EFFECTIVE DETECTION AND ELIMINATION OF IMPULSIVE NOISE WITH A MINIMAL IMAGE SMOOTHING

Igor Aizenberg, Jaakko Astola, Constantine Butakoff, Karen Egiazarian and Dmitriy Paliy

International Center for Signal Processing, Tampere University of Technology,
Korkeakoulunkatu 1/PO Box 553, FIN-33720, Tampere, Finland,
E-mail: igora@netvision.net.il (IA), jta@cs.tut.fi (JA),
cbutakoff@yahoo.com (CB), karen@cs.tut.fi (KE), paliy@cs.tut.fi (DP)

ABSTRACT

Impulsive noise filtering is an important problem of image processing. The problem of noise elimination in an image has a companion problem, the problem of maximal preservation of image edges. The requirement of maximal preservation of edges is especially important for images, corrupted by impulsive noise with a low corruption rate. To avoid smoothing of the image during filtering, all noisy pixels must be detected. Then only these detected pixels must be corrected. We present in this paper two solutions to the preservation problem. The first one is an impulse detector. This detector is based on a comparison of signal samples within a narrow rank window. It is quite efficient for precise detection of impulses in images corrupted by impulsive noise with a low corruption rate. The second solution is based on threshold Boolean filtering, when the binary slices of an image, obtained by the threshold decomposition, are processed by Boolean functions.

1. INTRODUCTION

As a rule, impulsive noise can significantly damage an image. A commonly used approach to filter impulsive noise is median filtering [1]. Usually it is possible to completely eliminate impulsive noise using this classical approach. A significant disadvantage of median filtering is image smoothing. In other words, although the noise is removed, image edges are not preserved. Other nonlinear filters, proposed for impulsive noise reduction (for example, rank-order filters [1-[3], stack filters [1], weighted median filters [1, [2]), preserve image edges, but in general, the results are not good enough.

A good way to solve the preservation problem is noise detection. If the noisy pixels are detected and they are a priori known before filtering, then the filter can be applied only to these pixels. Several impulse detectors developed recently should be mentioned. In [4] a multi-pass filter, which is based on both global image statistics and statistics of samples inside the filter window, was proposed. The first pass of this algorithm marks each image sample as either "no filtering", "edges" or "noisy". The information collected on the first pass is used, as a set of parameters, for the second pass, which is weighted median filtering. A disadvantage of this filter is its orientation only towards the "salt and pepper" noise model. A more robust detector is proposed in [5]. This is also a two-pass method, which is based on an analysis of the so-called “edge flag image”, created on the first pass.

We want to propose here two new solutions that are directed to effective detection and elimination of impulsive noise, especially the noise with a low corruption rate. The first solution is based on a priori impulse detection. Behind this detection lies a comparison of signal samples within a narrow rank window, which is a significant development of the results presented in [6]. The second solution is based on threshold Boolean filtering [1, [7], when the signal’s binary slices, obtained by threshold decomposition, are processed by a Boolean function. The Boolean functions that are used here were proposed in [8] and then considered in [6] in the context of cellular neural Boolean filtering, when the image’s binary planes obtained by direct decomposition (according to the binary representation of a decimal number) are processed separately. Here we use the same Boolean functions for threshold Boolean filtering.

2. THE IMPULSE DETECTOR

Since impulsive noise significantly changes the brightness value of a pixel, it can be identified by the height of the brightness jump in comparison to the surrounding pixels. Thus impulse detection can be reduced to an analysis of local image statistics within a window, whose size is defined by a filter.

It is well known that the difference between the rank of an impulse and the rank of the median in a local window is usually large [1]. Let us consider the variational series (pixels from a filter window arranged by their value in ascending order) for a given filter window. The median is always located in the center of the variational series, while any impulse is usually located near one of its ends. This gives a natural and simple idea for impulse detection. This idea is based on a comparison between the rank of the pixel of interest and a threshold value:

$$\left(R(x_{ij}) \leq s\right) \vee \left(R(x_{ij}) \geq N - s + 1\right), \quad (1)$$

where x_{ij} is the pixel of interest, $s>0$ is the threshold and N is the length of the variational series. $R(x)$ is the function that returns the rank (from 1 to N) of an element x in the variational series. So, if the condition (1) holds for a given pixel x_{ij} then it is classified as corrupted by impulsive noise.

The detector (1) has been considered in [6]. It is very simple and gives good results. But it has a disadvantage, which makes the level of misdetection very high. This detector takes into account only the ranks of signal's values, but it does not consider these values themselves. It means that although it is usually possible to detect all the impulses by (1), many pixels may be classified as corrupted by mistake. A problem is that if there are no impulses in the analyzed window, pixels with the smallest or largest ranks will be classified by (1) as impulses.

To overcome this disadvantage, it is necessary to take into account not only the rank of the pixel of interest, but also to consider its brightness value. We are going to consider here the additional estimation, the difference between the pixel of interest and its closest neighbor in the variational series:

$$d_{ij} = \begin{cases} \left|x_{ij} - Var\left[R\left(x_{ij}\right) - 1\right]\right| & \text{, if } R\left(x_{ij}\right) > \underset{i,j}{MED} \\ \left|x_{ij} - Var\left[R\left(x_{ij}\right) + 1\right]\right| & \text{, if } R\left(x_{ij}\right) < \underset{i,j}{MED} \\ 0 & \text{, otherwise,} \end{cases} \quad (2)$$

where $Var(k)$ returns the value of the pixel whose rank is k; $\underset{i,j}{MED}$ – is the median in a local window around ij[th] pixel. Combining (1) and (2) we obtain the following detector:

$$\left(\left[R\left(x_{ij}\right) \leq s\right] \vee \left[R\left(x_{ij}\right) \geq N - s + 1\right]\right) \wedge \left(d_{ij} \geq \Theta\right) \quad (3)$$

Analyzing each pixel by two different estimators, the criterion (3) allows for quite precise detection of impulses. It shows especially good results for images with a relatively low (up to 20%) corruption rate. For low corruption rates it is even possible to fix the values of s and Θ. For example, we can set $s=1$ to detect the noise with a corruption rate of less than 5% because with a very high probability every 3x3 local window contains not more than one corrupted pixel. It is also very important to take into account that any filter (even the median filter for example) in combination with the detector (3) can be applied to the image iteratively, while still preserving most of details from smoothing. In this case it is possible to detect impulses with greater precision (for example, experience shows that in many cases two iterations of filtering with $s=1$ give better results than one iteration with $s=2$).

3. THRESHOLD BOOLEAN FILTER

Another approach to efficient impulsive noise filtering is development of new filters that can perform very careful signal averaging. In [8] it was proposed to use the direct image decomposition into binary planes followed by their separate processing using a Boolean function and integration of the resulting binary planes back into a gray-scale image. This approach shows the best results for images with the lowest possible corruption rate (below 3%), while for higher corruption rates the filter may replace one impulse by another one. A modification of this algorithm combined with the detector like (1) has been considered in [6]. We want to use here the same Boolean function as proposed in [6, [8] for elimination of impulses. But instead of the direct decomposition of an image into binary planes we will use the threshold decomposition, which is usual for threshold Boolean filtering [1, [7]. The following Boolean function was proposed to detect and remove impulses from binary images [8]:

$$\mathrm{Y}\begin{bmatrix} x_1 & x_2 & x_3 \\ x_4 & x_5 & x_6 \\ x_7 & x_8 & x_9 \end{bmatrix} = \begin{cases} \bar{x}_5 & , if \left|\left\{x_i \mid x_i = \bar{x}_5\right\}\right| = 5 \\ x_5 & \text{, otherwise} \end{cases} \quad (4)$$

where $|A|$ is cardinality of a set A.

The basic idea behind (4) is to compare the value of the window's central element to the values of majority of other elements from the same window. Actually this procedure is equivalent to the classical stack filtering, because the value of the central element x_5 is replaced by the median. Let us consider a more adaptive case, when the number of elements, to which x_5 is being compared, is defined by a threshold parameter t. For $t=5$ we obtain the classical stack filtering function, while for $t>5$ we obtain more careful filter. The corresponding Boolean function is defined as follows:

$$f(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9) = \\ = \left[x_5 \wedge \left(\bigwedge_{j=1}^{T} \left(\bigvee_{\substack{k=i_{j_1} \\ k \neq 5}}^{i_{j_t}} x_k\right)\right)\right] \vee \left[\bar{x}_5 \wedge \left(\bigvee_{j=1}^{T} \left(\bigwedge_{\substack{k=i_{j_1} \\ k \neq 5}}^{i_{j_t}} x_k\right)\right)\right] \quad (5)$$

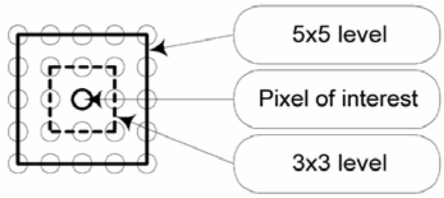


Fig. 1. Construction of a 5x5 window

where t is the threshold: $5 \le t \le 8$, $T = C_8^t$ is the number of all possible elementary conjunctions of t variables out of 8. The function (4) can be generalized for the 5x5 window, like it was done for the function (4) in [6]. In this case we obtain a function of 25 variables. It was proposed in [6] to consider 3x3 and 5x5 levels around the central pixel separately (see Fig. 1), because an additional analysis of a 5x5 window allows for more careful noise detection.

Therefore function (5) is transformed into the following function:

$$f_{5x5}(x_1,...,x_{25}) = f \wedge$$
$$\wedge \left[x_5 \wedge \left(\bigwedge_{j=1}^{P} (\bigvee_{\substack{k=i_{j1} \\ k\neq 5}}^{i_{js}} x_k) \right) \right] \vee \left[\bar{x}_5 \wedge \left(\bigvee_{j=1}^{P} (\bigwedge_{\substack{k=i_{j1} \\ k\neq 5}}^{i_{js}} x_k) \right) \right] \quad (6)$$

where f is the function (5) applied to the 3x3 level, x_5 is the central pixel of the window, s is the threshold value for the 5x5 level ($p \le 16$) and $P = C_{16}^p$ is the number of all possible elementary conjunctions of s variables out of 16 (the 5x5 level contains 16 pixels).

To remove impulsive noise from grayscale images, we propose to use the threshold Boolean filter based on either the function (5) or (6). To start with let us consider binary signals $x^{(k)}(i,j)$, obtained by the following threshold decomposition of M+1-valued signal [1]:

$$x^{(k)}(i,j) = \begin{cases} 1 & \text{, if } x(i,j) \ge k \\ 0 & \text{, otherwise} \end{cases} \quad (7)$$

where $k = 1,2,...,M$; M is the maximal possible signal value (for n-bit image $M = 2^n - 1$), and (i,j) are the pixel's coordinates. According to the threshold decomposition (7) we obtain M binary slices of an image. To continue with the threshold Boolean filtering, we need to process the obtained binary slices by the Boolean function (5) or (6) depending on the chosen window size (3x3 or 5x5, respectively). Then these binary images, obtained as the processing result are integrated back into a grayscale image.

Therefore we obtain the following formula for the threshold Boolean filter:

$$y(i,j) = \sum_{k=1}^{M} F(X^{(k)}) \quad (8)$$

where (i,j) are the coordinates of the processed pixel, F is the Boolean function (5) or (6), $X^{(k)}$ is the binary vector containing the elements of the local 3x3 or 5x5 window around the (i,j)th pixel (depending on the function used for processing, (5) or (6)). The filter (8) with carefully chosen parameters provides more precise noise removal than the classical stack filter. In particular, the filter defined by the (8) and (5) with t=5 coincides with a classical stack filter. The choice of threshold parameters t and s in (5) and (6) is based on the corruption rate. Thus t and s may be made approximately equal to the number of corrupted pixels in the filter window. On the other hand t and s can be fixed (t=7 or 8, s=13 or 14) and then the filter (8) can be applied iteratively. This can increase the precision of noise reduction. To preserve image edges, it is also a good idea to use the filter (8) together with the noise detector (3).

4. SIMULATION RESULTS

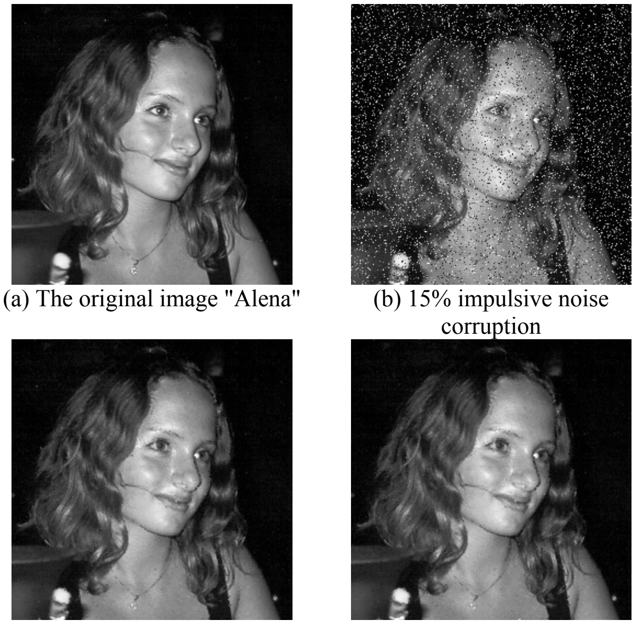
To check the efficiency of the proposed solutions, the test image (Fig. 2a) was artificially corrupted by impulsive noise with the corruption rates of 1%, 5% and 15% respectively. The images obtained were processed using the solutions presented above and using several classical filters. The results are summarized in the Table I. Some of the images are presented in Fig. 2. It is easy to see that both solutions, proposed in this paper, give much better results in comparison with the classical filters. The detector (3) combined with different filters significantly decreases amount of the pixels whose values in the resulting image differ from the corresponding original values. As a result, PSNR for the corresponding resulting images is much higher. The threshold Boolean filters (8)-(5) and (8)-(6) allow for better preservation of image edges. They give especially good results in combination with the detector (3).

5. CONCLUSIONS

The new impulse detector and the threshold Boolean filter based on the original Boolean functions have been developed in the paper. Both solutions show good results for impulsive noise detection and elimination with minimal image smoothing. Both the solutions are also effective in their computing implementation.

Table I
The results of comparison the technique proposed here to the existing solutions. The best results are given in bold.

Image	PSNR	Amount of the pixels different from the original
Original "Alena"	-	0
"Alena" with 1% impulsive noise	26.49	1%
• filtered by (8)-(5), t=7	36.98	7%
• **filtered by (8)-(5), t=7 and (8)-(5), t=8**	**39.80**	**3%**
• filtered by rank-order (ER) [3] 3x3, r=4	34.27	70%
• filtered by simple median 3x3	31.60	76%
• filtered by simple median 3x3 with detector (3) (s=1, Θ=5), 2 iterations	36.04	5%
• filtered by classical stack filter 3x3	31.55	76%
"Alena" with 5% impulsive noise	19.99	5%
• filtered by (8)-(5), t=7	33.78	31%
• **filtered by (8)-(5), t=6 with detector (3) (s=2, Θ=10), 2 iterations**	**35.90**	**5%**
• filtered by rank-order (ER) [3] 3x3, r=4	31.98	76%
• filtered by simple median 3x3	31.32	76%
• filtered by simple median 3x3 with detector (3) (s=2, Θ=10), 2 iterations	35.22	7%
• filtered by classical stack filter 3x3	31.27	76%
"Alena" with 15% impulsive noise	15.38	15%
• filtered by (8)-(6) t=6, h=8 and (8)-(6) t=6, h=8 with detector (3) (s=5, Θ =15), 5 iterations	31.80	20%
• **filtered by (8)-(5), t=5, (8)-(5), t=6 and (8)-(5), t=7, with detector (3) (s=3, Θ=15), 2 iterations**	**32.89**	**14%**
• filtered by rank-order (ER) [3] 3x3, r=4, 2 iterations	30.18	76%
• filtered by simple median 3x3, 2 iterations	30.17	78%
• **filtered by simple median 3x3 with detector (3) (s=3, Θ=15), 4 iterations**	32.87	**14%**
• filtered by classical stack filter 3x3, 2 iterations	30.14	78%



(a) The original image "Alena"

(b) 15% impulsive noise corruption

(c) Filtering by (8)-(5), t=5, (8)-(5), t=6 and (8)-(5), t=7, with detector (3) (s=3, Θ=15), 2 iterations

(d) Filtering by the median filter with 3x3 window and detector (3) (s=3, Θ=15), 4 iterations

Fig. 2. The testing results

REFERENCES

[1] J.Astola and P.Kuosmanen *Fundamentals of Nonlinear Digital Filtering.* CRC Press, NewYork, 1997.

[2] I. Pitas and A.N.Venetsanopoulos *Nonlinear Digital Filters: Principles and Applications*, Kluwer Academic Publishers, Boston, 1990.

[3] L. P. Yaroslavsky and M.Eden, *Fundamentals of Digital Optics: Digital Signal Processing in Optics and Holography*, Springer Verlag, 1996.

[4] H.-L. Eng and K.-K. Ma, "Noise adaptive soft-switching median filter" *IEEE Transactions on Image Processing*, Vol. 10, pp. 242-251, 2001.

[5] K.Kondo, M.Haseyama and H.Kitajima "An Accurate Noise Detector for Image Restoration", *Proc. of 2002 IEEE International Conference on Image Processing*, Vol. 1, pp. 321-324, 2002.

[6] I. Aizenberg, T.Bregin and D.Paliy "New Method for the Impulsive Noise Filtering Using its Preliminary Detection", *SPIE Proceedings on Image Processing: Algorithms and Systems,* Vol. 4667, pp. 204-214, 2002.

[7] K.D.Lee and Y.H.Lee "Threshold Boolean Filters", *IEEE Transactions on Image Processing*, Vol. 42, No 8, pp.2022-2036, 1994.

[8] I. Aizenberg "Processing of Noisy and Small-Detailed Gray-Scale Images Using Cellular Neural Networks", *Journal of Electronic Imaging*, Vol. 6, No 3, pp. 272-285, 1997.