Removal Of Random-Valued Impulse Noise using Adaptive Centre Weighted Median Filters And Detail Preservation Method

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ABSTRACT
This paper proposes a two-stage iterative method for removing random-valued impulse noise. In the first phase, we use the adaptive center-weighted median filter to identify pixels which are likely to be corrupted by noise (noise candidates). In the second phase, these noise candidates are restored using a detail-preserving regularization method which allows edges and noise-free pixels to be preserved. In the this paper these two phases are applied alternatively. Simulation results indicate that the proposed method is significantly better than those using just nonlinear filters or detail preservation method only.

General Terms
Image processing, Image denoising,Noise removal algorithms with different techniques

Keywords
impulse noise, high density noise, median filter, non linear filter, Adaptive centre weighted median

1. INTRODUCTION
Digital images could be contaminated by impulse noise during acquisition and transmission. The intensity of impulse noise has the tendency of either relatively high or low. Corruption of images by impulsive noise is a frequently encountered problem in acquisition, transmission, and processing of images, therefore one of the most common signal processing tasks involves the removal of impulsive noise from signals. Preservation of image details while eliminating impulsive noise is usually not possible during the restoration process of corrupted images. However, both of them are essential in the subsequent processing stages Due to this it could severely degrade the image quality and cause some loss of image information. Keeping the image details and removing the noise from digital image is a challenging part of image processing. Various filters have been proposed for denoising in the past and it is well known that linear filters could produce serious image blurring. As a result, non-linear filters have been widely exploited due to their much improved filtering performance, in terms of noise removal and edge/details preservation. However, one of the simplest and fast filtering algorithm [1] is median filter, very much suitable for impulse noise filtering. The main drawback of the median is that it also modifies pixels which are not contaminated by noise, thus removing fine details in the image [2]. Finding a method that is efficient in both noise reduction and detail preservation is an active area of research. To trade
off detail preservation against noise reduction, somemsolutions have been proposed in the literature. Examples of decision- based filters are the centerweighted median filter [5], the adaptive center-weighted median filter (ACWMF) [9], the adaptive median filter [14] and the median filter based on homogeneity information [9]. These filters are good in locating the noise, even in a high noise ratio. However, the main drawback is that the replacement of the noisypixels by the median filter entails blurring of details and edges, especially when the noise ratio is high. Recently, a detail-preserving variation method (DPVM) has been proposed to restore impulse noise [7]. It uses a non smooth data-fitting term (e.g.,) along with edgepreserving First, noisy pixels are detected using ACWMF; then these pixels are selectively restored by DPVM. Since in each iteration the edges and the details are preserved for the noise candidates by the regularization method, and no changes are made to the signal candidates, the performance of this combined method is much better than just using either ACWMF or DPVM, especially when the noise ratio is high. Our
method can restore large patches of noisy pixels because it introduces pertinent prior information via the regularization term. It is most efficient to deal with high noise ratio, e.g., ratio as high as 50%. Different remedies of the median filter have been proposed, e.g. the adaptive median filter [7], the multi-state median filter [11], or the median filter based on homogeneity information [12], [1]. These so-called "*decision-based*" or "*switching*" filters first identify possible noisy pixels and then replace them by using the median filter or its variants, while leaving all other pixels unchanged. These filters are good at *detecting* noise even at a high noise level. Their main drawback is that the noisy pixels are replaced by some median value in their vicinity without taking into account local features such as the possible For images corrupted by Gaussian noise, least-squares methods based on edge-preserving regularization functionals [4], [9], [10], [22] have been used successfully to preserve the edges and the details in the images. These methods fail in the presence of impulse noise because the noise is heavy tailed. Moreover the restoration will alter basically all pixels in the image, including those that are not corrupted by the impulse noise. Recently, non-smooth data-fidelity terms (e.g. `1) have been used along with edge preserving regularization to deal with impulse noise [19]. In this paper, we propose a powerful two-stage scheme which combines the variational method proposed in [19] with the adaptive median filter [17]. More precisely, the noise candidates are first identified by the adaptive median filte and then these noise candidates are selectively restored using an objective function with data-fidelity term and an edge-preserving regularization term. Since the edges are preserved for the noise candidates, and no changes are made to the other pixels, the performance of our combined approach is much better than that of either one of

the methods. Salt-and-pepper noise with noise ratio as high as 90% can be cleaned quite efficiently. The outline of the paper is as follows. In Section II, we review ACWMF. Our denoising scheme is given in Section III. In Section IV, we demonstrate the effectiveness of our method using various images.

2.REVIEW OF ACWMF

ACWMF is a good method for removing random-valued impulse noise when the noise ratio is not high—see [9] or Figs. 1(b) and 2(b) in Section IV. Here, we give a brief review of the filter. Let the window size be h and $L = 2h(h+1)$. Denote $x_{ij}$by the gray level of the noisy image at pixel location Let Y_{ij}^{2k}=median $X_{i-u,j-v,}(2k) <> X_{ij}| -h \leq u,v \leq h\}$ where 2k is the weight given to pixel , and<> represents the repetition operation. Clearly, is the output of the standard median filter whereas is the output of the identity filter $K > L$ We define the differences by $d_k = Y_{ij}^{2k} - X_{ij}$ Where k = 0,1,…,L-1. It is readily seen that $d_k \leq d_{k-1}$ for k≥1 To determine whether the current pixel (i,,j) is corrupted a set of threshold T_k is employed .where $Tk -_1 > T_k$ for K=1.2,…..,L-1. If any one of the

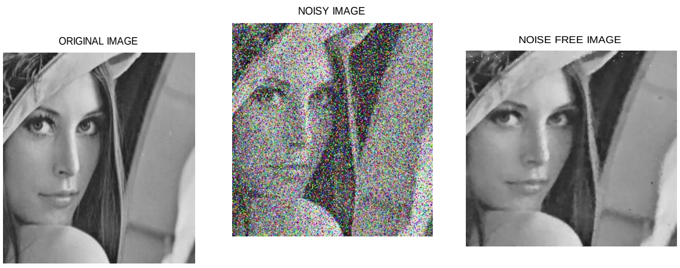


Fig. 1. (a) Image with 30% noise. Restored images by (b) ACWMF with s = 0:6, , and (c) our method with _ β = 2; s = 0:6 and four iterations

inequalities $d_k > T_k$ is true, then $X_{ij}$is regarded as a noise candidate and replaced by the median i.e Y_{ij}^{0} ., Otherwise, X_{ij} is regarded as a signal candidate and will not be changed. If 3 ×3 windows are used (i.e. h=1 and L=4,), four threholds are used. The median of the absolute deviations from the median (MAD), which is defined as **MAD= median{$X_{i-u,j-v} - Y_{ij}^{0}$ |:-h$\leq u,v \leq h\}$….** (1) is a robust estimate of dispersion [12], [2] and its scaled form are used as the thresholds. Specifically, one sets

$$T_k = s.MAD + \partial_k \,, 0 \leq k \leq 3 ...... (2)$$

$$[\partial_0, \partial_1, \partial_2, \partial_3] = [40,25,10,5] .... (3)$$

and $0.6 \leq s \leq 2$(see [9]). This choice yields satisfactory result in filtering random-valued impulse noise when the noise ratio is not high [see Fig. 1(b)]. However, for a high-level noise ratio,the filter cannot preserve the fine features in the images [seFig. 2(b)].

III OUR METHOD

When the noise ratio is high, ACWMF may falsely detect some noise-free pixels as noisy pixels. If these erroneous noise candidates form patches, and are located near to edges, DPVM will distort them. To alleviate the problem, we apply our method iteratively with different thresholds.

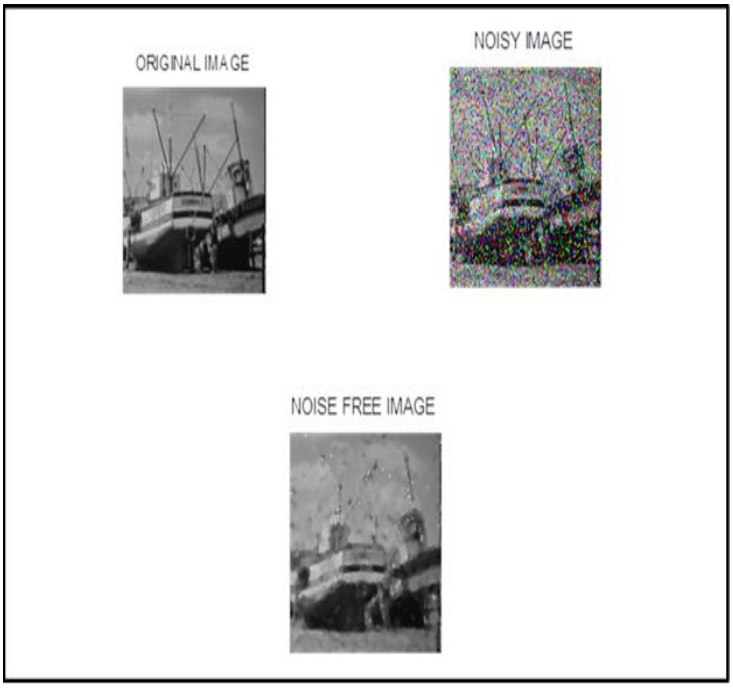


Fig. 2. (a) Image with 30% noise. Restored images by (b) ACWMF with s = 0:6, , and (c) our method with _ β = 2; s = 0:6 and four iterations.

More precisely, at the early iterations, we take large thresholds in ACWMF so that it will only select pixels that are most likely to be noisy. Then we restore them by DPVM. by the regularization successfully in each iteration, the restored image will not be distorted by the method. In the following we give our algorithm.

3. ALGORITHM

Let , not including (i,j)

1)Set r=0. Initialize $X^{(r)}$ to be observed image

2)Apply ACWMF with the threshold $T_k^{(r)}$,$\leq k \leq 3$,to the image $X^{(r)}$ to get the noisy candidate V_{ij} be the set ofthe four closest neighbors (i,j) of set $M^{(r)}$

3) Let $N^{(r)} = U_{t=0}^{r}\ M^{t}$

4) For all (i,j)$\notin N^{(r)}$ take $Y_{ij}^{\wedge} = X_{ij}^{r}$

5)Restore all pixels in $N^{(r)}$ by minimizing the following function over $N^{(r)}$

$$f(Y) = \sum\{((|Y_{ij} - X_{ij}^{r}| + \frac{\beta}{2} \sum \varphi(Y_{ij} - Y_{mn}) + \sum \varphi(X_{mn}^{(r)} - Y_{ij})))\}$$ where φ is an edge preserving potential.

6)The minimizer Y is obtained by using algorithm given in paper [7].

7) Set $(X^{(r+1)}$ = Y

8)If r < r_{max} set r = r +1 and go back to step 2 probable choices for ψ in step 4 are

$$\boldsymbol{\varphi(t) = \sqrt{\alpha} + t^2\ \ \alpha > 0}$$

$$\boldsymbol{\varphi(t) = t^{\alpha}\ \ 1 < \propto > 0}$$

$$\boldsymbol{\varphi(t) = \{\propto t^2\ \ |2, if\ t| \leq 1|\varphi \qquad \propto > 0}$$

We use 3×3 window and follow the form

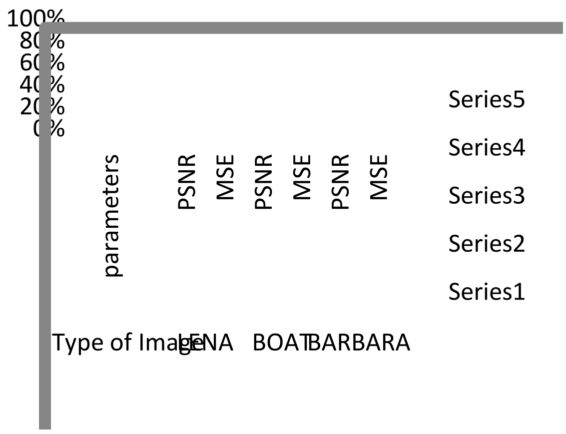
$$\boldsymbol{Tkr = s.MADr + \partial k + 20(rmax - r)}$$
$$\boldsymbol{\leq k \leq 3, \leq r \leq r_{max}\ and\ \leq s \leq 0.6}$$

IV Simulations

. The 256-by-256 picture of Lena is used as the true image. Then 30% and 50% of the pixels are corrupted by random noise uniformly distributed on its dynamic rangea)]. Henceforth, we use the potential function . In the simulations, for each noise level, the parameters in (2) and(β) in (4) are chosen to give the best restoration in terms of peak to-noise-ratio (PSNR)(From Figs. 1–2, we see that there are noticeable noise patches in the images restored by either ACWMF or DPVM, especially when the noise ratio is 50%. In contrast, our method has successfully suppressed the noise while preserving most of the details and the edges in both cases. To assess the effectiveness of our method in processing various images, we tried four other 256-by-256 gray scale images. The parameters and were chosen to be the same as in the previous simulations. The results in terms of PSNR and the mean absolute error (MAE) , are summarized in *Table I* From the tables, we see that our method are significantly better than the other two methods.1 Overall, our restored images are significantly better than those restored by the other two methods. We end by considering the complexity of our algorithm. Since ,the algorithm requires four applications of ACWMF and four applications of DPVM restricted to the set of the noisy pixels . Like other medium-type filters, ACWMF can be done very fast. The application of DPVM is the most time-consuming part as it requires the minimization of the functional in (4). The timing can be improved by better implementations of minimization routines for solving (4)

RESULTS						
Type of Image	**parameters**	**NOISE DENSITY**				
		10%	**20%**	**30%**	**50%**	**60%**
LENA	**PSNR**	**32.49**	**31.2**	**30.81**	**28.42**	**27.70**
	MSE	**1.203**	**1.48**	**1.681**	**2.240**	**2.637**
BOAT	**PSNR**	**24.57**	**24**	**23.58**	**22.27**	**21.75**
	MSE	**2.242**	**2.73**	**2.836**	**3.199**	**3.685**
BARBARA	**PSNR**	**27.1**	**26.1**	**25.78**	**24.58**	**23.69**
	MSE	**2.420**	**2.62**	**2.968**	**3.795**	**4.047**

Table No1



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[13]An Improved Adaptive Median Filtering

Method for Impulse Noise Detection

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