A SIGNAL-DEPENDENT RANK ORDERED MEAN (SD-ROM) FILTER - A NEW APPROACH FOR REMOVAL OF IMPULSES FROM HIGHLY CORRUPTED IMAGES

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ABSTRACT

We propose an efficient nonlinear algorithm to suppress impulse noise from highly corrupted images while preserving details and features. The method is applicable to all impulse noise models, including fixed valued (equal height or salt and pepper) impulses and random valued (unequal height) impulses, covering the whole dynamic range. The algorithm is based on a detection-estimation strategy. If a signal sample is detected as a corrupted sample, it is replaced with an estimation of the true value, based on neighborhood information. Otherwise it is kept unchanged. The technique achieves excellent tradeoff between the suppression of noise, and preserving the details and edges without undue increase in computational complexity. Extensive simulation tests indicate that our method performs better than other existing algorithms, including the well known median filters. Illustrative examples included in the paper verify the capability of the proposed approach.

1. INTRODUCTION

Images are often corrupted by impulse noise due to a noisy channel or faulty image acquisition device and much research has been done on removing such kind of noise. The objective is to suppress the impulse noise while preserving the integrity of edges and detail information. Linear techniques do not usually perform well for impulse noise removal, and many nonlinear methods have been found to provide more satisfactory results. The most frequently used nonlinear filter is the median filter [1], which is superior to linear filters in its ability to suppress impulse noise and preserve edges. In median filtering, whether a pixel is corrupted or not, it is replaced with its local median within a window. Although noise suppression is obtained, too much distortion is introduced and the image features and details become blurred, particularly with a large size window.

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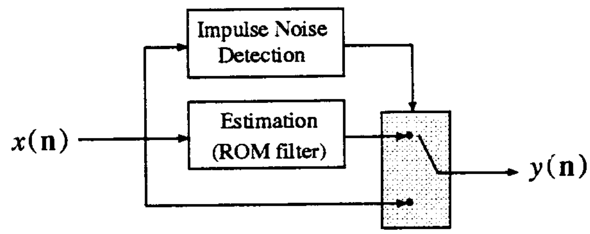

Figure 1: The SD-ROM filter structure

In this paper we present a new nonlinear method to remove impulse noise from highly corrupted images while preserving details and features. The algorithm is based on a detection-estimation strategy. All the pixels in the image are examined by an impulse noise detector. Only those pixels which are detected as corrupted are replaced with an estimation of the true value, based on the neighborhood information. The remaining pixels are kept unchanged.

In a variety of impulse noise models for images, corrupted pixels are often replaced with values equal to or near the maximum or minimum of the allowable dynamic range. For 8-bit images, this typically corresponds to fixed values near 0 or 255. In our experiments, we consider a more general noise model in which a noisy pixel can take on arbitrary values in the dynamic range according to some underlying probability distribution. Let $v(\mathbf{n})$ and $x(\mathbf{n})$ denote the luminance values of the original image and the noisy image, respectively, at pixel location $\mathbf{n} = [n_1, n_2]$. Then, for an impulse noise model with error probability p_e, we have

$$x(\mathbf{n}) = \begin{cases} v(\mathbf{n}), & \text{with probability } 1 - p_e \\ \eta(\mathbf{n}), & \text{with probability } p_e \end{cases} \quad (1)$$

where $\eta(\mathbf{n})$ is an identically distributed, independent random process with an arbitrary underlying probability density function. For our computer simulations, we generate corrupted images using both fixed-valued impulse noise (salt and pepper) and impulse noise described by a uniform distribution from 0 to 255.

2. THE SD-ROM FILTER

Figure 1 shows a block diagram of the proposed filter structure. The input signal is filtered depending on the decision of the impulse detector. If a signal sample is detected as a corrupted sample, it is replaced with an estimation of the true value, otherwise it is kept unchanged.

Consider a 3×3 window centered at $x(\mathbf{n})$. We define $\mathbf{w}(\mathbf{n})$ as an eight element observation vector containing the neighboring pixels of $x(\mathbf{n})$ inside the window, (*excluding* $x(\mathbf{n})$, itself):

$$\begin{aligned}\mathbf{w}(\mathbf{n}) &= [w_1(\mathbf{n}), w_2(\mathbf{n}), \ldots, w_8(\mathbf{n})] = \\ & [x(n_1-1, n_2-1), x(n_1-1, n_2), \\ & x(n_1-1, n_2+1), x(n_1, n_2-1), \\ & x(n_1, n_2+1), x(n_1+1, n_2-1), \\ & x(n_1+1, n_2), x(n_1+1, n_2+1)], \quad (2)\end{aligned}$$

which corresponds to a left-to-right, top-to-bottom mapping from the 3×3 window to the 1-D vector $\mathbf{w}(\mathbf{n})$.

The observation samples can be also ordered by rank, which defines the vector

$$\mathbf{r}(\mathbf{n}) = [r_1(\mathbf{n}), r_2(\mathbf{n}), \ldots, r_8(\mathbf{n})], \quad (3)$$

where $r_1(\mathbf{n}), r_2(\mathbf{n}), \ldots, r_8(\mathbf{n})$ are the elements of $\mathbf{w}(\mathbf{n})$ arranged in ascending order, such that $r_1(\mathbf{n}) \leq r_2(\mathbf{n}) \leq \ldots \leq r_8(\mathbf{n})$.

Next, we define the *rank-ordered mean* (ROM) as $m(\mathbf{n}) = (r_4(\mathbf{n}) + r_5(\mathbf{n}))/2$ [1]. Finally, we define the *rank-ordered differences*:

$$\mathbf{d}(\mathbf{n}) = [d_1(\mathbf{n}), d_2(\mathbf{n}), d_3(\mathbf{n}), d_4(\mathbf{n})], \quad \text{where}$$
$$d_i(\mathbf{n}) = \begin{cases} r_i(\mathbf{n}) - x(\mathbf{n}), & x(\mathbf{n}) \leq m(\mathbf{n}) \\ x(\mathbf{n}) - r_{9-i}(\mathbf{n}), & x(\mathbf{n}) > m(\mathbf{n}), \end{cases} \quad (4)$$

for $i = 1, \ldots, 4$.

The rank-ordered differences provide information about the likelihood of corruption for the current pixel. For example, consider the rank-ordered difference $d_1(\mathbf{n})$. If this value is positive, then the current pixel $x(\mathbf{n})$ is either the smallest or largest value in the current window. If $d_1(\mathbf{n})$ is not only positive, but also large (greater than a threshold), then an impulse is very likely. Together, the differences $d_1(\mathbf{n})$ through $d_4(\mathbf{n})$ reveal even more information about the presence of a corrupted pixel—even for the case when multiple impulses are present in the current window.

The SD-ROM filter operates as follows.

Impulse noise detection:

The algorithm detects $x(\mathbf{n})$ as a noisy sample if any of the following inequalities are true:

$$d_i(\mathbf{n}) > T_i, \qquad i = 1, \ldots, 4. \quad (5)$$

where T_1, T_2, T_3, T_4 are threshold values, with $T_1 < T_2 < T_3 < T_4$.

Estimation of the true value:

If $x(\mathbf{n})$ is detected as a corrupted sample, it is replaced by $m(\mathbf{n})$, otherwise it is kept unchanged.

For the large variety of images we tested, we obtained excellent results using thresholds selected from the following set of values: $T_1 \in \{4, 8, 12\}, T_2 \in \{15, 25\}$, $T_3 = 40$, $T_4 = 50$. The algorithm works well even for suboptimally selected thresholds. In fact, the initial values $T_1 = 8$, $T_2 = 20$, $T_3 = 40$, $T_4 = 50$ should provide good to excellent results with most natural images corrupted with random-valued impulse noise.

Improved performance can be obtained if the algorithm is implemented in a recursive fashion. For this approach, the sliding window is redefined according to $\hat{\mathbf{w}}(\mathbf{n}) = [y_1(\mathbf{n}), \ldots, y_4(\mathbf{n}), w_5(\mathbf{n}), \ldots, w_8(\mathbf{n})]$ where $y_i(\mathbf{n})$ corresponds to the filter output for each noisy input pixel, $w_i(\mathbf{n})$.

Although we have described the algorithm for the case of 2-D signals, the method is general and applies to higher dimensional signals as well as to 1-D signals. Other window sizes and shapes are possible. The procedure in the general case follows similar steps. To detect the impulse noise, the samples inside a window, excluding the current sample, are rank-ordered, and the differences between the current sample and the ordered samples are compared to thresholds. A corrupted sample is replaced with the ROM value.

3. COMPUTER SIMULATION TESTS

We compared the performance of the proposed technique with that of median filters and other existing algorithms for impulse noise removal. For these tests, the occurrence rate of randomly distributed impulse noise (uniformly distributed from 0 to 255) was 20 percent. Table 1 shows the mean absolute error (MAE), mean squared error (MSE), and peek signal-to-noise ratio (PSNR) of the restored images "lena" and "miramar", obtained with the different methods used. The algorithms were implemented either recursively or nonrecursively according to which approach provided the best results. Thresholds and other parameters were adjusted for each method and degraded image. The method by Kim and Yaroslavskii was implemented using Eqs. (2.8) and (2.14) in [2]. Clearly, from Table 1, the SD-ROM provided significant improvement in performance over the other tested methods.

[1] Note that the ROM nearly corresponds to the definition of the median filter with the important distinction that $\mathbf{w}(\mathbf{n})$ does not include the center pixel of the original 3×3 window.

	Lena image			Miramar image		
	MAE	MSE	PSNR	MAE	MSE	PSNR
Median filter, 3×3	4.39	68.63	29.76 dB	9.43	206.4	24.98 dB
Median filter, 5×5	5.50	89.82	28.59 dB	11.87	284.8	23.59 dB
Kim and Yaroslavskii [2]	2.06	56.62	30.60 dB	4.43	160.0	26.09 dB
Weighted FIR median hybrid filter #5 [3]	4.77	97.58	28.23 dB	8.61	229.9	24.52 dB
Median filter with adaptive length [4]	1.94	49.57	31.17 dB	4.27	155.5	26.21 dB
Rank cond. rank selection filter, 9×9, M=2 [5]	3.44	99.03	28.17 dB	5.46	197.1	25.18 dB
Sun and Neuvo, Switching I [6]	2.00	49.63	31.17 dB	4.03	140.6	26.65 dB
Sun and Neuvo, Switching II [6]	1.91	68.70	29.76 dB	4.09	176.1	25.67 dB
Florêncio and Schafer [7]	2.90	77.86	29.21 dB	5.60	183.4	25.50 dB
SD-ROM	1.54	35.81	32.59 dB	3.73	126.2	27.12 dB

Table 1: Comparative results using different algorithms

With respect to perceptual quality, the SD-ROM achieved better trade-off between noise suppression and detail preservation. To illustrate this point, we show portions of the "miramar" image in Figure 2.

We repeated the simulations for many different images, varying the type and percentage of noise, and in all cases our method produced superior results.

4. GENERALIZED METHOD

As indicated in Figure 1, the filtered output $y(\mathbf{n})$ is switched between the input $x(\mathbf{n})$ and the ROM value $m(\mathbf{n})$. The switching operation is conditioned on the rank-ordered differences $\mathbf{d}(\mathbf{n})$ and fixed threshold values. Inspired by [8], we generalize our method by redefining $y(\mathbf{n})$ as a linear combination of $x(\mathbf{n})$ and $m(\mathbf{n})$:

$$y(\mathbf{n}) = c_1(\mathbf{d}(\mathbf{n}))x(\mathbf{n}) + c_2(\mathbf{d}(\mathbf{n}))m(\mathbf{n}), \qquad (6)$$

where $c_2(\mathbf{d}(\mathbf{n})) = 1-c_1(\mathbf{d}(\mathbf{n}))$, and $0\leq c_1(\mathbf{d}(\mathbf{n}))\leq 1$. The coefficients $c_1(\mathbf{d}(\mathbf{n}))$ and $c_2(\mathbf{d}(\mathbf{n}))$ are conditioned only on the rank-ordered differences (there are no thresholds). The values of $c_1(\mathbf{d}(\mathbf{n}))$ are obtained by performing optimization using training data. The SD-ROM output is a special case of Eq. (6), where $c_1(\mathbf{d}(\mathbf{n}))$ can take on only the values zero and one.

Computer simulations indicate that improved performance can result from the generalized method.

We are currently submitting for publication a paper with complete details of this approach [9].

5. CONCLUSION

We have presented an efficient nonlinear algorithm to suppress impulse noise from highly corrupted images. The algorithm is based on a detection-estimation strategy. Only signal samples which are detected as corrupted are replaced with an estimation of the true value, all the other samples remain unchanged. The method achieves an excellent tradeoff between noise suppression and detail preservation, and outperforms a number of well-known techniques, both in terms of measured distortion and perceptual quality, without undue increase in computational complexity. Comparative results have been presented.

6. REFERENCES

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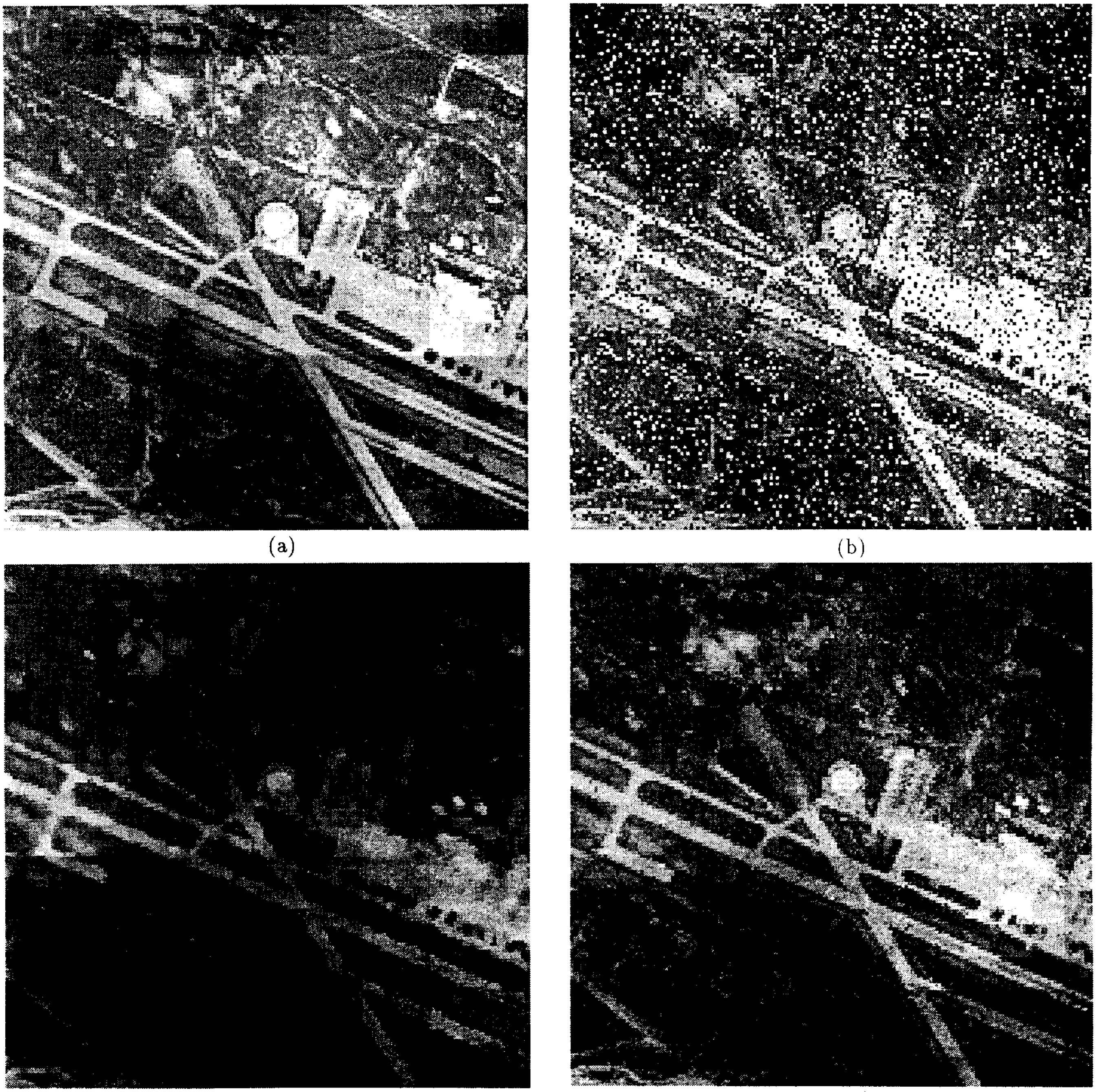

Figure 2: (a) Portion of original "miramar" image, (b) Portion of corrupted "miramar" image, (c) Restored using 3×3 median filter, and (d) Restored using the SD-ROM with $T_1 = 8$, $T_2 = 25$, $T_3 = 40$, $T_4 = 50$.