# Restoration of Impulse Noise Corrupted Images Using Long-Range Correlation

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***Abstract*—In this letter, we present a new algorithm that can remove impulse noise from corrupted images while preserving details. The algorithm is fundamentally different from the traditional methods in that it can utilize information not just of a local window centered about the corrupted pixel, but also of some remote regions in the image. Computer simulations indicate that our algorithm outperforms many existing techniques.**

***Index Terms*— Image enhancement, impulse noise, nonlinear filter.**

## I. Introduction

IMAGES are often corrupted by impulse noise due to errors generated in noisy sensors or communication channels. So far, many techniques have been proposed to remove impulse noise from the corrupted images [1]–[5]. A general framework for them can be described as follows. For each pixel, we extract a window (usually with a size of 3 × 3, 5 × 5, or 7 × 7) centered about it from the image. Based on the information within the window, a noise cancellation scheme is then applied to replace the pixel with a new value, which makes it comply with some predefined constraints on the local window. Nevertheless, a drawback of this framework is that it can "see" only local information. Because the window size is often too small to reflect the real structure of the local region, the noise cancellation filters developed on them are not very effective in preserving many detail areas. In this letter, we propose a fundamentally different technique where the new value of a corrupted pixel is determined by long-range correlation between its neighborhood window and some remote regions in the image.

## II. Restoration Algorithm

Our algorithm is composed of two parts—impulse detection and noise cancellation. Many previously published algorithms such as those in [3] and [4] used an impulse detector to determine whether a pixel should be modified. A difference in our algorithm is that the detection results are also used to help the process of the second part—noise cancellation.

Let $x_{ij}$ and $x_{ij}^{(\mathrm{new})}$ represent the pixel values at position $(i,j)$ in the corrupted image and the restored image, respectively. The goal of the impulse detector is to generate a binary flag map where each pixel $(i,j)$ is given a binary flag $f_{ij}$ indicating whether it is considered as an impulse, i.e., $f_{ij}=1$ means $(i,j)$ is a corrupted pixel and $f_{ij}=0$ means $(i,j)$ is noise free. In Sun and Neuvo's switching I scheme [3], they used the difference between the pixel value itself and the median value of a local window centered about it as the measurement to detect impulses. This measurement is easy to operate and is effective when the image is slightly contaminated with impulse noise. However, it can not perform well when noise ratio is high. To further improve the detection accuracy, we developed a modified version of Sun and Neuvo's method [5]. In this letter, we use such an improved technique to generate the binary flag map.[1]

During the noise filtering procedure, the good pixels with $f_{ij}=0$ are unaltered. That is

$$x_{ij}^{(\mathrm{new})} = x_{ij}. \tag{1}$$

The noise cancellation scheme is only applied to those pixels considered as impulses $(f_{ij}=1)$. For an impulse pixel at position $(i,j)$, two $(2N_c+1)\times(2N_c+1)$ sized windows are employed: The first window is the local window centered about the impulse pixel and the second window is a remote window located at a different place in the image with its center at position $(k,l)$. Since the whole image may contain a large number of complete $(2N_c+1)\times(2N_c+1)$ windows, the remote window should be selected from one of them. In our algorithm, a candidate remote window must satisfy the following conditions.

1) It is not the same as the local window, i.e., $i \neq k$ or $j \neq l$.
2) It must be completely covered by a larger $(2M+1)\times(2M+1) (M > N_c)$ window called search range window which is centered about the impulse pixel $(i,j)$.
3) Its center $(k,l)$ is a good pixel, i.e., $f_{kl}=0$.

All the $(2N_c+1)\times(2N_c+1)$ candidate remote windows will compete for the best match to the local window. The measurement is based on the mean square error (MSE) in the good part of the local window and the candidate remote

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[1] The impulse detection algorithm is not what this letter is mainly concerned with. Readers who are interested in more detailed information regarding the impulse detection method and the parameter selection scheme can refer to [5].

TABLE I
COMPARATIVE RESTORATION RESULTS IN PSNR FOR 20% IMPULSE NOISE FOR IMAGE LENA. FOR FIXED-VALUED IMPULSE NOISE, IMPULSES TAKE ON ONLY THE VALUES ZERO OR 255 WITH EQUAL PROBABILITY. FOR RANDOM-VALUED IMPULSE NOISE, IMPULSE VALUES ARE UNIFORMLY DISTRIBUTED BETWEEN ZERO AND 255

| Filtering Algorithm | Fixed-valued Impulses | Random-valued Impulses |
|---|---|---|
| Median filter (3×3) | 28.57 dB | 29.76 dB |
| Median filter (5×5) | 28.78 dB | 28.59 dB |
| Median filter with adaptive length[1] [1] | 30.57 dB | 31.18 dB |
| Rank conditioned rank selection filter[1] [2] | 31.36 dB | 30.78 dB |
| Sun and Neuvo, Switch I median filte[1] [3] | 31.97 dB | 31.34 dB |
| Sun and Neuvo, Switch II median filter[1] [3] | 29.96 dB | 32.04 dB |
| Abreu et al. ($M$=2, no training)[1] [4] | 33.47 dB | 32.47 dB |
| Abreu et al. ($M$=1296, outside training set)[1] [4] | 34.65 dB | 32.95 dB |
| Abreu et al. ($M$=1296, inside training set)[1] [4] | 35.70 dB | 33.37 dB |
| Our new approach | 36.95 dB | 33.43 dB |

[1] See reference [4] for more details with regard to methods and parameter selections.

TABLE II
COMPARATIVE FILTERING RESULTS IN PSNR FOR IMAGE LENA CORRUPTED WITH VARIOUS PERCENTAGES OF RANDOM-VALUED IMPULSE NOISE

| Filtering Algorithm | Percentage of Random-valued Impulse Noise | | | | |
|---|---|---|---|---|---|
| | 10% | 15% | 20% | 25% | 30% |
| Abreu et al. ($M$=2, no training)[1] [4] | 35.18 dB | 33.94 dB | 32.47 dB | 31.18 dB | 29.87 dB |
| Abreu et al. ($M$=1296, inside training set)[1] [4] | 36.02 dB | 34.44 dB | 33.37 dB | 31.77 dB | 30.49 dB |
| Abreu et al. ($M$=1296, outside training set)[1] [4] | 36.64 dB | 34.72 dB | 32.95 dB | 31.52 dB | 29.99 dB |
| Our new approach, 1 iteration | 36.69 dB | 34.83 dB | 33.43 dB | 31.76 dB | 30.01 dB |
| Our new approach, 2 iterations | 36.11 dB | 34.71 dB | 33.75 dB | 32.54 dB | 31.50 dB |

[1] See reference [4] for more details with regard to methods and parameter selections.

window. That is, we arrive at (2), shown at the bottom of the page. Note that the square error of a pixel pair will be computed only if both of its two corresponding pixels in the local and remote windows are good. Each of the candidate remote windows will result in $\mathrm{MSE}_g$ and the one with the minimal $\mathrm{MSE}_g$ becomes the winner. Finally, the corrupted pixel is replaced by the center pixel of the winning remote window as follows:

$$x_{ij}^{(\mathrm{new})} = x_{kl}. \tag{3}$$

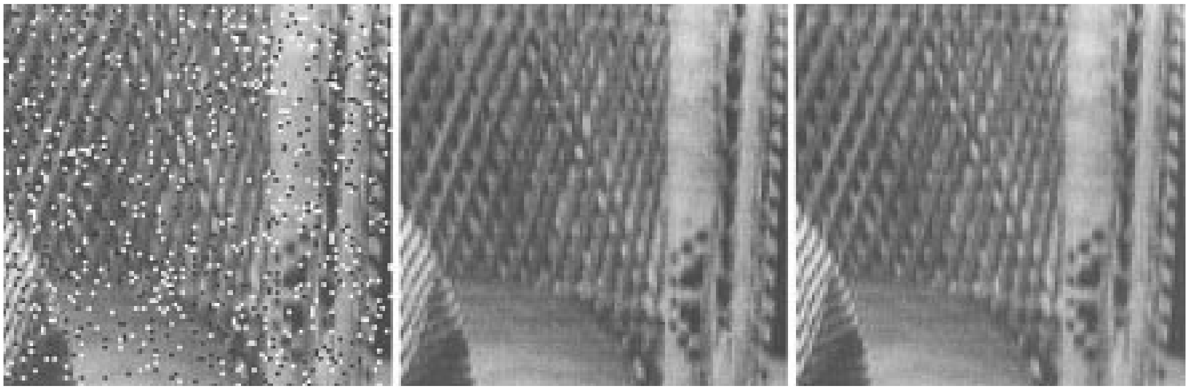
## III. EXPERIMENTAL RESULTS

Some computer simulations are carried out to assess the performance of our method. The original test images are some standard 8 b/pixel gray-scale images. Two types of impulse noises are tested. The first is fixed-valued impulse noise where the impulses take on the values of zero or 255 with equal probabilities. The second is random-valued impulse noise where the impulse values are uniformly distributed between zero and 255. Peak SNR (PSNR) is used to give a quantitative evaluation on the filtering results. In this letter, we always use the same set of parameters, $N_c = 3$ and $M = 10$, in all the experiments.

In [4], Abreu *et al.* reported many restoration results in PSNR for images corrupted by both 20% fixed-valued and 20% random-valued impulse noises. We list some of those data in Table I and add the results of our algorithm at the end of the table. For fixed-valued noise, our algorithm provides significant improvement over all the other approaches, while for random-valued noise, the result of our algorithm is also the best. Only Abreu *et al.*'s approach with inside training set [4] is close to our algorithm. In Table II, we show the filtering results for the Lena image corrupted by random-valued impulse noise with various probabilities ranging from 10–30%. The results of Abreu *et al.*'s approach are also given [4]. In most cases, the performance of the proposed algorithm is close to the best result of Abreu *et al.*'s approaches. Notice that our algorithm does not include any training procedure.

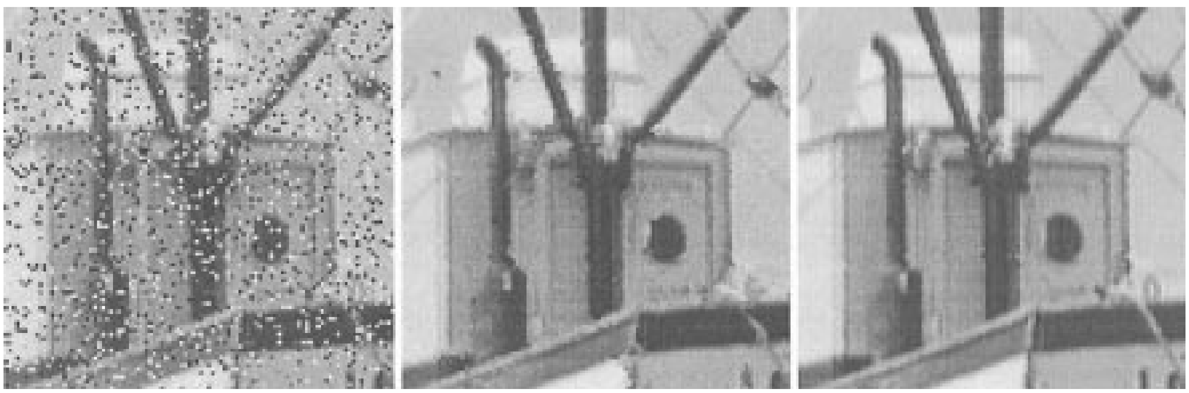
It should be mentioned that the restoration results may be further improved simply by iteratedly applying the proposed algorithm, especially when the noise probability is high. For

$$\mathrm{MSE}_g = \frac{\sum_{m=-N_c}^{N_c} \sum_{n=-N_c}^{N_c} (1 - f_{i+m,j+n}) \cdot (1 - f_{k+m,l+n}) \cdot (x_{i+m,j+n} - x_{k+m,l+n})^2}{\sum_{m=-N_c}^{N_c} \sum_{n=-N_c}^{N_c} (1 - f_{i+m,j+n}) \cdot (1 - f_{k+m,l+n})} \tag{2}$$



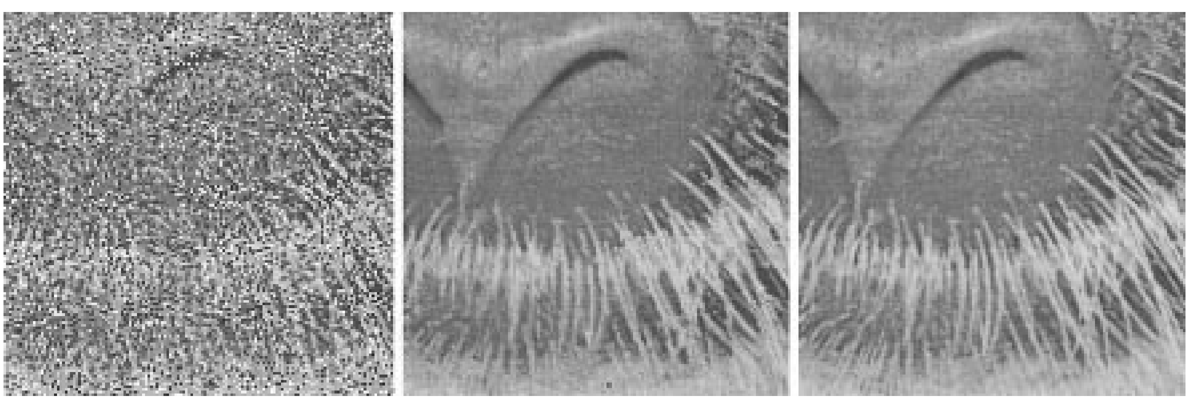
(a) (b) (c)

Fig. 1. Restoration performance for an enlarged area from Barb image. (a) Image corrupted by 10% fixed-valued impulse noise. (b) Restored image. (c) Original image area.



(a) (b) (c)

Fig. 2. Restoration performance for an enlarged area from boats image. (a) Image corrupted by 20% random-valued impulse noise. (b) Restored image. (c) Original image area.



(a) (b) (c)

Fig. 3. Restoration performance for an enlarged area from the baboon image. (a) Image corrupted by 30% fixed-valued impulse noise. (b) Restored image. (c) Original image area.

example, when image Lena is corrupted with 20% random-valued impulse noise, an additional iteration can raise PSNR from 33.43 to 33.75 dB. In the last row of Table II, we list the PSNR performance after two iterations.

In Figs. 1–3, we give some enlarged areas of our test images to show how the proposed algorithm performs on different kinds of image details. The visual qualities of the restored images are relatively good considering the abundance of image details and the high noise probabilities.

## IV. Conclusions

In this letter, we present a new impulse noise removal scheme by employing long-range correlation in the image.

The proposed filtering algorithm breaks through the traditional framework in that it can make use of both local and remote information in the image. Experimental results indicate that the proposed algorithm provides major improvement over many other well-known methods.

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