Novel Peer Group Filtering Method Based On The CIELab Color Space For Impulse Noise Reduction

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Abstract

This paper presents a novel peer group filtering method, called the NPGF method, for impulse noise reduction. The main contributions of the proposed method are two-fold. First, we propose that the impulse noise detection is performed in the CIELab, instead of the RGB, color space to enhance noise detectability. Secondly, the proposed method employs two different-sized windows in determining the status for each pixel, alleviating the problems in correcting non-corrupted pixels in the neighborhood of edges in the textured regions. Based on three typical color images, experimental results demonstrate that the proposed NPGF method achieves better performance in noise detection when compared to the existing method.

Keywords: *Color image denoising, Impulse noise reduction, Peer group filter, CIELab color space.*

1. INTRODUCTION

The impulse noise reduction problems have been widely investigated because of their fundamental importance for image processing. During image acquisition or transmission, impulse noises are often introduced. Many impulse noise reduction methods have been developed [1]–[18]. These methods perform filtering operations on an image where the intensities of noisy or corrupted pixels are modified while preserving the intensities of non-corrupted or noise-free pixels to improve the image quality. The previous developed impulse noise reduction methods could be broadly classified into four categories — vector median based filtering method [1]–[3], fuzzy-logic based filtering method [4]–[7], switching filtering based methods [8]–[11], and peer group based methods [14]–[18].

In the category of vector median filtering methods, Astola *et al.* [1] proposed a VMF method, which is the earliest vector median based filtering method. The VMF method, an extension of the scalar median filter, is a vector processing technique and can be derived as a maximum likelihood estimation approach when the probability density is the double exponential. In the category of fuzzy-logic based filtering methods, fuzzy logic approach is used to deal with nonlinear image noise and process the inherent uncertainty in image structures. Camarena *et al.* [7] proposed a two-step fuzzy procedure which first performs a quick diagnosis based on the rank-ordered difference statistics [19], to determine the status of pixels in simpler cases. and then a strict diagnosis is used to deal with the pixels which are more difficult to classify. Then, the corrupted pixels are modified using the VMF method and the rest of the pixels is unchanged. In the family of switching filters, the methods are based on a detection-correction strategy where the filters are only applied to the corrupted pixels, indicating that the switching based filtering method can preserve more image edges. Jin and Li [8] proposed a switching filtering method by using quaternion rotation theory [12]. The methods in [10]–[11] use the difference between the central pixel and neighboring pixels in four directions to determine the status of central pixel. Neuvo and Ku [13] proposed the first peer group based filtering method. The central idea behind the peer group filtering method is that the pixel with significantly different intensity from those of neighboring pixels is more likely to be a noise. This method counts the number of neighboring pixels with similar intensities to deduce if the pixel is a noise. Thresholds on the similarity and the number of similar pixels are used and the pixel with small number of similar pixels is deduced to be a noise. Camarena *et al.* [17] proposed a fast peer group based filtering method in which a pixel is identified as non-corrupted when the size of peer group is larger than a threshold in the fuzzy metrics context. Morillas *et al.* [16] used a reduced ordering of color vectors to detect and replace the corrupted pixels for simultaneous reduction of impulse noises and preservation of the textured edges. Camarena *et al.* [18] further proposed a two-stage peer group filtering method, called the IFPGF method, to detect the corruption status of a pixel. In the first stage, a pixel is classified as either non-corrupted or undetermined. Only the undetermined pixels enter the second stage for further investigation. This two-stage method suffers from the problem of false alarm near the edges in textured regions of an image.

This paper presents a novel peer group filtering method, called the NPGF method. The ideas behind the proposed method are two-fold. First, we show that to achieve good pixel corruption detection, working in CIELab color space [20] achieves better corruption detection than other color spaces. Secondly and more importantly, we propose a novel two-window approach for detecting corrupted pixels which suppresses the false alarms near the edges in textured regions of images. Based on three typical colored images, experimental results show that the proposed NPGF method achieves better performance in noise detection when compared to the IFPGF method.

The rest of the paper is organized as follows. Section 2 presents in detail the IFPGF by Camarena *et al.* [18] and the proposed NPGF method. In Section 3, the experimental results are demonstrated to show the superiority of the proposed NPGF method. The final section concludes the paper.

2. THE PROPOSED PEER GROUP FILTERING METHOD BASED ON THE CIELAB COLOR SPACE

In this section, we first illustrate the basis of peer group filtering methods for impulse noise reduction, using the image shown in Fig. 1 as an example.

To simplify the discussion, gray values, instead of the values in the CIELab color space, are used in Fig. 1. To determine if a pixel is corrupted, a window of certain size (e.g., 5×5) is constructed with the pixel located in the center. The peer group corresponding to the central pixel of a window is defined as the set of pixels which have similar gray values (e.g., difference in gray values less than or equal to some similarity-threshold) with the central pixel. If the size of the peer group is large (e.g., larger than or equal to some size-threshold) then we tend to classify the corresponding pixel as a non-corrupted pixel. Using similarity-threshold 5 and size-threshold 10, the central pixel in Fig. 1 is classified as a corrupted pixel since the size of the peer group is 3. Camarena *et al.* [18] proposed an improved fast peer group filtering method, called IFPGF, to increase the filtering speed. The IFPGF first divide the image into non-overlapping 5×5 windows. The central pixel of each window can either be classified as a non-corrupted if the peer group is large or an undetermined pixel. Once the central pixel is classified as a non-corrupted pixel, all the pixels in the corresponding peer group are classified as non-corrupted. Then, for each undetermined pixel, a 5×5 window is constructed to determine its status.

General peer group filtering methods suffer the problem of falsely deducing a pixel in a textured region as a corrupted pixel since the size of the corresponding peer group tends to be small. To alleviate this problem, we propose a novel two-stage peer group filtering method, called NPGF, which employs two different-sized windows to determine the peer group. In the first stage, a 5×5 window is constructed and the similar pixels with the central pixel are included in the peer group. In the second stage, for each of the eight pixels around the central pixel which are similar to the central pixel, a 3×3 window is constructed. For each 3×3 window, the pixels similar to the central pixel, excluding the identified similar pixels in the first stage, are included in the peer group corresponding to the central pixel in the first stage. Finally, the pixel with large peer group is deduced as a non-corrupted pixel; otherwise, a corrupted pixel. The central idea behind the proposed two-stage peer group filtering method is to use the central pixel of the 3×3 window as the bridge for capturing the gradual changes on the gray values of edges in the textured regions.

3	3	3	3	4
3	3	3	4	4
3	3	96	4	4
3	4	4	4	93
4	4	4	93	93

Figure 1: Example for illustrating peer group filtering.

The proposed impulse noise detection is performed in the CIELab, instead of the RGB, color space to enhance the noise detectability since the color distance between neighboring pixels is larger in the CIELab color space. To transform an RGB-based input image into the CIELab color space, Hunt [20] first transforms the image from the RGB color space into the CIEXYZ color space by

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3575 & 0.1804 \\ 0.2126 & 0.7151 & 0.0721 \\ 0.0193 & 0.1191 & 0.9502 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}. \quad (1)$$

Then the CIEXYZ-based image is converted into the CIELab-based image by

$$\begin{aligned} L &= 116 \times f(Y/Y_n) - 16 \\ a &= 500 \times [f(X/X_n) - f(Y/Y_n)] \\ b &= 200 \times [f(Y/Y_n) - f(Z/Z_n)], \end{aligned}$$

with

$$f(t) = \begin{cases} t^{\frac{1}{3}}, & \text{if } t > (\frac{6}{29})^3, \\ \frac{1}{3}(\frac{29}{6})^2 t + \frac{4}{29}, & \text{elsewhere,} \end{cases}$$

where $(X_n, Y_n, Z_n) = (95.047, 100.00, 108.883)$ is the position of the white point in the CIEXYZ color space. The color distance in CIELab color space between pixels p and q is defined as

$$d(p,q) = \sqrt{(L_p - L_q)^2 + (a_p - a_q)^2 + (b_p - b_q)^2},$$

where (L_p, a_p, b_p) and (L_q, a_q, b_q) are coordinates of pixels p and q, respectively, in the CIELab color space.

Denote by $|PG(p)|$ the size of the peer group corresponding to pixel p. Let $W_i(p)$ denote the window of size $i \times i, i = 3, 5$, with central pixel p. The pseudo-code for determining if pixel p is corrupted and the following noise-reduction operation using the proposed NPGF can be described as follows.

1. Determine $PG(p)$:

   1.1 For $p_i \in W_5(p)$ and $p_i \neq p$, if $d(p_i, p) \leq t_s$ then $p_i \in PG(p)$.

   1.2 For $p_j \in PG(p)$ and $p_j \neq p$, construct $W_3(p_j)$. For $p_k \in W_3(p_j)$, $p_k \notin PG(p)$, and $p_k \neq p_j$, if $d(p_k, p_j) \leq t_s$ then $p_k \in PG(p)$.

2. If $|PG(p)| \geq t_z$ then deduce pixel p as non-corrupted.

3. For each deduced corrupted pixel, replace its CIELab coordinates by applying the arithmetic mean filtering operation on a 3×3 window centered at the corrupted pixel.

Since the proposed NPGF method alleviates the problem of misidentifying non-corrupted pixels as corrupted in the textured regions, it can preserve, as supposed to, the edges in the textured regions.

3. EXPERIMENTAL RESULTS

We compare the proposed NPGF method with the IFPGF method based on three typical test color images, Lena, Flower, and Statue, as shown in Figure 2. For fair comparison with the IFPGF method, the proposed NPGF method is only used to determine the status of the undetermined pixels generated by the first stage in the IFPGF method. The similarity threshold $t_s = 15$ was used for images Lena and Flower and $t_s = 20$ for image Statue in the proposed NPGF method. The corresponding similarity thresholds 30 and 40 were used in the IFPGF method. As for the threshold t_z on the peer group size, number 12 was used for both NPGF and IFPGF methods. All comparisons are performed and implemented with Borland C++ Builder 6.0 and run on a standard PC with AMD Athlon 64x2 4800+ CPU (2.5GHz) and 1.87GB of RAM.

We compare the accuracy in detecting the corrupted pixels based on five conventional accuracy measures: (a) recall, (b) specificity, (c) precision, (d) accuracy, and (e) F-measure. Recall is the proportion of correctly deduced corrupted pixels within the true corrupted pixels. Specificity is the proportion of correctly deduced non-corrupted pixels within the true non-corrupted pixels. Precision is the proportion of true corrupted pixels within the deduced corrupted pixels. Accuracy is the weighted average of recall and specificity with weights proportional to the numbers of true corrupted and non-corrupted pixels. The F-measure is the harmonic mean of recall and precision. The F-measure is high only when both recall and precision are high since the harmonic mean of two proportions tends to be low if one of the two proportions is low. Let TP and TN denote respectively the number of pixels that are correctly deduced as corrupted and non-corrupted pixels. And denote respectively by FP and FN the number of pixels that are erroneously deduced as corrupted and non-corrupted pixels. Then we have

$$\begin{aligned} \text{recall} &= \frac{TP}{TP+FN}, \\ \text{specificity} &= \frac{TN}{TN+FP}, \\ \text{precision} &= \frac{TP}{TP+FP}, \\ \text{accuracy} &= \frac{TP+TN}{TP+FP+TN+FN}, \\ \text{F-measure} &= \frac{2}{\frac{1}{\text{recall}}+\frac{1}{\text{precision}}}. \end{aligned}$$

Empirical results are listed in Tables 1 through 4, for different percentages of corruption, respectively. Based on the empirical results, the following general conclusions are obvious:

1. The proposed NPGF has higher detection accuracy than the IFPGF method on all the accuracy measures considered.
2. The proposed NPGF has better but not significantly higher specificity than the IFPGF method for all the cases considered.
3. The proposed NPGF has significantly higher recall and precision than the IFPGF method for all the cases considered, leading to a significantly higher F-measure.
4. The proposed NPGF has significantly higher recall but not significantly higher accuracy since the images only encompass a small proportion of corrupted pixels.

Table 1: Comparisons of detection accuracy with corruption percentage 5%.

NPGF (IFPGF)	recall	specificity	precision	accuracy	F-measure
Lena	94.05% (93.48%)	99.85% (99.14%)	96.29% (79.28%)	99.56% (98.86%)	95.16% (85.80%)
Flower	96.29% (81.57%)	99.78% (99.47%)	94.80% (87.26%)	99.61% (98.58%)	95.54% (84.32%)
Statue	95.06% (77.94%)	99.71% (99.25%)	93.09% (81.96%)	99.48% (98.18%)	94.06% (79.90%)

Table 2: Comparisons of detection accuracy with corruption percentage 10%.

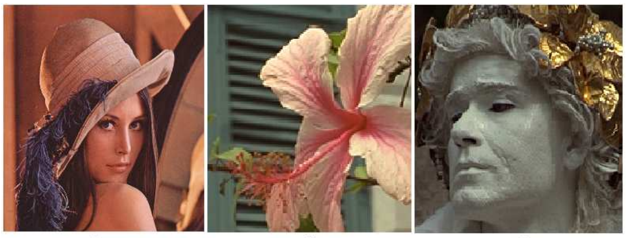
NPGF (IFPGF)	recall	specificity	precision	accuracy	F-measure
Lena	96.92% (96.71%)	99.67% (98.04%)	96.66% (79.71%)	99.40% (97.91%)	96.79% (87.39%)
Flower	98.30% (90.38%)	99.58% (98.84%)	95.56% (87.73%)	99.45% (97.99%)	96.91% (89.04%)
Statue	97.55% (86.32%)	99.34% (98.35%)	93.20% (82.99%)	99.16% (97.15%)	95.33% (84.62%)

Table 3: Comparisons of detection accuracy with corruption percentage 20%.

NPGF (IFPGF)	recall	specificity	precision	accuracy	F-measure
Lena	98.24% (98.15%)	99.21% (95.87%)	96.62% (81.63%)	99.02% (96.33%)	97.42% (89.13%)
Flower	99.11% (94.12%)	98.90% (97.38%)	95.16% (88.43%)	98.94% (96.73%)	97.09% (91.19%)
Statue	98.55% (93.01%)	98.64% (96.64%)	93.95% (84.86%)	98.62% (95.91%)	96.20% (88.75%)

Table 4: Comparisons of detection accuracy with corruption percentage 30%.

NPGF (IFPGF)	recall	specificity	precision	accuracy	F-measure
Lena	98.67% (98.30%)	98.84% (93.76%)	97.11% (83.62%)	98.79% (95.12%)	97.88% (90.37%)
Flower	99.02% (94.59%)	98.39% (96.25%)	95.90% (90.43%)	98.58% (95.75%)	97.44% (92.46%)
Statue	98.85% (94.38%)	97.61% (94.53%)	94.00% (86.04%)	97.98% (94.49%)	96.36% (90.02%)



(a) (b) (c)

Figure 2: Three typical test images, (a) Lena, (b) Flower, and (c) Statue.

4. CONCLUSION

We propose a novel peer group-based filtering method to reduce the impulse noises for the color images. The key contributions of this work are two-fold. First, we propose that the impulse noise detection is performed in the CIELab, instead of the RGB, color space to enhance noise detectability. Secondly, the proposed method employs two different-sized windows in determining the status for each pixel, alleviating the problems in correcting non-corrupted pixels in the neighborhood of edges in the textured regions. Experimental results demonstrate that the proposed NPGF method achieves better detection ability in terms of all the accuracy measures considered when compared to the IFPGF method.

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