IF u is small and v is large, THEN $\mu[w]$ is small,
Rule 3: IF u is large and v is small, THEN $\mu[w]$ is small,
Rule 4: IF u is large and v is large, THEN $\mu[w]$ is very small,

where u denotes the absolute difference between the input x and the median value m, that is,

$$u = |x - m| \tag{2}$$

and v is another index that is the average of a and b, where $a = |s_1 - x|$, $b = |s_2 - x|$, and s_1 and s_2 are the two closest pixels to x. u is simple and able to eliminate prominent impulse noise, and v has ability to eliminate erroneous judgment when u cannot separate the impulse noises. The values of u and v are represented as large when an impulse noise is assumed to exist in the window, and small when an impulse noise does not exist.

Both u and v are employed to isolate the impulse noises from the fine components of signals. For example, assuming that an image contains very fine components such as line components, x is on the line, which is just one pixel wide and there is no impulse noise in the window. The value u is large, since m must not approach x. So an impulse noise is assumed to be located at the centre location of the window according to u. However v is very small as a and b are very much similar to x, and v is the average of a and b. So, according to v, x is not an impulse. Therefore, the inference system shows that an impulse noise is not located at the centre of the window.

3. **Proposed Fuzzy Based Median Filter.** An efficient impulse noise detection scheme is needed to filter out the impulse noise without damaging the healthy pixels. The scheme should have high rate of impulse noise detection (*true hit*). While wrong detection of the healthy pixel as a noise (*false hit*) and subsequent filtering results in unnecessary smoothing, wrong detection of an impulse to be a healthy pixel (*miss hit*) leaves the noise unfiltered. An ideal detection mechanism should minimize both these types of errors. The existing impulse noise detection techniques are based on the following principles:

- The rank of the centre pixel with respect to the other pixels in the filtering window is an indicator for the presence of an impulse. If this rank is one of the extreme ranks, the current pixel is likely to be corrupted by an impulse. This principle is utilized in the rank-conditioned median filtering [7, 8, 9].
- An impulse noise may be considered as an outlier and techniques for outlier detection in statistical data may be applied to detect an impulse. The absolute deviation from the median has been used to detect outliers [6]. Thus the absolute difference between the centre pixel and the median of the pixels in the window is a measure of the corruption of the central pixel by an impulse. The switching scheme I [18] of Sun and Neuvo is based on this principle.

The first detection scheme in the proposed algorithm decides about the impulse on the basis of the rank of the current pixel. The second scheme uses the deviation of the central pixel from the median by comparing with one predefined threshold. Besides these, there are other impulse detection schemes. Some of them are Chen and Wu's adaptive centre-weighted median filter [19], Mitra's SD-ROM filter [20], tri-state median filter [21] etc. Arakawa's fuzzy median filter is also a special case of median filter that utilizes soft thresholding for the detection of impulse noise from the image. The centre pixel is always replaced by a new value (not present in the window) if $\mu[w] = 1$.

The proposed fuzzy based median filter combines the impulse noise detection scheme of the rank-conditioned median filter [7-9] and Arakawa's fuzzy median filter [11]. It forms two sets: Crisp set and Fuzzy set. An element that belongs to the crisp set has 100% degree for belongingness, and one that does not belong to it has 0% degree for belongingness. On the other hand, an element belong to the fuzzy set by a degree known as membership value that takes a real number in the interval between 0 and 1.

The proposed scheme considers rank-conditioning as the primary step for the detection of impulse noise from images for its computational simplicity and high percentage of true hits. It ranks the pixels in the windows according to their magnitudes. A crisp set known as trimming set is formed that includes all rank-ordered pixels excluding the extremes, and the extremes form another set known fuzzy set. The centre pixel that belongs to the trimming set is a healthy pixel that should not be filtered. However, a healthy centre pixel may appear at one of extremes after ranking if its value is slightly either bigger or smaller than neighbouring pixels. Consider the pixels representing the end of a thin line in a uniform background as shown in figure 1. The darkened feature pixels are distinct from the rest of the pixels and appear at on extreme after ranking. In such a case, rank-conditioning alone may alone work properly and trigger to replace the centre pixel, which is a part of the feature, by a non-feature pixel.

A secondary step is incorporated into the impulse detection procedure to reduce the problem of false hits. The centre pixel belongs to the fuzzy set indicated by a membership value. This value is found in the proposed scheme by using Arakawa's fuzzy based scheme. The joint probability that a healthy pixel will be wrongly detected to be an impulse by both the primary and secondary steps is considerably lower than the probability of being wrongly detected by each of the steps. In other words, the probability of false hit is reduced by simultaneous application of the primary and secondary steps. The pixel will be declared as an impulse if it is simultaneously detected to be an impulse both by the primary and secondary steps.

The proposed scheme can be expressed as follows:

$$x_{FM} = \begin{cases} x & if \quad i \le rank(x) \le N + 1 - i \\ y & \text{otherwise} \end{cases} \tag{3}$$

where $y = m + \mu[w]x - m$ is the output of the fuzzy median filter, i is the rank of lower healthy pixel in the sorted pixel values and $N = n \times n$ is the total number of pixels in the window.

The centre pixel is not replaced by a new value if it belongs to trimming set. The proposed filter replaces the corrupted pixel by summation of the median value and product of the difference between the centre pixel and median and a membership value, which is based on the degree of the corruption of the centre pixel by the impulse noise.

4. **Computational Complexity Analysis.** In quick sort ordering, the number of comparison/swapping operations is $2n^2\log2_2 n$. The proposed filter involves the following computations:

(1) $2n^2\log_2 n$ comparisons/swappings for sorting the pixels in the window,
(2) 2 comparisons to check whether the centre pixel belongs to the trimming range,

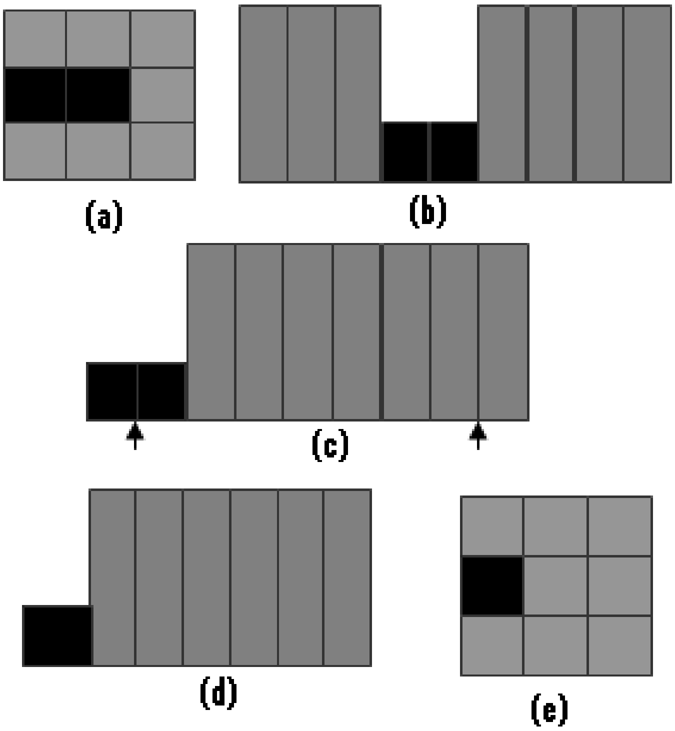


FIGURE 1. First stage of impulse detection in proposed methods: (a) end of a line in a 3×3 window, (b) set of pixels, (c) set of rank-ordered pixel, (d) trimming range and (e) result of filtering.

(3) 1 comparison and 1 subtraction operations to find $u = |x - m|$,
(4) 7 comparison,$n^2 + 4$ subtraction, 1 division/multiplication operations to find the value of v,
(5) 6 comparison, 6 subtraction and 4 multiplication operations to calculate the membership values of u and v,
(6) 1 comparison, 1 multiplication and 2 addition/subtraction operations (1 subtraction operation overlaps with that in step (3)) for replacing the corrupted pixel value.

Thus, the proposed filter involves $2n^2\log_2 n + 17$ comparison, $n \times n + 12$ subtraction, and 6 multiplication operations. Arakawa's fuzzy median filter involves $2n^2\log_2 n + 15$ comparison,$n \times n + 12$ subtraction, and 6 multiplication operations.Neuvo's median filter involves $2n^2\log_2 n + 1$ comparison and 1 subtraction operations. The CWM filter involves $n^2 + 2n^2\log_2 n - 1$ and $w - 1$ insert operations, where w is the centre weight of the centre pixel in the window. The order of the computational complexity of the various filters is given in Table 1. The proposed filter requires additional addition and multiplication operations in comparison with the SM filter.

TABLE 1. Order of the computational complexity in a $n \times n$ window size.

Filters	**Additions**	**Comparisons**	**Multiplications**	**Insertions**
SM	...	$O(n^2)\log_2 n$	...	...
CWM	...	$O(n^2)\log_2 n$	...	$O(1)$
Neuvo's	$O(1)$	$O(n^2)\log_2 n$	...	...
Arakawa	$O(n^2)$	$O(n^2)\log_2 n$	$O(1)$	...
Proposed	$O(n^2)$	$O(n^2)\log_2 n$	$O(1)$	...

5. **Experimental Reselts.** The proposed algorithms were tested on a number of 8-bit gray-scale images from a test image database. Each of the images is of size 512 × 512. The results of experiments on the Lena, Mandrill, Airplane, Lake, Pepper, House and Miramar images are reported here. fixed-valued and random-valued impulses were artificially injected into these images at various noise ratios. fixed-valued impulse noise has noise values of 255 and 0 only. Random-valued impulse noise has range of impulse noise values between 0 and 255. The quality of impulse detection was evaluated in terms of the number of corrupted pixels that are detected correctly (true hit), healthy pixels that are detected wrongly as corrupted pixels ($false\ hit$), corrupted pixels that are left undetected (*miss hit*) and the correctly detected percentage (% *true hit*) of the corrupted pixels. The performance of the proposed algorithms was evaluated in terms of the visual quality, the peak-signal-to-noise-ratio (PSNR) and the stability of the performance of filters on different types of images. The PSNR is given by

$$PSNR = 10\log_{10}\frac{I_{MAX}^2}{MS} \quad (4)$$

where I_{MAX} is the maximum gray level in the original image and MSE represents the mean square error between the filtered image and the original image.

The first set of experiments was carried out to study the performance of the detection schemes in identifying the noisy pixels in the Lena image at different impulse noise ratios. The experimental results in terms of true hit, false hit and miss hit are reported here. The PSNR of the corresponding detection-based median filter outputs is also included. In the first stage, each of the following detection schemes was separately applied on the noisy image:

(a) Rank-conditioned median filter
(b) Neuvo's median filter

The trimming range in rank-conditioned median filter was fixed corresponding to the best performance. Tables 2 and 3 show the relative detection performance of the detection schemes on the Lena image at different noise ratios for fixed-valued and random-valued impulses respectively. From the tables following observations are made:

(1) Both true hit and false hit are high for the rank-conditioned median filter in case of both types of noise.
(2) The percentage of true hit is uniformly high for Neuvo's median filter.

The proposed filter used the detection scheme of the rank-conditioned median filter and hence its ability in detecting impulse noise from the corrupted image is same as that of the RCM filter.

The second set of experiments was conducted to find out the most appropriate trimming set. figure 2 shows the variation of the PSNR of the RCM-filtered Lena image with respect to the impulse-noise percentage for different values of the trimming range index i It has been observed that the most appropriate value of i that optimises PSNR values is 2 for fixed-valued impulse noise. For random-valued noise, we get marginally better PSNR

performance for $i = 3$. In the rest of the experiments, we shall take $i = 2$ or fixed-valued impulse and $i = 3$ for random-valued impulse. Experimental results on different images suggest that the above values of the trimming range index are independent of the choice of images.

The third set of experiments investigates the improvement of performance achieved by the proposed filters over existing variants of median filters. The following filters were used for comparison with the proposed filter

(1) Standard median (SM) filter

Table 2. Detection performance on the Lena image for fixed-valued impulse noise.

% Impulse noise ratio	5	10	15	20	25	30	35	40
Total corrupted pixels	13107	26214	39321	52429	65535	78643	91749	104860
(a) Rank-conditioned median filter								
True hit	13107	26214	39321	52429	65535	78643	91749	104860
False hit	63416	54671	47275	41095	35235	29555	26111	22344
Miss hit	0	0	0	0	0	0	0	0
% True hit	100	100	100	100	100	100	100	100
PSNR	37.92	37.07	36.28	35.09	34.01	32.62	31.82	31.00
(b) Neuvo's median filter								
True hit	13086	25944	38890	52329	65314	78381	91205	104106
False hit	398	631	778	1012	1246	1526	1803	1961
Miss hit	21	270	431	100	221	262	544	754
% True hit	99.73	99.70	99.58	99.59	99.53	99.50	99.38	99.19
PSNR	41.76	38.64	36.18	34.90	33.17	32.07	30.51	29.22

Table 3. Detection performance on the Lena for random-valued impulse noise.

% Impulse noise ratio	5	10	15	20	25	30	35	40
Total corrupted pixels	13107	26214	39321	52429	65535	78643	91749	104860
(a) Rank-conditioned median filter								
True hit	12391	24193	36405	47682	58753	68864	78588	87574
False hit	140681	130125	119856	110066	100295	91511	83214	75281
Miss hit	716	2021	2916	4747	6782	9779	10161	17286
% True hit	94.54	92.29	92.58	90.95	89.65	87.57	85.66	83.52
PSNR	35.77	34.61	33.46	32.57	31.74	30.62	29.87	28.81
(b) Neuvo's median filter								
True hit	10458	20781	30969	41307	51253	61803	72231	81938
False hit	2712	5488	8151	11042	14012	16701	19488	22445
Miss hit	2649	5433	8352	11122	14282	16840	19518	22922
% True hit	79.41	79.11	79.10	78.91	78.53	78.73	78.75	78.50
PSNR	38.03	35.53	33.75	32.20	31.16	29.98	29.11	27.90

(2) Centre-weighted median (CWM) filter
(3) Rank-conditioned median (RCM) filter
(4) Neuvo's median filter
(5) Arakawa's fuzzy median filter

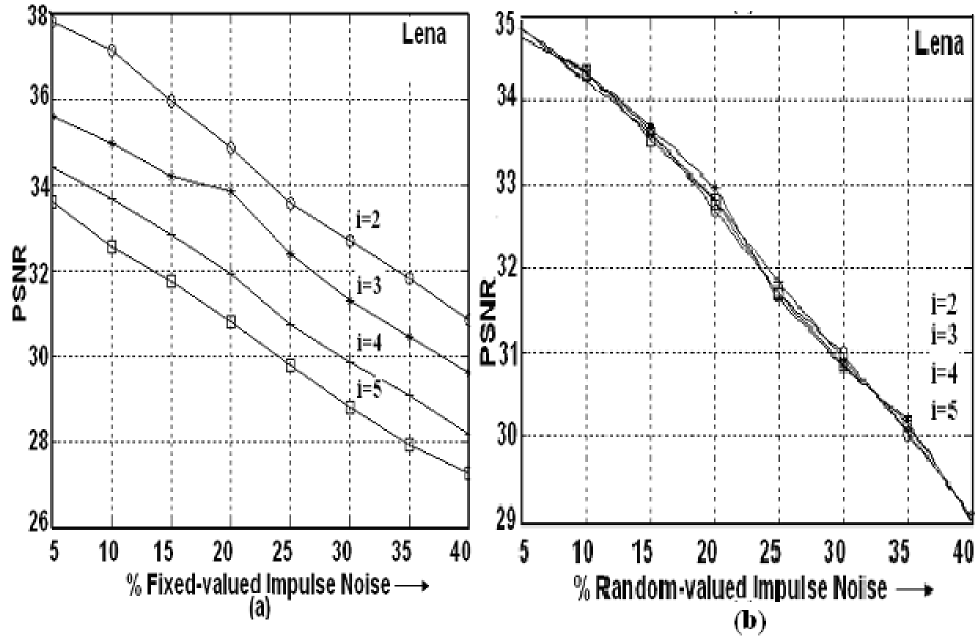


FIGURE 2. Variation of PSNR with respect to the impulse-noise percentage for different values of the trimming range index i: (a) on the Lena image for fixed-valued impulse noise and (b) on the Lena image for random-valued impulse noise..

In all cases, a window of 3×3 size was used. All the algorithms were implemented recursively: the estimate of the current pixel being dependent on the new values of the previously processed pixels in the filtering window.

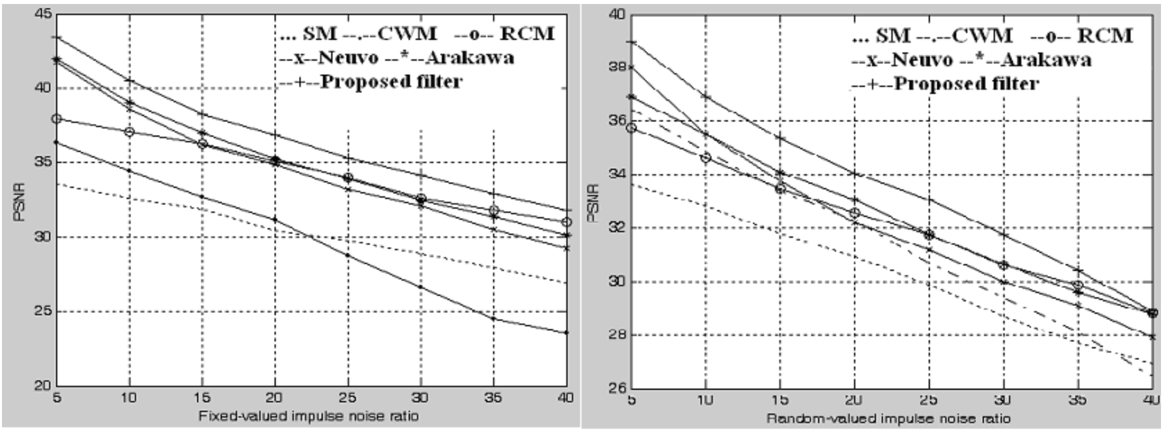
The results on the Lena image are shown in Table 4, where the noise ratios for the two types of impulses range from 5% to 40%. The performance of the RCM filter is better than that of the SM and CWM filters at different noise ratios. It has been seen from the tables that filtering based on the proposed method provides superior results to other methods under consideration in removing both types of impulse noise at different noise ratios. The results from Table 4 were plotted graphically in figure 3. It was observed from the figure that the proposed filter gave superior performance in removal of both types of impulse noise from the Lena image corrupted with impulse noise from 5% to 40% noise ratios.

The fourth set of experiment is on comparison of different types of median filters. Table 5 shows the comparative performance of various filters under consideration applied on different types of images in removal of fixed-valued and random-valued impulse noise corrupted these images with 20% impulse noise ratio. It was found that the performance of the standard median (SM) is the worst in term of the PSNR values for both types of impulse noise. It is due to the fact the filtering was applied to all pixels irrespective of whether impulse noise is present on that location or not. It produces blurring effect, be- cause the centre pixel was replaced by a median value even in the absence of impulse noise.

The performance of the centre-weighted median filter was good for low impulse noise ratios, but its performance became worsen at high impulse noise ratios. It is due to the fact that the CWM filter always tries not to replace the centre pixels in the window. Many leftover impulse noises were present in the output of this type of filter. This is why its PSNR values were low at high impulse noise ratios.The performance of the rank-

Table 4. Comparative performance of different filters in filtering the Lena image corrupted with 5% to 40% impulse noise.

% Noise ratio	Fixed-valued impulse noise						Random-valued impulse noise					
	SM	CWM	RCM	Neuvo	Arak	Propose	SM	CWM	RCM	Neuvo	Arak	Propose
5	33.58	36.37	37.92	41.76	41.95	43.43	33.64	36.47	35.77	38.03	36.90	38.98
10	32.61	34.47	37.07	38.64	39.03	40.48	32.82	34.88	34.61	35.53	35.50	36.92
15	31.85	32.71	36.28	36.18	36.98	38.25	31.78	33.40	33.46	33.75	34.09	35.35
20	30.39	31.12	35.09	34.90	35.25	36.86	30.93	32.29	32.57	32.20	33.05	34.05
25	29.76	28.72	34.01	33.17	33.93	35.32	29.88	30.68	31.74	31.16	31.76	33.06
30	28.91	26.65	32.62	32.07	32.44	34.17	28.69	29.39	30.62	29.98	30.65	31.76
35	27.90	24.46	31.82	30.51	31.35	32.90	27.69	28.10	29.87	29.11	29.60	30.41
40	26.90	23.52	31.00	29.22	30.10	31.81	26.91	26.44	28.81	27.90	28.75	28.88



(a) (b)

Figure 3. Comparative performance of proposed filter with SM, CWM, RCM, Neuvo's and Arakawa's median filters.

conditioned median filter was very good in term of PSNR values for different types of images. This improved performance was due to its ability to detect impulse noise. filtering was applied to the corrupted pixels only and healthy pixels were left undisturbed. A variant of median filter proposed by Neuvo showed very good performance in term of PSNR values on different types of images. It had the ability to detect the presence of impulse noise by comparing the centre pixel in the window with the neighbouring pixels.

Arakawa's median filter is a variant of the Neuvo's median filter, but it uses soft thresholding for giving weight to the corrupted pixels in replacement. It showed very improved performance to the Neuvo's median filter in term of PSNR values on different types of images for both types of impulse noise.

The proposed filter outperformed all filters under consideration in term of PSNR values for both types of impulse noises on different types of images. It is due to the fact that

Table 5. Comparative PSNR performance of filters in filtering different images corrupted with 20% impulse noise.

Images	Fixed-valued impulse noise						Random-valued impulse noise					
	SM	CWM	RCM	Neuvo	Arakawa	Proposed	SM	CWM	RCM	Neuvo	Arakawa	Proposed
Lena	30.39	31.12	35.09	34.90	35.25	36.86	30.93	32.29	32.57	32.20	33.05	34.05
Mandrill	22.22	23.09	24.88	24.45	24.43	25.84	22.62	23.54	22.83	22.57	22.90	23.29
Airplane	26.86	29.46	33.11	30.82	30.87	33.16	27.51	30.33	30.77	29.94	30.13	31.85
Lake	26.65	27.91	31.05	28.73	29.49	31.52	27.20	28.77	28.73	28.37	28.82	29.93
Pepper	27.94	29.38	34.96	32.22	32.84	34.23	28.75	31.82	32.51	31.75	32.63	33.18
House	25.48	28.08	31.16	29.50	29.55	30.98	25.93	28.54	28.35	28.32	28.89	29.77
Miramar	24.59	25.69	27.89	28.90	29.45	29.51	25.26	26.22	25.74	25.70	25.77	26.66

this filter integrates both the good detection ability of the rank-conditioned median filter and Arakawa's median filter.

The comparative performance of all filters is shown in figures 4 and 5 in the removal of both types of impulse noise from the Lena image corrupted with 20% impulse noise.

6. **Conclusion.** As a roundup of the present paper, we briefly discussed the achievements, compared the proposed algorithms and suggested possible extensions. The work concerned with developing fuzzy-based filtering algorithm for removing impulse noise from an image. The rank-conditioned median filter is based on impulse noise detection by applying detection condition with an aim to reduce the probability of detecting a healthy pixel as an impulse and the probability of detecting a noisy pixel as healthy. Arakawa's fuzzy-based median filter, on the other hand, checks in the images whether impulse noise is present in the sliding window or not, and if present it further clarifies whether it is impulse noise or feature points (like thin straight line, end of the line, corner or edge). Median filtering is applied after it classifies that the pixel belongs to impulse noise. The proposed fuzzy- based median filter integrates the rank-conditioned median filter and Arakawa's fuzzy- based median filter. The rank-conditioning ensures that an impulse noise does not belong to trimming set, because its value is either very large or very small. Impulse noise is an outlier, which is entirely different from the rest of the other pixels in the window. It has been shown experimentally that the rank-conditioned median filter outperformed the standard median filter by large margin in term of PSNR values and visually also. On the other hand, Arakawa's fuzzy-based median filter is soft-thresholding approach that has ability to differentiate between impulse noise and feature points. The proposed algorithm takes advantages by integrating the rank-conditioned median filter and Arakawa's fuzzy-based median filter. The future plan of the proposed method is to extend it further for removing impulse noise from colour images.


(a)
(b)
(c)
(d)

Figure 4. (a) Original Lena image, (b) Lena image corrupted with 20% fixed-valued impulse noise, (c), (d), (e), (f), (g) and (h) are the filter outputs of median filter, centre- weighted median filter, rank-conditioned median filter, Neuvo's median filter, Arakawa's median filter and proposed method respectively.


(a)
(b)
(c)
(d)

FIGURE 5. (a) Original Lena image, (b) Lena image corrupted with 20% random-valued impulse noise, (c), (d), (e), (f), (g) and (h) are the filter outputs of median filter, centre- weighted median filter, rank-conditioned median filter, Neuvo's median filter, Arakawa's median filter and proposed method respectively.

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