A Switching Median Filter for Extremely Corrupted Images With Great Disparity Between Low and High Intensity Impulse Noise

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Abstract: Though boundary discriminative noise detection (BDND) method is frequently considered as an efficient method for image denoise, however when corruption density of salt or pepper noise of image corrupted by impulse noise is larger than 50%, research shows that this method is no longer valid because its performance becomes seriously deteriorated. Thus a modified BDND method is proposed in this case. In this method the nearest intensity value to 128 is selected as the separating point in each subimage instead of the median being separating point in original BDND method, so as to avoid separating point selected in corrupted area. The new method can obviously improve PSNR value of reconstruction images as well as remain the advantages of the original BDND with almost no addition of complexity.

Key words: image processing, image denoising, median filter, impulse noise

CLC number: TN911 **Document code**: B **Article ID**: 1672-1292(2008)03-0056-05

一种亮暗比例悬殊的脉冲噪声重污染图像去噪方法

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[摘要] 虽然目前边界分离噪声检测(BDND)算法被普遍认为是一种较好的去除图像脉冲噪声方法,然而研究发现当"盐"或"胡椒"噪声污染比例之一超过 50%,其性能却急剧下降,几乎无法去噪.为此在 BDND算法基础上提出了改进的噪声检测方法(Modified BDND),对每个子图,新方法选取与"128"最接近的灰度值作为分界点,从而避免原方法因选取中值为分界点而可能落入污染区域的问题.该方法既可保留 BDND算法优点,而且还能明显提高此时图象的重建效果.通过对 Lena图象仿真处理说明了本算法的有效性和优越性.

[关键词] 图像处理, 图像去噪, 中值滤波, 脉冲噪声

1 Introduction

In the processing of acquisition or transmission, digital images are often contaminated by impulse noise. This random impulse noise may corrupt the image pixel resulting in the fact that the intensity value of corrupted pixel can be changed into two values, i.e. the higher intensity value (salt) or lower intensity value (pepper) compared with those pixel in the adjacent regions[1]. Impulse noise not only affects the digital image quality, also affects the post processing like segmentation, edge detection, recognition, etc. Especially at higher noise density interference, it can even generate loss of information details[2-4]. Thus, impulse noise removal is one of important

Received date: 2008-04-05.
Foundation item: Supported by Postdoctoral Fund of Jiangsu Province(2007-337).
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stage in image processing.

Up now there are a lot of methods for image denoise and usually they are classified into linear and nonlinear categories and the later one is more researched because of its better applicability for impulse noise. The earliest-proposed nonlinear filtering method is the famous standard median (SM) filtering method[2], which has been widely applied for its distinct advantage of excellent noise suppression ability and small computation work. After that the most research activity is on the study of various improved methods based on SM filtering theory, where the most improvement is to divide SM filtering into two stages. The first stage is to decide each pixel one by one whether it is corrupted from impulse noise, i.e. the so-called detection process, and the second stage is filtering of corrupted pixel. In this way, the intensities of un-corrupted pixel are reserved so as to keep image details better. For the key stage of detection, some idea were presented such like detection approach based on human visual system[5], image reconstruction algorithm for slightly-corrupted random-valued impulse noise based on Dempster-Shafer theory[4], and also boundary discriminative noise detection (BDND) given by Ng[6]. These methods have their own characteristics, and BDND has better reconstruction result for extremely corrupted images. Moreover this method does not need setting artificial parameters and thus is more available in application. However, even if for BDND algorithm, it may also face the extreme deterioration problem in detection and reconstruction when the corruption density of salt or pepper noise is larger than 50%, which implies there is big difference between the densities of high-intensity and low-intensity impulse noise. Therefore in this paper, a modified boundary discriminative noise detection (Modified BDND) method is presented for this great disparity between low and high intensity impulse noise. Modified BDND can remain the advantage of BDND as well as improve the image reconstruction performance distinctly, as described in follows.

2 Image Reconstruction for Disparity Between Low and High Intensity Impulse Noise

For general purpose, monochrome image is selected as example in followings to demonstrate the image reconstruction when the density of salt or pepper corrupted noise is larger than 50%. It is also assumed that the gray level of high-intensity corrupted pixel is 255 for monochrome pixel and that of low-intensity corrupted pixel is zero. Also BDND algorithm is adopted for noise filtering.

Usually BDND algorithm is organized by two stages, one is detection and the other is filtering. Detection process is referred to judging the pixel of image one by one whether it is corrupted by impulse noise. At the stage of detection, firstly a 21×21 local window is selected surrounding the center of the considered pixel and those pixel in this subimage are sorted in a sequence in the ascending order of their intensity values and the median med is selected as separating point. One boundary b_1 is determined by all low-intensity pixel in the sequence before "*med*" and the separating point "*med*", and this boundary is corresponding to the maximum difference of low-intensity sequence. Similarly, another boundary b_2 is determined by all high-intensity pixel after "*med*" and the separating point "*med*", this boundary is corresponding to the maximum difference of high-intensity sequence. Finally, it is now to detect the intensity of considered pixel to see whether it is located between boundary b_1 and boundary b_2. If it is true, then this pixel is not corrupted. Otherwise it is corrupted. In order to decrease false alarm, it is necessary to do above detection once more for the being-judged corrupting pixel where the size of local window is reduced to be 3×3, and then this second-detection result is considered as final result. The validation of this discrimination has been done through an example of a 5×5 windowed sub-image in reference[6] where the density of high intensity impulse noise is 32% and density of low intensity impulse noise is 28% which are both less than 50%. However, it will show another case of non-effective of BDND method from following example when density of high or low intensity impulse noise is larger than 50%.

Example 1: Assuming $W_{5 \times 5}$ is a 5×5 windowed sub-image with the center pixel "255" (bold),

$$W_{5\times5}=\begin{pmatrix} 255 & 255 & 47 & 255 & 39 \\ 50 & 255 & 255 & 90 & 0 \\ 255 & 0 & 255 & 224 & 255 \\ & & & & \\ 62 & 255 & 0 & 255 & 0 \\ 255 & 72 & 255 & 255 & 179 \end{pmatrix} \quad (1)$$

the processing of BDND and its result are given below.

First, pixel intensities are sorted in the ascending order and represented as a vector v_0, where the median med is $\underline{255}$, i. e., v_0 = [0 0 0 0 39 47 50 62 72 90 179 224 $\underline{255}$ 255 255 255 255 255 255 255 255 255 255 255 255]. Assumed that the vector of intensity differences is computed: v_D = [0 0 0 39 8 3 12 10 18 **89** 45 $\underline{31}$ **0** 0 0 0 0 0 0 0 0 0 0 0]. Then for the pixels with intensities between 0 and med in the v_0, the corresponding maximum difference in the v_D is 89, which is the difference between the pixel intensities 90 and 179. For the pixels with intensities between med and 255 in the v_0, the maximum difference in the v_D is 0, which is the difference between the pixel intensities 255 and 255. Hence, the boundary b_1 is 90 and the boundary b_2 is 255. Thus, the lower intensity cluster is {0 0 0 0 39 47 50 62 72 90}, the medium-intensity cluster is {179 224 255}. At the end of discrimination process, center pixel "255" is classified as an "uncorrupted" pixel, since it belongs to the middle cluster.

In this example, the density of high intensity impulse noise is 52% or larger than 50% results in the fact that the separating point of median "med = 255" is not located in the uncorrupted image while in the corrupted image of high intensity impulse noise, thus let two boundaries of b_1、b_2 hard to be determined correctly, and as a result the pixel of intensity equal to 255 of high intensity impulse noise missed the detection. This drop of detection probability can seriously affect image reconstruction, and that is substantial reason why PSNR value suddenly drops greatly in the simulation results of Table III and Table IV in Ref [6] where density of high or low intensity impulse noise is larger than 50% and BDND method become no effective.

It can be found that when corruption density of high or low intensity pixel is larger than 50% and there is great disparity between high and low intensity impulse noise, the median med in the ascending order sequence of pixel intensity will certainly enter into corrupted pixel cluster, as a result, the separating point med can not satisfy with the requirement of 'locating in un-corrupted pixel cluster'. The high and low intensity clusters separated by this separating point med hardly involve together corrupted pixel as well as un-corrupted pixel. That means, one cluster involves only one type of corrupted pixel, however, the other cluster involves both un-corrupted pixel and also high and low intensity corruption pixel.

Therefore, in such high or low intensity pixel cluster it is impossible to select the appropriate boundaries b_1 or b_2 which is used to show the difference between corrupted and un-corrupted pixel intensities, thus it makes the miss detection probability of BDND algorithm bigger and its performance become worse suddenly.

3 An Detecting Algorithm for Disparity Between Low and High Intensity Impulse Noise: Modified BDND Algorithm

Corresponding to the image reconstruction of disparity problem between high and low intensity corruption as said above, a modification BDND algorithm is proposed in this paper. Considering intensity value of image pixel, the un-corrupted pixel is usually located between high and low intensity impulse noise. The high intensity impulse noise is close to 255 and low one close to 0. Thus about intensity, the pixel intensity of most far away from the high and low impulse noise should be equal to 128 and then those pixel of which the intensity value is most close to 128 should belong to un-corrupted pixel. Consequently, the separating point med in the modified BDND algorithm should be selected as the intensity value that is most close to 128 in the subimage pixel. This adaptive selection process guarantees that the determined separating point med always located in the un-corrupted pixel intensity range of image and ensures to achieve the appropriate boundaries b_1, b_2 used in modified BDND algorithm. The implementation of modified BDND and its application in processing Example # 1 are given in below.

Procedure of modified BDND algorithm implementation

Step 1 Impose a 21 × 21 window, which is centered around the current pixel.

Step 2 Sort the pixels in the window according to the ascending order and find the intensity which is the nearest value to 128, *med*, of the sorted vector $\boldsymbol{v}_0$, i.e.

$$med = \min_{v_0(i)} | v_0(i) - 128 |. \quad (2)$$

Step 3 The following process is similar to Step 3-Step 8 of BDND algorithm as described in Reference[8].

Processing Example 1 by modified BDND ALgorithm

• Pixel intensities of sub-image w are sorted in the ascending order and represented as a vector $\boldsymbol{v}_0$ = [0 0 0 0 39 47 50 62 72 <u>90</u> 179 224 255 255 255 255 255 255 255 255 255 255 255 255 255], where the separating point of most closed to the intensity value of 128 is selected as $med = 90$.

• The vector of intensity differences is computed: $\boldsymbol{v}_D$ = [0 0 0 39 8 3 12 10 <u>18</u> 89 45 31 0 0 0 0 0 0 0 0 0 0 0 0].

• For the pixels with intensities between 0 and med in the $\boldsymbol{v}_0$, the corresponding maximum difference in the $\boldsymbol{v}_D$ is 39, which is the difference between the pixel intensities 0 and 39.

• For the pixels with intensities between med and 255 in the $\boldsymbol{v}_0$, the maximum difference in the $\boldsymbol{v}_D$ is 89, which is the difference between the pixel intensities 90 and 179.

• Hence, the boundary b_1 is 0 and the boundary b_2 is 90. Thus, the lower intensity cluster is {0 0 0 0}, the medium-intensity cluster is {39 47 50 62 72 90} and the higher intensity cluster is {179 224 255}.

• Since the center pixel "255" belongs to the higher intensity cluster, hence, the second iteration needs to be invoked and a 3 × 3 window is imposed and centered around it.

$$\boldsymbol{W}_{3\times 3} = \begin{pmatrix} 255 & 255 & 90 \\ 0 & 255 & 224 \\ 255 & 0 & 255 \end{pmatrix} \quad (3)$$

• Now, the pixel intensities are sorted and presented in the vector form: $\boldsymbol{v}_0$ = [0 0 <u>90</u> 224 255 255 255 255 255], where the separating point of most closed to the intensity value of 128 is selected as $med = 90$.

• As before, the vector of intensity differences is computed: $\boldsymbol{v}\boldsymbol{v}_D$ = [0 **90** **134** 31 0 0 0 0].

• The first maximum difference is 90, which is the difference between the pixel intensities 0 and 90. The second maximum difference is 134, which is the difference between the pixel intensities 90 and 224.

• Hence, the boundary b_1 is 0 and the boundary b_2 is 90. Thus, the lower intensity cluster is {0}, the medium-intensity cluster is {90} and the higher intensity cluster is {224 255}.

• At the end of the discrimination process, center pixel "255" is classified as a "corrupted" pixel, since it belongs to the higher cluster.

The above example shows that compared with BDND algorithm, the separating point med appeared in modified BDND algorithm can just be selected as the pixel intensity of most closed to 128 in subimage. The adaptive selection process of determining separating point med can ensure this intensity point far away from high and low intensity of corrupted pixel, and is made to be always in the intensity range of un- corrupted pixel so as to obtain the appropriate boundaries b_1, b_2 for modified BDND algorithm. Thus, the determination process and its result are more reasonable.

4 Simulation and Discussion

In order to do further verification of reconstruction result for modified BDND algorithm, the comparison between BDND result and Modified BDND result is given based on the extremely corrupted image of great disparity between high and low intensity impulse noise as shown in Fig 1 to Fig 3. Fig 1 is a Lena image with 60% corruption density of high intensity, 10% of low intensity and 70% of total corruption density. Fig 2 and Fig 3 represent the denoise results respectively of BDND algorithm and Modified BDND algorithm, which can be seen that not only the intuitive visual result of Fig 3 is better than that of Fig 2, also according to the objective estimation parameter

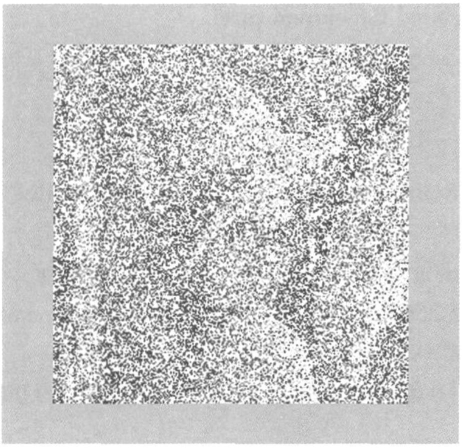

Fig.1 Lena image with 60% of high-intensity, 10% of low-intensity and 70% of total corruption density

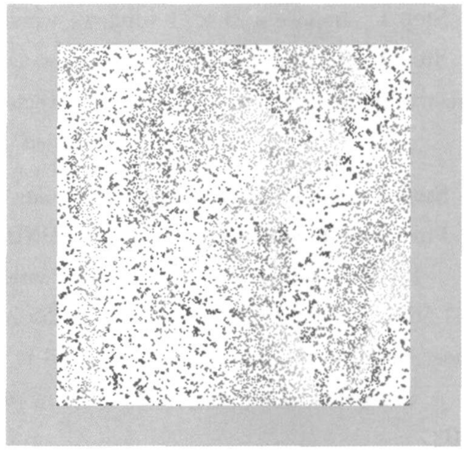

Fig.2 Processing result of Lena image of Fig.1 by BDND algorithm, PSNR = 6.37

PSNR given by Ref[6] modified BDND algorithm can further achieve 13 dB improvement of PSNR.

Generally, the merit of modified BDND algorithm is that it can adaptively find out the separating point for distinguishing high and low intensity pixel according to the intensity characteristic of extremely corrupted image. Also the high and low intensity clusters both involve corrupted pixel as well as un-corrupted pixel so as to solve the problem that when great disparity between high and low intensity of image appears, the simple separating-point selection of median intensity often fails to choose correct boundaries. Therefore, the new algorithm reduces the miss detection probability and improves denoise result for such type of corrupted image.

Fig.3 Processing result of Lena image of Fig.1 by Modified BDND algorithm, PSNR = 19.55

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